Proceedings of the Sixth International Brain-Computer Interface Meeting: BCI Past, Present, and Future

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Foreword

The International Brain-Computer Interface (BCI) Meeting Series occupies a unique place among conferences for BCI research by bringing together researchers and stakeholders from diverse disciplines. Neurologists, computer scientists, rehabilitation engineers, physicians, sensor engineers, psychologists, speech-language pathologists, ethicists, and actual BCI users are all active participants in the BCI Meeting Series. Further, the inclusive, retreat-like atmosphere of the BCI Meeting Series provides extensive opportunities for interaction and development of collaborations.

Growing interest expressed in discussions over the course of the BCI Meeting Series (1999, 2002, 2005, 2010, and 2013) led to the establishment of the BCI Society in 2015. The purpose of this international society (http://bcisociety.org/) is "*to foster research and development leading to technologies that enable people to interact with the world through brain signals*." To further this purpose, the BCI Society is organizing the Sixth International BCI Meeting from May 30th – June 3rd, 2016 at the Asilomar Conference Grounds in Pacific Grove, California, United States. The 2016 BCI meeting has a theme of BCI: Past, Present, and Future. The diversity of BCI researchers represented in the planning of the 2016 BCI meeting has resulted in a vibrant, exciting Meeting with more collaborative, interactive activities and increased involvement from the many sectors that make up BCI research.

The papers in these Proceedings show the diversity of applications for which BCIs are developed and the diversity of data and analyses that contribute to progress in BCI research and the development of BCI products. Intended applications for people with impairments include control of assistive devices, communication, and therapeutic effects for rehabilitation. Applications also extend beyond user groups of people with physical impairments. BCIs are being used for basic research to discover more about brain function, neural feedback and brain-training, and a variety of entertainment applications, both for people with impairments and for the general population.

Together, the 2016 BCI Meeting and its Proceedings represent the breadth of BCI research and help us to build on the rich past of BCI research, leverage the diverse and exciting present, and create a future of BCIs as successful, beneficial tools both for people with disabilities and for the general populace.

On behalf of the BCI Society and the Program Committee for the 2016 BCI meeting, I thank you for your interest in the BCI Meeting and hope to see you at this and future installments in the BCI Meeting Series.

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A New Region-based BCI Speller Design using Steady State Visual Evoked Potentials

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Introduction: To implement a brain computer interface (BCI) system, one approach is to use repetitive visual stimuli that develop stable voltage oscillation pattern in electroencephalogram (EEG), namely steady state visual evoked potential (SSVEP). Paradigm presented in this paper was designed to create a SSVEP BCI speller that is based on our previous work in P300 region-based speller [1].
Material, Methods and Results: Figure 1 depicts the visual stimuli as presented on a computer screen. Instead of LED light sources [2], a computer monitor is used to present fast flickering graphical display which is also efficient for instant manipulation of the types of characters including their size, color and adjacency [3]. The implementation was done using PsychToolbox [4] inside MATLAB. The speller paradigm in this study contains seven different group of characters placed on seven locations on the screen [1]. In our earlier study, four different paradigms (single character; row/column; regions with alphabetical order; and regions with the frequency of the characters' usage) were compared [5]. However, the region based paradigm with the frequency of characters' usage outperformed others with more than 90% spelling accuracy. In the proposed SSVEP design (Figure 1), the outermost circular boundary of each region encloses a combination of different geometrical shapes such as a cross vanishing point and a flickering circular bubble. SSVEP frequencies of 15, 16, 17, 18, 19, 20, and 21 Hz were selected for seven regions. In this two-level paradigm, after a region is selected in the first level (Figure 1.a), a character from the same region is identified in the following level (Figure 1.b). In this design, seven objects were flickering simultaneously and the distance between two such adjacent objects was maintained at as high as 5 cm, thereby reducing the subjects' annoyance and fatigue caused by the crowding effect [5]. It was shown that the user acceptability is higher in region-based paradigm than single character and row/column paradigms [5]. The minimum energy method and a linear discriminant analysis has been applied to classify these EEG signals.

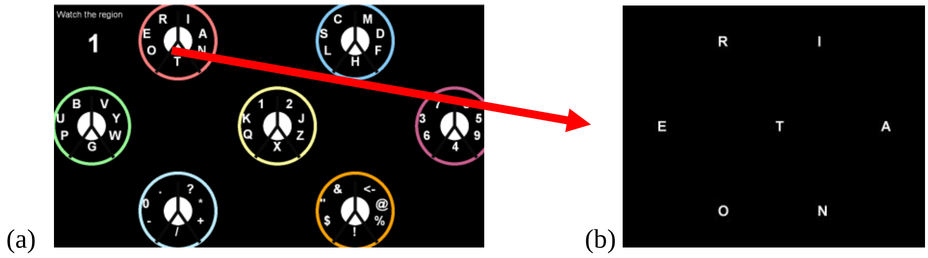

Figure 1. *SSVEP visual stimulation paradigm in level 1 (a) and 2 (b). During the moment the screen shot was taken, the program is asking the user to focus on region one. Each region is colored differenly to indicate that they have different flickering frequency. In the second level, the charcters of the detected region expands as shown on the screen and flicker.*

Discussion: Seven flashing frequency was used in the proposed SSVEP BCI speller paradigm to achieve a speller with 49 characters. The next steps in this study are to (1) combine the proposed paradigm with the P300 region based; (2) compare SSVEP, P300 and hybrid region based paradigms; and (3) compare the developed region-based hybrid speller with the other hybrid spellers [6].

Significance: One of the limitations of a SSVEP paradigms is the number of control commands generated by the SSVEP BCI. In the proposed SSVEP paradigm, 49 characters were controlled only with 7 flickering frequencies. Therefore, the outcome of this study will be a step forward toward implementation of a SSVEP-based BCI in real-life applications.

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A Transfer Learning Approach for Adaptive Classification in P300 Paradigms

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Introduction: The P300 is one of the most widely used brain responses in BCIs today, popularized by none other than the P300 speller itself. However, most systems still require significant subject-specific training to achieve accurate, reliable classification of brain signals. We present an approach to classification that allows for classification with zero subject-specific data and also improves as data is collected. It does this through the use of data from other subjects in order to intelligently regularize the subject-specific solution with a prior over the weight vector. This approach has already been validated on spectral data [1] and so by validating on P300 data as well we show that it is a classification technique that is agnostic to how features are computed from the EEG time series so long as there are multiple subjects or sessions involved. We further introduce a novel method for estimating parameters that drastically reduces the time necessary to implement transfer learning.

Material, Methods and Results: To validate our approach in direct comparison with other approaches on the data we opted to use pre-processing and classification code from a previously validated dataset [2]. Data and code were used as it includes data from both patients and healthy subjects. All participants performed a six-class P300 paradigm over two sessions on two different days. We tested both approaches by taking varying amounts of subject-specific training data from the first session to learn a decision boundary both with our approach and the one from [2]. Then, classification accuracy was computed on the remaining data. In contrast to the approach in [1] we did not cross-validate to determine the mixing coefficient between the prior over previous subjects and the subject-specific data but rather used an iterative maximum-likelihood procedure, which shortened the time to compute the prior over previous subjects to less than five minutes. For each level of subject specific data we generated 50 random partitions into test and training in order to estimate the distribution of single-trial classification accuracies.

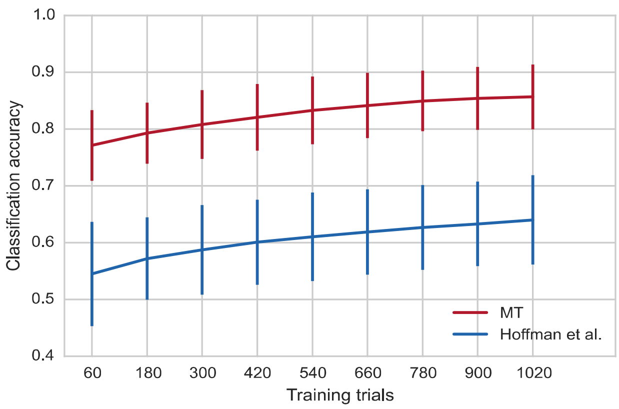

Figure 1. *Plot of single-trial classification accuracy in P300 paradigm for best single-subject approach versus our novel transfer learning approach, averaged over all subjects with 95% confidence interval. Blue shows accuracies achieved with our approach and red shows accuracies with the approach published in [2]*

Discussion and Significance: The problem of varying signal statistics across sessions has been widely documented in source identification and classification approaches alike for BCIs. However, the most widely-used methods for dealing with this in the classification domain tend to involve only looking at single subject data. To date, there is no easily applicable paradigm that can deal with both spectral and time-domain features across multiple datasets. Our results show that the method we previously proved to be effective for transfer learning in the case of spectral features can be effortlessly applied to time-domain features as well. While the high number of samples makes the decomposition approach in [1] unnecessary, the regular regression approach is robust to unequal trials from both conditions through the use of bootstrapping, and straightforwards both to understand and use. We hope that the popularization of this and related techniques allows for a general increase in the use of transfer learning throughout the field.

Acknowledgements: We would like to extend our heartfelt gratitude to Hoffman et al. for publicly disseminating their data and related code.

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An Online Brain-Computer Interface Using Dynamically Detected Steady-State Visual Evoked Potentials

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Introduction: The performance of steady-state visual evoked potential (SSVEP)-based brain-computer interfaces (BCIs) has been considerably improved in the past few years [1, 2]. In conventional SSVEP-based BCIs, the speed of a single target selection is fixed towards high performance based on the analysis of preliminary offline data. However, due to inter-trial variability, the optimal selection time to achieve sufficient accuracy could vary across trials. To optimize the performance of SSVEP-based BCIs, our previous study proposed a dynamic stopping method that can adaptively determine the selection time in each trial by applying the threshold to the probability of detecting a target [3]. This study aims to extend our previous study to demonstrate the feasibility of the dynamic stopping approach in an online BCI system.

Material, Methods and Results: This study employs the dynamic stopping method based on a Bayesian approach proposed in our previous study [3] to reduce the average selection time without decreasing the target identification accuracy in online operation. Fig. 1 depicts the diagram of the proposed online BCI system. In the training phase, target identification accuracy for different data lengths was calculated based on the combination method of the canonical correlation analysis (CCA) with individual training data [4] and the filter bank approach [5]. Subject-specific probability density functions of the likelihood for target and non-target feature values were estimated by kernel density estimation with individual optimal data length that led to the highest accuracy. In the online operation, posterior probabilities for target and non-target classes are calculated based on the Bayes' rule with sequentially obtained electroencephalogram (EEG) signals from a data buffer. This process is repeated every 100 ms until the posterior probability of single trial feature values meets the stopping criterion. Here, all of data stored in the buffer are used for feature calculation to maintain the reliability of the probability distribution. Once the posterior probability exceeds a threshold derived from the training phase, target identification is conducted by the aforementioned method and the buffer is flushed.

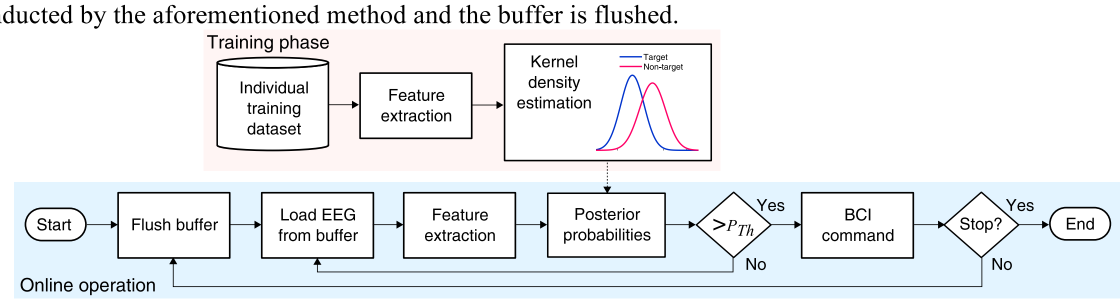

Figure 1. *Diagram of the proposed online SSVEP-based BCI system with the dynamic stopping method.*

Discussion: In our previous study, the simulated online experiments showed that the dynamic stopping method could reduce the averaged selection time compared with a conventional fixed stopping method with comparable accuracy [3]. As the result, the simulated online information transfer rate (ITR) with the dynamic stopping method was also significantly higher than that of the fixed stopping method. Based on these results, the proposed system has potential to significantly improve the online performance of SSVEP-based BCIs.

Significance: The proposed online SSVEP-based BCI system with the dynamic stopping method has the potential to lead to numerous applications that require high-speed communication for both patients with motor disabilities and healthy people.

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Bio-inspired Filter Banks for SSVEP BCIs

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Introduction: Brain-computer interfaces (BCI) have the potential to play a vital role in future healthcare technologies by providing an alternative way of communication and control [1]. More specifically, steady-state visual evoked potential (SSVEP) based BCIs have the advantage of higher accuracy and higher information transfer rate (ITR). In order to fully exploit the capabilities of such devices, it is necessary to understand the features of SSVEP and design the system considering its biological characteristics. This paper introduces bio-inspired filter banks (BIFB) for a novel SSVEP frequency detection method. It is known that SSVEP response to a flickering visual stimulus is frequency selective and essentially gets weaker as the frequency of the stimuli increases. In the proposed approach, the gain and bandwidth of the filters are designed and tuned based on these characteristics while also incorporating harmonic SSVEP responses.

Material, Methods and Results: In order to test the proposed BIFB method, two datasets available online (i.e. AVI [2], RIKEN-LABSP [3]) are used in this study. Initially, higher bandwidth and gain are set to frequencies with low SSVEP response in the BIFB design. Subsequently, these parameters are optimized for individual users in order to counter frequency selective nature of SSVEP response. Fig.1 presents BIFB design for the first dataset and reveals frequency selective nature of the SSVEP response. The second filter bank in Fig. 2 designed for RIKEN-LABSP dataset deals with the weakening of SSVEP response as the frequency increases.

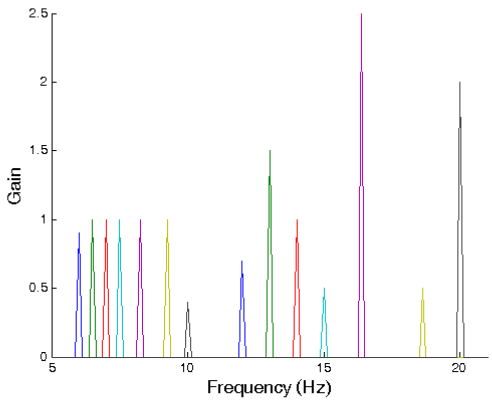

***Figure 1**. Sample BIFB design for AVI Dataset.*

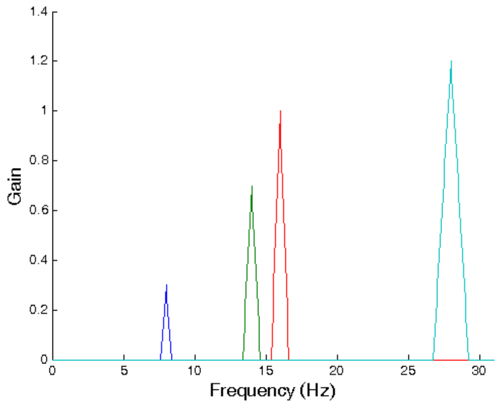

***Figure 2**. Sample BIFB design for RIKEN-LABSP Dataset.*

Once the BIFB parameters are trained the EEG signal is preprocessed (filtering, windowing, etc.) and power spectrum is estimated by multiplying each signal's FFT with the BIFB in order to obtain the class value for each target frequency. The SSVEP frequency is labeled as detected when the same class occurs as maximum at least three times in the last four iterations. The BIFB method achieved reliable performance when compared with two well-known SSVEP frequency detection methods, power spectral density analysis (PSDA) and canonical correlation analysis (CCA). For example, BIFB provided %97.8 accuracy, whereas CCA and PSDA provided %89.1 and %83.7 respectively on AVI dataset. Although, the mean detection time was shorter for CCA method (4.9 sec), BIFB (7.4 sec) achived comparable ITR performance due to its higher accuracy [4].

Discussion: The results show that the BIFB method provides both reliable accuracy and sufficient ITR performance which is comparable with CCA due to its bio-inspired design. It is true that BIFB requires a longer training, or calibration process compared to CCA. However, the preliminary results shows that even without any training, using a non-user specific filter bank design, the accuracy of BIFB is still comparable with CCA.

Significance: This method not only improves the accuracy but also increases the available number of commands by allowing use of stimuli frequencies which elicit weak SSVEP responses.

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Boosting BCI accuracy using wavelet enhanced CBLE scores as a classifier feature

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Introduction: Thompson et al., 2013 proposed a classifier based latency estimation technique (CBLE) for estimating Brain-Computer Interface (BCI) performance [1]. The method itself provides the classifier scores as a function of time shifts, which can be used to estimate P300 latency. Here, we have used the wavelet approximation coefficients of the CBLE output to predict characters in an attempt to account for latency jitter.

Material, Methods and Results: This work is an offline analysis of data from [1]. We used only data from the 10 participants with amyotrophic lateral sclerosis (ALS). In [1] there were three data files on each of three days; this study includes data from all three files on day one, and only one file each from day two and three.

Figure 1 shows the classifier scores as a function of time shifts from an ALS participant. We can see smooth peaks around 0 time shift in the scores for target characters that are absent for non-target characters. We computed the wavelet approximation coefficients of those scores and used them as classifier features for a support vector machine (SVM). Using only one data file from the first day, we selected the daubechies-4 mother wavelet.

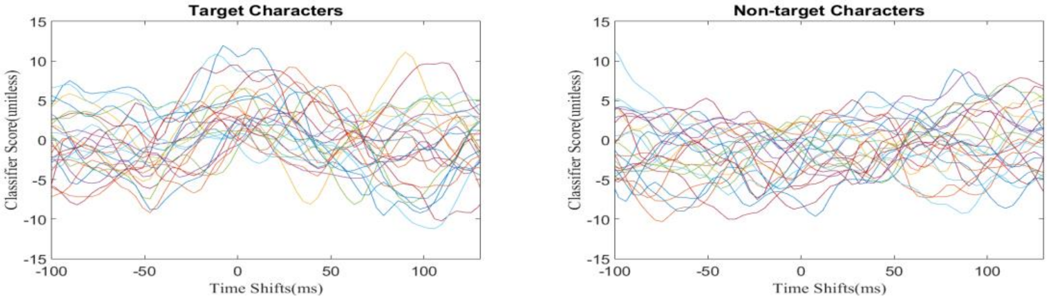

Figure 1. *Classifier scores as function of time shifts from CBLE method.*

Table 1 shows the performance of the proposed technique. Session one accuracy is the average of three files. The technique outperformed the original classifier for the four participants with the lowest online accuracies. The improvement was consistent across days: three participants had improved accuracy while a fourth was equivalent.

Subjects		**K145**	K146	K147	K152	K154	**K155**	K156	K158	**K159**	**K160**
Average Accuracy in Session 01 (%)	Online	58.89	96.29	95.14	90.26	93.22	59.90	93.05	88.00	81.14	70.56
	Wavele	61.11	94.44	93.86	91.33	93.22	62.96	93.05	86.00	82.00	73.94
Average Accuracy in Session 02 & 03 (%)	Online	85.00	86.65	82.42	49.07	0	69.36	88.14	57.83	80.67	32.14
	Wavele	91.93	88.37	85.60	45.37	0	73.34	86.29	58.67	83.42	32.14

Table I. Performance in different environments on Session 01 and performance on other Session.

Discussion: The technique appears to be helpful for the users with low accuracy. Note that while the accuracy changes are small, the change in user-corrected throughput can be significant. K155's 3 and 4 percentage-point improvements in accuracy correspond to 46.25% and 20.54% improvements in BCI-Utility [2]. For K145 and K159 improvements are 15.30%, 18.18% and 3.21%, 8.94%, respectively.

Significance: This method may help to improve the accuracy of the BCI system for those users who have low online accuracy with least-squares classifiers. Users with accuracies near 90% will not benefit.

Acknowledgements: The data were collected under NIDRR grant H133G090005 and award number H133P090008. The opinions and conclusions are those of the authors, not the respective funding agencies.

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Context Aware Recursive Bayesian Estimation in BCI for Graph Navigation

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Introduction: Noninvasive BCIs, specifically the ones that utilize EEG for intent detection need to compensate for the low signal to noise ratio of EEG signals. In many applications, the information from temporal dependency of consecutive decisions and the contextual data can be used to provide a prior probability for the upcoming decision [1]. In this study we proposed two probabilistic graphical models (PGMs), which use context information and previously observed EEG evidences to estimate a probability distribution over the decision space in graph based decision-making mechanism. In this approach, user navigates a pointer to the desired vertex in the graph in which each vertex represents an action. To select a desired vertex, either user utilizes a "Select" command, or a proposed probabilistic selection criterion (PSC) can be used to automatically detect the user intended vertex. We compare the performance of different PGM and decision criteria combinations, over a keyboard as a graph layout.

Material and Methods: In a hierarchical/pointer-based decision-making mechanism the user navigates the pointer in the connected graph with n vertices (number of actions) of degree m (number of EEG classes or the cardinality of decision space) to choose from several actions. Each navigation sequence to a desired vertex is finalized by a selection, based on a selection criterion. Here a sequence of navigations which lead to an action selection is called an epoch. Fig. 1, (a) represents a PGM used for the action/direction joint maximum a posteriori (MAP) inference and (b) shows the PGM utilizing the grid structure to estimate the direction of interest while marginalizing out the actions. In both models, the prior probabilities over the vertices are recursively updated as the user is navigating throughout the graph. The goal, is to estimate the next pointer location, s_{e_t}, at epoch e and iteration t. Here the context information, ω_e, defines a prior distribution over the actions. Moreover, X_{e_t} is the EEG evidence corresponding to s_{e_t}, and L represents graph structure. In graphical model (a), T_e represents the true state of the system in epoch e. Finally, in (b) y_{e_t} is the desired pointer location at iteration t of epoch e; and A represents a particular action assignment on the graph. Two decision criteria for epoch conclusion was utilized; first the user need to choose a "Select" command, second, if the ratio of the current pointer location probability, to the next most probable action exceeds a predefined threshold the system selects highlighted vertex. In this manuscript we refer to this condition as PSC.

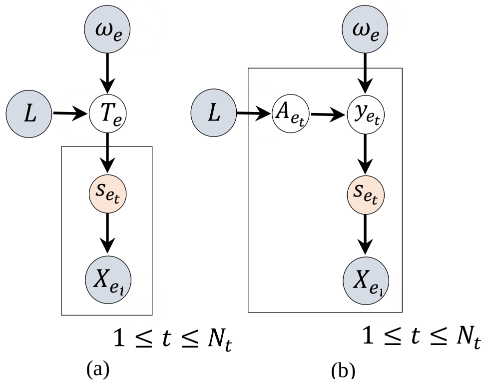

Figure 1. *Two proposed probabilistic graphical models.(a) joint inference. (b) marginalizing the estimated action probabilities.*

Results: In this study, a code visually evoked potential (c-VEP) based BCI gridded keyboard with 28[1] characters utilized to assess the effectiveness of PGMs and stopping criteria pairs. Here each character in keyboard represent one vertex of four degree in graph; $n = 28, m = 4$. 6-gram language model provide context information for each character. Twenty Monte Carlo simulations were used to mimic the system operation while typing ten different words. Seven pre-recorded calibration data sets with high, average, and low accuracies were utilized to run these simulations. Fig. 2 indicates using PGMs enhance the typing speed. This effect is clear on the performance of the users with low EEG classification performance. Overall, the PGM in figure1 (b) along with PSC provided the highest performance improvement. However, when the context information is more reliable, the PGM in Fig. 1 (a) along with PSC gave the best performance.

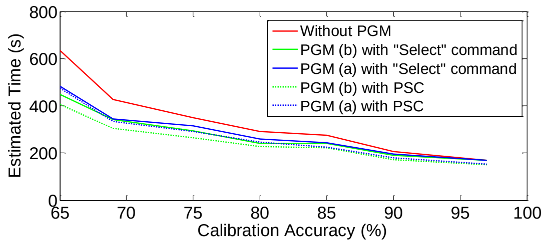

Figure 2. *Average estimated time based on 20 Monte Carlo simulations, to type ten words, employing different PGMs.*

Discussion and Significance: In this study, we proposed two PGMs which use context information and previously observed EEGs in addition to the EEG recorded during the current iteration. Our simulation results show PGMs along with PSC can enhance the typing speed especially for users with poor EEG classification performance.

Acknowledgement: This work is supported by NIH 2R01DC009834, NIDRR H133E140026, NSF CNS-1136027, IIS-1149570, CNS-1544895. For supplemental materials, please see http://hdl.handle.net/2047/D20199232 for the CSL Collection in the Northeastern University Digital Repository System.

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[1] 26 English alphabet letters, space and backspace symbols

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EEG Clustering Based on Phase Synchrony for Self-paced BCI Development

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Introduction: Task-dependent neural synchronization is a general phenomenon which has been theoretically and empirically linked to the dynamic organization of communication in the nervous system [1]. Hence, the study of phase synchrony patterns over time during a specific mental task might be useful to determine if such a task is suitable for self-paced BCI control. This work presents a method for analyzing the dynamics of instantaneous phase between EEG channels over a single trial via clustering using circular statistics for directional data over varying frequency ranges. Time-Frequency-Topography (TFT) maps [2] are used to visualize the distribution over the scalp of clusters of channels that are considered highly phase-locked.

Material, Methods and Results: The clustering method consists of the following steps: a) computation of the continuous wavelet transform of each channel with a complex Morlet wavelet at varying frequencies, b) extraction of phase information per epoch, c) generation of clusters (channel wise) according to phase-locking calculation for each time *t*. In order to gauge the degree of phase-locking and formation of clusters, we used the length of the so-called mean resultant vector $\bar{R}$, which is the foremost quantity for measurement of circular spread in directional statistics [3]. Length of $\bar{R}$ is close to 1 when EEG channels are highly phase-locked; it is close to zero otherwise (Fig. 1a). d) Construction of the TFT maps over specified time windows. Each topographic map represents the cluster modes of all samples for each electrode within the time window (Fig. 1b).

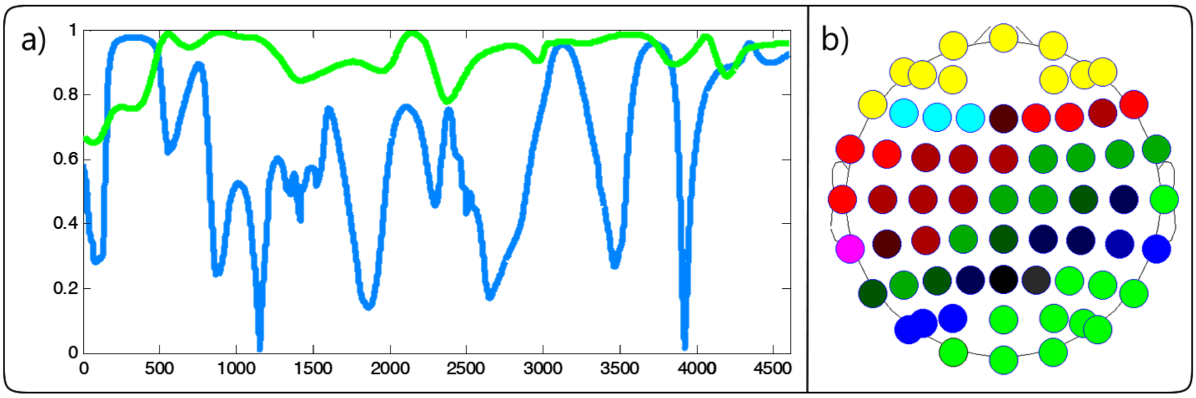

Figure 1. *a) Comparison between length values of $\bar{R}$ for each time t in a 18 seconds epoch of baseline (blue) and during imagined singing (green) for a group of EEG channels, centered at 12 Hz. b) Example of a TFT map, at 500 ms, centered at 7 Hz.*

Discussion: Our method provides a feasible way to address the analysis of phase-locking of EEG signals within single trials and characterizing their variability over time. As observed in Fig. 1a, it seems that values of vector $\bar{R}$ could be an effective feature for classification, which are clearly distinct between both conditions (baseline & imagined singing). We have developed a toolbox for both MATLAB and GNU Octave that implements our method and generates TFT maps, among other functionalities for asynchronous BCI design.

Significance: The majority of phase-locking measures so far suggested in literature, such as Phase-Locking Value (PLV) or Phase Cross Coherence (PCC) are calculated between two signals. The proposed method is an alternative for studying the behavior of the phase synchronization between all EEG channels at once in a given time window, within different bandwidths of interest.

Acknowledgements: CONACyT scholarships 271659 and 1077206.

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FLashLife™:A Context Aware Solution for Everyday Life

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Introduction: Brain Computer Interfaces (BCIs) have been under research and development for decades. Different brain responses are utilized such as Event Related Potentials (ERPs), P300, Visually Evoked Potentials (VEPs) and Event Related Synchronization / Desynchronizations (ERSDs). Every response has its own strengths and weaknesses. Mostly, BCIs have been utilized for specific tasks such as typing or control. However, every system needs some training, and it takes time to build the habit to use it comfortably.

FlashLife™; A system capable of supporting different applications through the same stimulation method. The main applications supported by FlashLife™, are FlashType™, FlashNav™, FlashGrab™, and FlashPlay™. FlashLife™, provides fast, reliable, robust classification while using only a single EEG electrode placed on the center of the visual cortex, at Oz. Taking advantage of code Visually Evoked Potentials (c-VEPs) and stimuli optimization [1], decision rate of 1 Hz and accuracies in the high 90s, a reliable channel for the participants is provided to interact with their target applications. In addition, calibration only takes less than three minutes and it is not required frequently. Individuals with gaze control can use FlashLife™ with eye tracking as an alternative input modality. A battery of *Calibration* sessions can be used for every user to optimize system parameters such as presentation rate and stimuli size and color and boost the performance even further. Stimuli roles play a key role in adaptability of FashLife™.

FlashType™; A context aware language independent typing brain interface [2]. It provides the user with a cursor, capable of navigating throughout a grid of symbols. The number of symbols is adjustable based on user preferences; default setting provides 28 symbols including the 26 English alphabet letters and space and backspace symbols. This keyboard consists of three main parts, *Static Keyboard*, *Character Suggestion*, and *Word Prediction*. By default, using a 6-gram language model and typing history, 7 highly probable characters and 3 most probable words are estimated and presented to the user. FlashType™, incorporates all the EEG collected from the user while navigating throughout the keyboard to make every selection. The separation among the keyboard and the stimuli makes the keyboard language independent. Users can rearrange the symbols in the *Static Keyboard* as they prefer. In the initial study, novice users have been able to reach rates of 6 seconds per character and build the habit of using different parts of the keyboard in just a few minutes.

FlashNav™; A context aware navigation brain interface. It can be used to navigate a wheelchair or control a robot remotely. Information such as environment map, objects and locations of interest and user habits can be used to boost the probabilistic decision making performance. In addition, destination selection along with autonomous navigation and collision avoidance mechanisms can decrease the cognitive load on the user.

FlashGrab™; A context aware object manipulation brain interface. Using Baxter, a low cost humanoid robot, and image processing techniques, graspable objects are detected[3] and labeled with numbers. A video feed shows the robot perception with the overlaid labels to the user. Depending on the number of graspable handles, a direct or a multistep decision will be made by the user.

FlashPlay™; An interface to a virtual environment such as a maze or a floor map. Training and entertaining the user are the main goals. Using a virtual environment makes the setup much simpler. A series of Mastery tasks have been designed with different difficulty levels, taking advantage of the probabilistic classifier and the virtual environment, to help the users to build the habit of using the system and attending to the stimuli effectively.

Significance: FlashLife™, considering user comfort, is the first its kind capable of providing means for the major needs in everyday life of a person i.e. control and communication, all through the same stimulation method.

Acknowledgements: This work is supported by NIH 2R01DC009834, NIDRR H133E140026, NSF CNS-1136027, IIS-1149570, CNS-1544895. For supplemental materials, please see http://hdl.handle.net/2047/D20199232 for the CSL Collection in the Northeastern University Digital Repository System.

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FlashType™:A Context Aware, Language Independent, Typing System using c-VEP or Eye Tracking

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Introduction: Communications have been one of the main motivations behind brain computer interfaces (BCIs). Different brain responses have been utilized towards building typing applications. Event Related Potentials (ERPs) and more specifically P300 responses have been used in different paradigms such as matrix or rapid serial visual presentation. In addition, Visually Evoked Potentials (VEPs) and its variations Steady State Visually Evoked Potentials (SSVEPs) and code Visually Evoked Potentials (c-VEPs) also have been utilized towards typing applications. While some methods have shown positive results, still the accuracy and robustness are big concerns. In these methods, characters are playing a role as part of the stimuli, which in turn makes factors such as the font and the size of the characters important. For example, similarly looking letters such as ‘O’ and ‘Q’ produce a weaker P300 response and letter ‘I’ produces a much weaker VEP response comparing to ‘B’.

Method: Taking advantage of our four stimuli c-VEP based system; we designed a cursor based typing interface. One of the key advantages in our design is the separation of the stimuli and the keyboard. Using a checkerboard based stimuli makes the system completely independent from the alphabet letters used in the keyboard. Stimuli consist of 4 reversed pattern checkerboards. Four different m-sequences of length 63 bit are used to control the flickering pattern at a bit presentation rate of 110 Hz. This translates to average decision time of less than a second. The probabilistic classifier will gather more trials if the confidence doesn’t reach a predefined ratio [1].

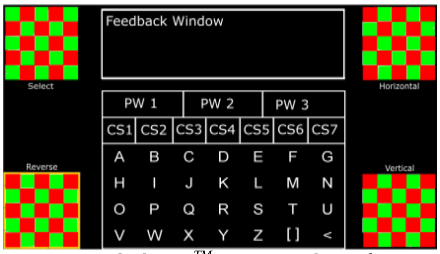

Figure 1: FlashType™ screen shot, first row Predicted Words (PW), second row, Character Suggestions (CS), third part is the Static Keyboard.

Keyboard consists of three parts, *Static Keyboard*, *Character Suggestions* and *Predicted Words*. In the default setting, the *Static Keyboard* consists of the 28 English alphabet letters and space and backspace symbols. A language model is used to estimate the probability of every letter while selecting the next character. These probabilities are marginalized towards the four commands based on the location of the cursor. The graphical model used to make the selections is described in a concurrently submitted journal paper [2]. Language model is put to two other uses as well, suggesting a few characters (~7) with the highest probability and predicting 3 or 4 highest probable words.

The stimuli provide the user with four simultaneous options, *Select*, *Horizontal*, *Vertical*, and *Reverse* to make a selection, make a horizontal or vertical movement in the active direction and reverse the active direction respectively. For every selection, cursor starts from the most probable character. Figure 1 shows a screen shot of the FlashType™ where PW stands for *Predicted Words*, and CS stands for *Character Suggestion*. CS1 is the default start point of the cursor. The vertical and horizontal movement is circular so the users can use the *Reverse* option to reach to their target on the opposite side of the grid faster. FlashType™, using an auto-scroll mode, can operate using only a single stimulus.

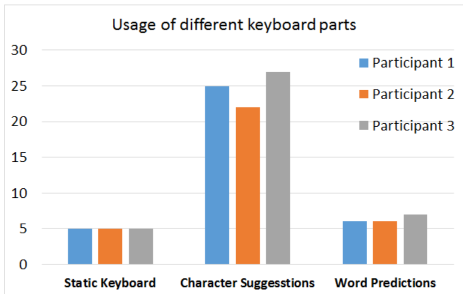

Figure 2: Usage of different keyboard parts by three participants while typing 10 different words.

Results: Figure 2 shows the usage of different parts of the keyboard by three participants while typing 10 different words. *Character Suggestions* have been the most favorite part of the keyboard. Novice users have been able to achieve an average of 6 seconds per character.

Significance: FlashType™, provides a fast, reliable and language independent typing interface, using a single EEG electrode or alternatively an eye tracker. Typing quality is improved using the *Character Suggestions*, *Predicted Words* and by incorporating the EEG from all the movements towards making a selection.

Acknowledgements: This work is supported by NIH 2R01DC009834, NIDRR H133E140026, NSF CNS-1136027, IIS-1149570, CNS-1544895. For supplemental materials, please see http://hdl.handle.net/2047/D20199232 for the CSL Collection in the Northeastern University Digital Repository System.

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Large Scale EC Horizon 2020 research projects: ComaWare and recoveriX

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Introduction: The European Commission recently launched the latest Horizon 2020 research program. The dedicated SME instrument encourages for-profit European SMEs to put forward their most innovative ideas. The instrument aims to fill gaps in funding for high-risk innovation and close-to-market activities to give a strong boost to breakthrough innovation. Brain-computer interface technology has the power to induce a paradigm shift in certain technological and medical application areas. At the moment, g.tec is coordinating two of these projects:

(i) ComaWare – COMmunication and Assessment With Adaptive Realtime Environments [1]

Imagine being able to hear, feel, and think – but not see or move. You cannot communicate in any way, but can hear doctors and family members saying that you are comatose and cannot understand or make decisions. Recent work has shown that this nightmarish situation is a reality for thousands of people worldwide, who have been diagnosed as comatose but may in fact have some ability to understand. More recent work has shown that brain-computer interface (BCI) systems can help with re-assessment of these patients [2].

The system developed in ComaWare consists of active EEG electrodes, a biosignal amplifier, a real-time processing system running the BCI analysis and experimental paradigms, loudspeakers and tactile stimulators. The system is able to run three different paradigms: (i) auditory evoked potentials, (ii) vibrotactile stimulation (with 2 or 3 stimulators for assessment and also communication) and (iii) motor imagery. The signal analysis calculates evoked potentials with statistical analysis for paradigms (i)-(ii) and event-related desynchronization maps for (iii). Additionally, a classifier is trained on the data to obtain an objective classification accuracy. The system was already successfully used with patients in minimal consciousness state or vegetative state (n=15) and gave useful information if the patient can perform the experimental paradigms. A low classification accuracy shows that the patient is not able to perform the tasks; a high classification accuracy shows that the patient can do the tasks and that the patient understood the instruction how to perform the experiment.

The system is currently tested by 10 validation partners in 8 different countries. In addition to providing assessment and communication, our new mindBEAGLE prototype will also be able to provide outcome prediction based on evoked potential analysis and rehabilitation with functional electrical stimulation. In addition to creating a new mindBEAGLE system specialized for severely disabled persons without vision, we will also develop, pilot-test, and launch a novel business focused on providing support for patients, their carers and clinicians.

(ii) recoveriX - Motor Recovery with Paired Associative Stimulation [1].

Patients around the world need therapy to improve motor function. Motor disabilities may result from many causes, including traumatic brain injury (TBI), stroke, congenital conditions and some diseases. New research from G.TEC and others has shown that novel brain-computer interface (BCI) systems can substantially improve motor rehabilitation outcomes while reducing burdens on patients, therapists, and carers. Our new approach relies on paired stimulation (PS), which adds real-time EEG-based analyses of motor imagery to conventional therapy systems. The system consists of active EEG electrodes, a biosignal amplifier, a real-time analysis system running motor imagery BCI experiments and functional electrical stimulators with 2 channels for two muscle groups. Patients are trained for 30 minutes to attempt left or right hand movement with 120 repetitions. The BCI system is able to detect the movement attempt in real-time and triggers the functional electrical stimulation of the muscle of the corresponding arm/hand so that it is actually moving.

The system was already successfully tested with sub-acute and chronic patients, and every patient (n=8) achieved good BCI accuracies and motor function improvements. Functional improvement were assessed with a 9-hole PEG test.

Interesting is that the BCI accuracy is an important marker if patients are participating and that this parameter can be used to coach the patient. It is also important that all patients improved their BCI accuracy with the training and many achieved accuracies above 95% [example in 2]. More importantly the motor functions improved for all patients (even for chronic patients).

The system is currently validated with 10 validation partners in 6 countries. We will also develop, pilot-test, and launch new businesses called recoveriX-Gyms, where patients can train with our system.

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Leveraging Temporal Confusion in P300 Spellers

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Introduction: A P300 classifier's performance depends on the time bin of the target stimulus. For example, a user may generate a different response when presented with a target early or late in a sequence. Further, knowing the target to be unique, a user may relax after seeing it such that pre and post-target P300 absent trials are different from each other.
There is structure to the accuracies and errors of P300 classifier which depend on the time bin a target stimulus is presented in. We aim to encapsulate and leverage this structure to build a speller which offers a better speed-accuracy trade-off. In particular, we incorporate the temporal confusion associated with a particular user-classifier pair for quicker and/or more accurate letter inference [1].

Material: We use g.USBamp, MATLAB and Psychtoolbox to build and simulate our BCI.

Methods: We describe the temporal confusion of a user-classifier pair by $P(\hat{X}|X)$ where X is the index of the unique time bin where the P300 is generated and $\hat{x}$ is our estimate. We estimate this confusion matrix by normalizing a count of our classifier's cross validated performance on a labeled training set. See Fig 1 for example.
The user-classifier pair of Fig 1 shows strong accuracy when the target is in the 4th time bin. Given this fact, we ought to trust a classification in favor of the 4th time bin more as it offers stronger evidence. We offer a Bayesian update which leverages this temporal confusion of P300 classifications; it accounts for the varying accuracy of each time bin in updating letter probabilities.

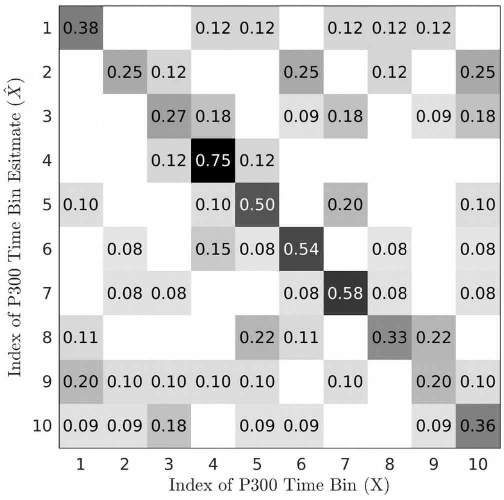

Figure 1. The temporal confusion matrix $P(\hat{X}|X)$ for a particular user-classifier pair. Note that this user-classifier shows stronger performance for targets which occur towards the middle of a sequence.

Results: As a preliminary work, we contrast the performance of an *Aware* decision scheme which uses the temporal confusion of Fig 1 against a *Naive* decision scheme which assumes accuracy is uniform across different target time bins. We simulate 100 recursive decisions (querying with a P300 sequence until a sufficient threshold is reached) under 4 different confidence thresholds. Fig 2 demonstrates that using this temporal structure can improve the speed-accuracy trade-off.

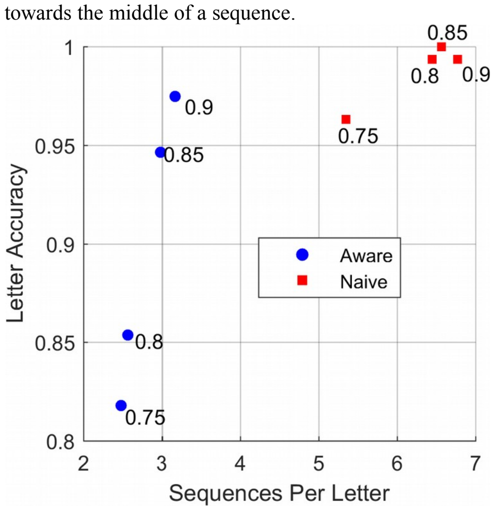

Figure 2: Each point represents the average of 100 decisions; probability thresholds are labeled next to their respective data points. In this simulation, the temporal confusion aware decision rule offers a better speed-accuracy tradeoff curve.

Discussion: While our simulation shows strong performance improvement, note that the *Aware* decision scheme has knowledge of the ground truth $P(\hat{X}|X)$ which the *Naive* doesn't. In practice we must estimate this distribution; we cannot provide a benefit without accurately doing so.

Some time bin classifications offer stronger evidence than others. In addition to performing letter inference, we seek to leverage the temporal confusion to construct stronger queries. Namely, we seek to arrange letters within the stimuli sequence such that we generate, on average, as strong evidence as possible.

Significance: For some user-classifier pairs, P300 classification accuracy strongly depends on the position of the target within the sequence. There may be a speed-accuracy benefit to leveraging this structure.

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Multisensory Stimulation Framework for BCI-based Communication in the ICU

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Introduction: Patients in the intensive care unit (ICU) often suffer from delirium, a mental condition that involves disorganized thinking, general confusion, and sometimes, hallucinations. Caretakers screen for delirium regularly since it affects 2 out of 3 hospitalized patients and is correlated to morbidity in the ICU [1]. The screening process requires verbal or physical methods of communication (e.g. eye blinks or hand squeezing); however, endotracheal tube and mechanical ventilators as well as traumatic brain injuries may prevent patients from communicating effectively. Brain computer interfaces (BCI) could potentially help patients who lack the motor control necessary for basic forms of communication. In this work, we present a multisensory stimulation framework for multi-modal BCIs.

Materials: EEG data acquisition is performed with g.USBAmp and MATLAB. Stimulus control is performed by a Beaglebone Black. The physical interface of the stimulation module is comprised of C-3 tactors (tactile), headphones (audio), and 5x5 LED arrays (visual). Visual and tactile stimuli are driven by a Xilinx Spartan3E FPGA. The audio stimulus is driven by a USB DAC.

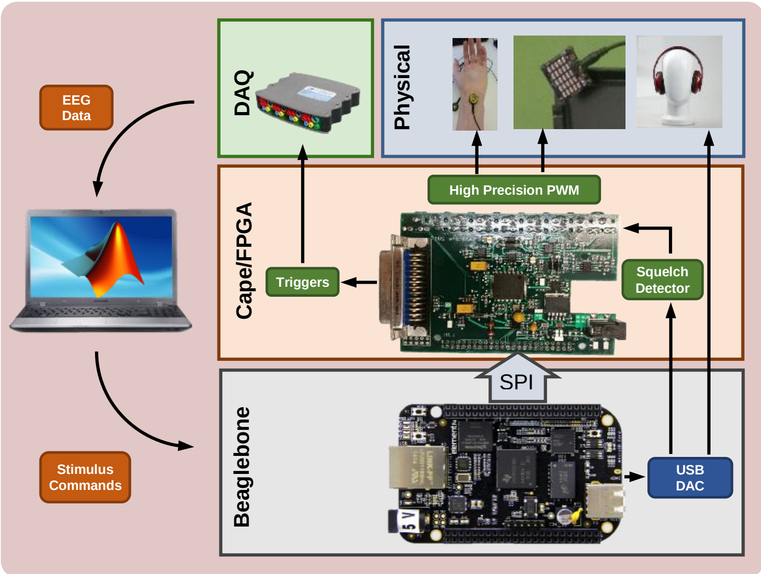

Figure 1: System diagram of multimodal stimulation framework.

Methods: The proposed system enables the user to communicate through visual, auditory, and tactile stimulation. Figure 1 shows the system diagram of the stimulus framework. A Beaglebone Black is used to control the stimuli and communicate with the main BCI application. The network interface is implemented using OpenDDS, a real-time publish-subscribe communication module. The visual stimulus is delivered using a set of LED arrays (4 channels) driven by a platform with a FPGA. The BCI developer can configure run-time frequency, pattern, and brightness with pulse width modulation (PWM) for each stimulus channel. Similarly, the tactile module is driven by the same FPGA, thus allowing users to configure and send vibration waveforms to the C-3 tactors (4 channels). Because of the FPGA size limitations, the audio stimulus module is driven by USB DAC. To satisfy the need for accurate stimulus timings, the hardware sends precise start-of-stimulation events (triggers) to the data acquisition component. In the visual and tactile modes, the FPGA outputs a direct trigger signal to the DAQ. In the audio mode, we implemented an external analog circuit that detects a non-audible high-frequency tone embedded in the sound presented to the user. Matlab and C++ APIs were developed to control the stimuli from BCI applications.

Results and Discussion: Trigger timings were all below EEG sample period (2 ms). Visual and tactile stimuli were tested under a binary communication setting with 98% accuracy for visual (3 seconds of SSVEP stimulation) and 70% accuracy for tactile (1 min oddball paradigm [2]). The testing involved asking the users questions from the confusion assessment test. A GUI was developed to run the prototype ICU application.

Significance: By providing a means for physicians to communicate with ICU patients who are unable to speak, or even move, our system could potentially enable the diagnosis of delirium in patients who were unable to be diagnosed before. Furthermore, our multimodal stimulation framework can be used with different BCI applications due to its portability and general communication interface.

Acknowledgements: This work was supported by NSF grant CNS-1136027.

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On the pursuit of classification of EEG recorded during imagined speech

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Introduction: Allowing direct communication is one of the main purposes of BCIs. This was firstly focused on handicapped persons but nowadays its scope has increased to healthy persons, due to the necessity of a private channel of communication, to be used even in public spaces; with less effort than voice and free of audible noise. Nevertheless, common EEG-based BCIs use 4 broad neuroparadigms (SCPs, motor imagery, p300 signals and SSVEPs) that need translation to language domain. Consequently, we are exploring a alternative neuroparadigm called imagined speech, which refers to the internal pronunciation of words without emitting sounds or doing facial movements [1]. Specifically, we used a dataset composed of EEG signals recorded using an EPOC headset from 27 subjects (S1-S27) while internally pronouncing five Spanish words (“arriba,” “abajo,” “izquierda,” “derecha” and “seleccionar”) corresponding to (“up,” “down,” “left,” “right” and “select”).
Material Methods and Results: We are facing this issue following three approaches developed in a parallel way. They are; multi-objective channel selection, fuzzy classification and EEG textification approaches. The first of them searches for a minimal subset of channels to accomplish the task of recognizing imagined speech. The second approach consists on the assessing of fuzzy classifiers over the EEG classification problem. Finally, the third approach looks for assessing if EEG signals from unspoken words can be better recognized in the text domain through the textual representation of sequences of high energy brain activations.
A) Multi-objective channel selection: A method for channel selection based on a multi-objective approach was implemented, to minimize the error rate using random forest classifier and the number of channels used. This method is based, different from previous works, on a fuzzy inference system (FIS) for automatically selecting a single solution (combination of channels) from the Pareto front. The FIS was composed by three membership functions for each variable (error rate, number of channels and selection level). The method performance was assessed using this channel combination and an unused test set during the exploration of the possible channel combinations. The reduction of channels applying the proposed method achieved similar performance to the method using all the channels; the average accuracies were 68.18% and 70.33%, respectively.
B) Fuzzy classification approach: We assessed two neuro-fuzzy classifiers never applied to the imagined speech classification problem: Adaptive Neuro-Fuzzy Classifier with Linguistic Hedges (ANFCLH) and an ensemble of them based on random subspace (RS), called Fuzzy Random Electrode selection for ensemble (FRESE). FRESE handles all features of each channel as a unique entity unlike RS. For each subject’s data, we applied instance selection guided by artefact removal detected by both independent components and gyroscope signals. Later, discrete wavelet transform and instantaneous energy were computed to create feature vectors of each instance of subject’s data. Later, we classified using ANFCLH and FRESE whose best performances were 66.88% and 71.45%, respectively.
C) EEG textification: In this approach we first obtain sparse time-frequency maps applying the bump modeling algorithm. This technique allows us to transform the brain signal into a map of high energy events. Then we codified every bump modeling map of events as a document of textual sentences. From this document, we obtain the sequence of events applying an N-gram technique. The extracted signal N-grams are reduced applying attribute selection and then classified using a Support Vector Machine (SVM). We obtained an average classification accuracy of 72.63 ±11.92%. Specifically, S8 was the best classified with 81.75 ±11.35% whereas S25 was the worst with 48.31±12.73%.
Discussion: Fuzzy classification obtained similar performance compared to random forest using all channels with 71.45% and 70.33%, respectively. Also, the performance could be statistically kept using around 7 channels selected by the M.O. channel selection method. Finally, the classification results applying EEG textification showed that the consideration of the sequence of events improves the classification of the unspoken words compared with previous works [1]. On the other hand, to provide evidence for the validity of the results gotten during the classification of imagined speech we applied a permutation test ($N = 1000$, $\alpha = 0.05$). Results showed that dependence exists between EEG data and imagined words (p-value≈0.0009).
Significance: Our study provides evidence of the utility of the application of novel techniques as multi-objective channel selection, fuzzy classifiers and EEG textification on imagined speech classification problem.
Acknowledgements: The authors would like to thank the INAOE and the CONACYT for their support in the development of this work.
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Predicting BCI Performance with the Detectability Index

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Introduction: Predicting a user's performance with a BCI is important for several reasons. For example, the predictions can be used to select parameters for the current stimulus paradigm (e.g. the amount of data to collect), to estimate the impact of switching to a new stimulus paradigm, or to avoid the frustrating scenario of a user attempting to use the system despite the low likelihood of success. However, prediction can be challenging since previous performance may not always be indicative of current performance. A previous method to predict P300 speller performance was limited to the row-column paradigm (RCP) and static data collection [1]. With the increased interest in other stimulus paradigms and dynamic stopping algorithms, a generalized method is desirable. We have developed a Bayesian-based method for predicting BCI performance that is independent of stimulus paradigm and accounts for dynamic data collection. The prediction method relies on data that is already available from system calibration and accounts for possible changes in user performance after calibration.

Material, Methods and Results: The focus of this work is on P300 spellers; however, this technique could be applied to any probabilistic decision-based BCI in which 1-of-M choices is selected. A user's performance level with the P300 speller depends on how well the system's classifier can distinguish between target and non-target electroencephalography (EEG) responses. Under a Gaussian assumption, this performance level can be quantified by the parameters of the two class conditional classifier likelihoods via a distance measure called the *detectability index*, d [2]. The classifier likelihoods, and therefore d, can be estimated from the BCI calibration data to initially pre-asses BCI performance, and changes in user performance level accounted for by different d values. Our new method to predict performance for a Bayesian dynamic stopping (DS) algorithm is independent of stimulus paradigm and relies on analytical calculations or Monte Carlo (MC) simulations, parameterized by d.

Given a stimulus paradigm, detectability index and data collection limit, performance estimates can be derived based on the cumulative likelihood ratio for each character. For stimulus paradigms with (i) a two-stage character selection process, (ii) equally-sized and pairwise disjoint flash groups at each stage, and (iii) fixed character-to-flash group assignments during a selection process (e.g. RCP), we derive tractable analytical solutions for approximating accuracy, and the lower bound of the expected stopping time. For other paradigms that satisfy only the last property, we propose an alternate analytic solution to approximate accuracy. Alternatively, performance estimates for any paradigm can be obtained from MC simulations of P300 spelling runs. The proposed methods were initially verified with MC simulations using synthetic and EEG data, and validated with results from several online studies. Fig. 1 shows that the user performances from an online ALS participant study [3] follow the trends predicted by offline simulations, according to their respective detectability indices.

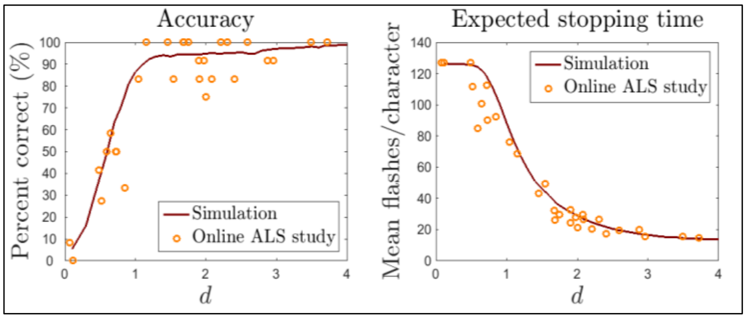

Figure 1. *Online vs. predicted P300 speller performances with Bayesian dynamic stopping using the checkerboard paradigm, based on a user's detectability index, d.*

Discussion: We have shown that the detectability index metric allows us to predict the performance of the Bayesian DS algorithm for a given stimulus paradigm. This provides a convenient way to potentially compare the performance of stimulus paradigms across a range of performance levels prior to online testing. Future work includes using objective performance functions based on the detectability index to develop custom-designed stimulus paradigms that facilitate the distinction between characters via their respective flash patterns, and take into account physiological limitations (e.g. refractory effects) to improve P300 speller performance.

Significance: The proposed method provides a useful tool to pre-asses BCI performance with the Bayesian DS algorithm with a given stimulus paradigm without extensive online testing. It can also be used to determine a suitable data collection limit to achieve a certain accuracy level given a user's performance level.

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Robust, accurate spelling based on error-related potentials

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Introduction: One of the principal goals of brain-machine interface systems is provide a communication channel to users with severe motor disabilities. Here, we describe a novel speller paradigm driven by the decoding error-related potentials (ErrP) [1] and the exploitation of shared-control (or context-aware) algorithms.

Methods and Results: The speller is composed of a character matrix, in which a moving cursor automatically scans the available characters (c.f., Fig. 1 *Left*). Contrasting to conventional systems, the cursor does not move in a pre-defined or a random manner. Instead it moves towards the most probable character as inferred based on the decoding of ErrP (c.f., Fig. 1 *Middle*) and a language model. During operation, users simply monitor the cursor movements, which makes discrete steps between adjacent characters in the matrix every 1000 ms. After each cursor movement, EEG is decoded to detect the presence of an ErrP indicating that the user considers the cursor did not move *towards* the intended character. Then, a reinforcement-learning (RL) algorithm re-estimates the probability of each character to be the next one to be written [2,3] based on the classifier output.

The use of a language model and RL to estimate the character's probabilities makes the system less sensitive to misclassification of the ErrP signal. Experimental tests in simulation showed that the system is able to correctly write the intended words even if there are up to 30% of classification errors. Furthermore, the parameters of the RL-based character inference can be tuned depending on the performance of the ErrP decoding (i.e. the RL learning rates can be higher for those users for whom the ErrP decoder is more accurate, and viceversa).

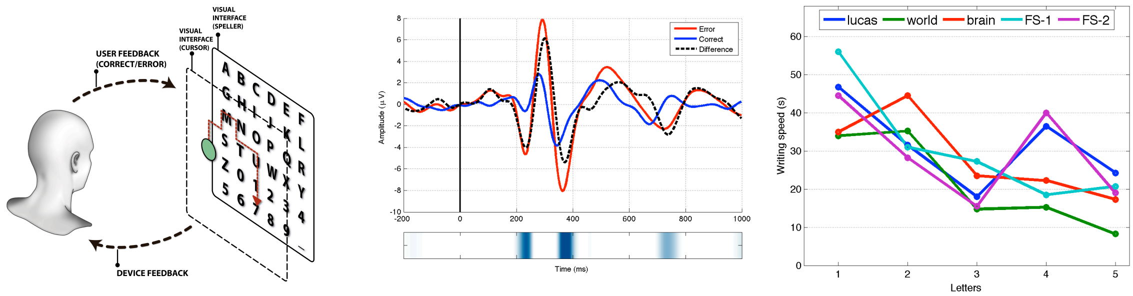

Figure 1. *Left: Diagram of the ErrP-based speller. Middle: ErrPs (FCz electrode) observed in this protocol. Right: Average number of seconds required to write each letter of a five-letter word in the online rund (FS-1,FS-2: Free-spelling runs)*

EEG was recorded using 16 active electrodes over fronto-central, central and parietal areas on healthy subjects (N=4). Signals were filtered in the [1-10] Hz range and decoded using linear-discriminant analysis (same methods as in [3]). Users first went through a calibration period composed of four copy-spelling runs (two five-letter words each), where cursor movements were erroneous 30% of the time. Then, users moved to an online operation phase where they performed 3 copy-spelling runs (words: 'lucas', 'world', 'brain') and two free-spelling runs. ErrPs elicited in this protocol were consistent with previous experiments (Fig. 1 *Middle*). Average decoding performance in the online runs was 0.74, which together with the shared control approach, led to selecting the correct letter 93% of the time for all subjects combined. On average, users took 43.2 s to write the first letter of each word, while this time decreased for subsequent letters (Fig. 1 *Right*). This is due to the use of the RL-algorithm and the language model, yielding an overall average of 28 s per letter (i.e. 2.13 chars/min).

Discussion: The proposed speller paradigm, combining a language model and RL algorithms into a shared-control scheme, allows for efficient typewriting even in case of misclassification of ErrPs. Since the user's task is to monitor the movements of the cursor, (s)he receives immediate feedback on the performance of the system (whether it moves towards the intended letter), as opposed to P300-based systems, where the decoded symbol is only presented after several scanning repetitions. Although evaluation in intended users is yet to be performed, it is worth noticing that ErrP signals have been already reported in subjects with locked-in syndrome [4].

Significance: We present a novel speller paradigm based on decoding error-related potentials. Combination of reinforcement learning and language models yields accurate, efficient typewriting.

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A "yes/no" auditory-based BCI: trying to communicate with complete locked-in patients

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Introduction: Severe motor disabilities can impede communication. The most tragic situation is the locked-in syndrome (LIS), due to a brainstem lesion. This situation can also be met after some severe brain damage or in advanced Amyotrophic Lateral Sclerosis (ALS). In these patients, even brain-computer interfaces (BCI) based on visual event-related potentials could be inefficient due to oculomotor impairments. Recent studies suggest that auditory BCI could restore a communication through a « yes-no » code [1]–[3]. We developed such an EEG-based interface which makes use of voluntary modulations of attention.

Methods: This binary BCI uses repeated speech sounds (alternating "yes" on the right and "no" on the left) corresponding to either standard (short) or deviant (long) stimuli. Users are required to pay attention to the relevant stimulus only. We tested this BCI with 18 healthy subjects and 5 brainstem damaged patients (4 "classical" locked-in and 1 complete locked-in). We report online BCI performance and finer offline ERP analysis.

Results: On average in healthy subjects, BCI accuracy reached about 86% based on 50 questions. Ten subjects had an accuracy above 90%. However, all patients tested so far obtained online performance at chance level. Offline ERP analysis revealed an evoked component to the attended sounds known as the "processing negativity" [4].

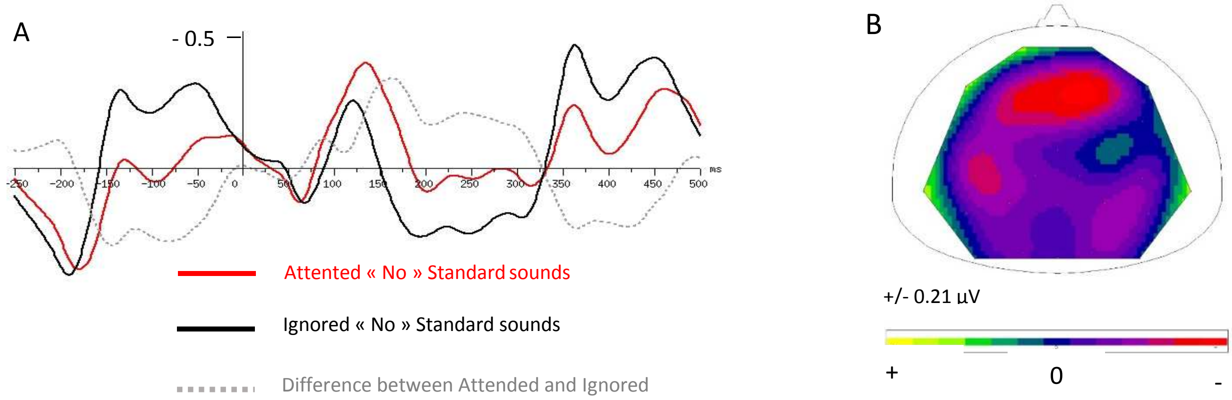

Figure 1: Effect of attention on evoked responses to standards. Grand average data from the 15 healthy subjects with BCI performance above chance level. (A) ERP at Fz location to attended and ignored standards are depicted in red and black, respectively. The difference ERP is represented by a dashed black line. (B) Scalp topography of the difference ERP for time window 150–300ms.

Discussion: To our knowledge, our study is the first to use both attentional ERP to standard and deviant speech sounds. This yields one of the shortest online time to answer (18 sec), which we could reduce down to 6s offline, with no loss of performance. In our study, only three control subjects out of 18 could not achieve online control. In the remaining subjects, accuracy proved fairly high compared to the ones reported in the literature [1]–[3], but still not 100% accurate. The patient study is ongoing. The few tested patients so far had poor BCI performance. This raises important questions on how to adapt BCI protocols from healthy subjects to patients, and eventually to each patient individually [5].

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A user-focused study of auditory P300 brain-computer interface design

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Introduction: Attention-mediated neural signals such as the P300 response allow some paralyzed patients to communicate via a speller device. New auditory speller devices that aid a listener's ability to selectively listen may increase the bit rate of communication. However, basic psychophysical studies probing stimulus design and ergonomic issues are lacking. Furthermore, there are untested usability concerns related to learning and memory load of new fixed-order and alphabetic-based auditory P300 BCI design, such as the new *charStreamer* paradigm [1].

Methods: Trials were divided into three conditions: alphabetic, fixed-order (non-alphabetic), and random (changing order). The alphabetic condition closely matches the *charStreamer* paradigm proposed in [1]: tokens (letters plus several additional commands) were parsed into three spatial locations in alphabetic order (left to right). In the fixed-order condition, tokens with similar pronunciations (like letters 'b', 'c', 'e') were separated. The random condition also began with this same separation of similar letters; however, the ordering was pseudo-randomly shuffled, such that subjects could not predict when the target token would occur. In order to investigate learning effects, data was analyzed at the initial (first 9 trials) and final (last 9 trials) stage of the experiment (27 trials in total). *Behavioral:* To test each subject's ability to detect target tokens in each condition, subjects were asked whether the target occurred once or twice. *Physiological:* Pupillometry is a corollary of the attention-based effort and brain activation in a task [2]. Pupillometry was measured using EyeLink1000 eye tracker. *Subjective:* To assess the subject's experience of cognitive load, the NASA Task Load Index (TLX; [3]) survey was completed after the experiment.

Results: *Behavioral:* There were no significant differences between the accuracies of any condition in the initial trials or the final trials ($p>0.12$, all) or between any one condition's accuracy from initial to the final trials ($p>0.3$, all). *Physiological:* Mean pupil size in the fixed-order condition was significantly greater than alphabetic and random in early trials ($p=0.04$, $p=0.02$ respectively; uncorrected, Fig. 1a). Within the fixed-order trials, mean pupil size decreased from the initial trials to the final trials ($p=0.03$). *Subjective:* Subjects rated the random condition significantly harder than both the fixed-order and alphabetic condition ($p=0.04$, $p=0.0005$ respectively; uncorrected, Fig. 1b). The greater difficulty of fixed-order vs. alphabetic was not significant ($p=0.07$).

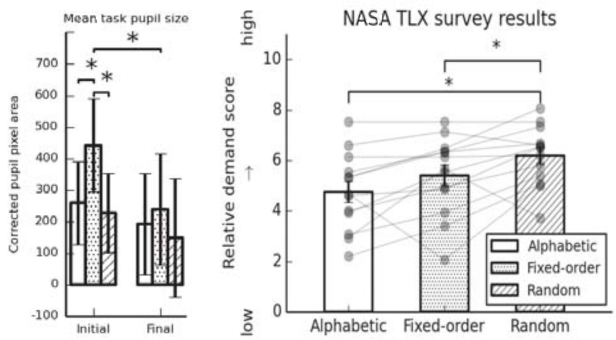

Figure 1. Bars indicate the subject mean (± SEM) *a) Physiological (left):* Mean pupil size (baseline corrected) for each condition for the first 9 trials (initial) vs. the last 9 trials (final). *b) Subjective (right):* Reported weighted difficulty according to the NASA TLX survey.

Discussion: *Behavioral*: Accuracy in discriminating the target was the only measure used that relates each condition to a projected bit rate, thus these findings mainly provide an opportunity to compare usability issues. *Physiological*: The fixed-order condition elicits the highest relative pupil size ($p=0.03$), which is likely due to the relatively high cognitive load involved in memorizing the fixed-ordering—an activity that would not have been necessary in alphabetic-order or feasible in random-order trials. The significant decrease in pupil size for only the fixed-order condition from the initial to final trials (Fig. 1b) suggests that subjects learned and used the fixed-ordering over the course of the experiment. *Subjective*: Subjects rated the fixed-order condition as easier than the random-order condition, which also suggests that they were able to learn the fixed ordering as an informative cue to reduce task difficulty. From these findings we conclude that, with exposure, a paradigm with an arbitrary, but fixed-order presentation, may approach the same usability as a known (i.e., alphabetic) order, whereas an unpredictable pattern may always impact usability. Therefore, alphabetic-ordering or alternative fixed-orderings may increase the usability of speller systems.

Significance: These findings suggest that leveraging both subjective and objective measures of user effort can lead to further optimizations of BCI speller paradigms.

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An Audiovisual BCI for Awareness Evaluation in Patients with Disorder of Consciousness

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Introduction: Currently, clinical diagnosis and awareness evaluation of patients with disorder of consciousness (DOC), such as vegetative state (VS) and minimally conscious state (MCS), relies mainly on behavioral observation scales such as the Coma Recovery Scale-Revised. There exists a high misdiagnosis rate (ranging from 37% to 43%) because these patients cannot provide sufficient behavioral responses. Brain-computer interfaces (BCIs) may represent a potential solution, as they can directly detect the endogenous brain activities. However, there are large differences in both recognition levels and brain signals between healthy subjects and DOC patients with severe brain injuries, it is thus a challenging task to design effective BCIs for these patients.

Material, Methods and Results: In the GUI of our audiovisual BCI, there are two number buttons (two numbers randomly drawn from 0-9) located on the left and right sides, and two speakers are placed laterally to the monitor. The two buttons flash in an alternative manner. When a number button is visually intensified, the corresponding spoken number is presented from the ipsilateral speaker. In this way, the user is presented with a temporally, spatially and semantically congruent audiovisual stimulus that lasts for 300 ms, where the inter-stimulus interval is randomized from 700 to 1500 ms. Ten healthy subjects participated in the first experiment, which consisted of three sessions administered in a random order, corresponding to the visual-only, auditory-only, and audiovisual conditions. In each session, the subject first performed a training run of 10 trials, and then a test run of 30 trials. The online average accuracies across all healthy subjects were 95.67%, 86.33% and 62.33% for the audiovisual, visual-only and auditory-only sessions, respectively. The audiovisual BCI thus significantly outperformed the visual-only and auditory-only BCIs. As shown in Fig. 1(a), the ERP waveforms at the electrode "Pz" indicated that for the target stimuli, there were stronger P100, N200 and P300 responses in the audiovisual condition than in the visual-only and auditory-only conditions. It followed from Fig. 1(b) that there were more discriminative features for the audiovisual condition than for the visual-only and auditory-only conditions. The enhanced ERP components associated with audiovisual stimuli, such as P100, N200 and P300, improved the performance of the audiovisual BCI system.

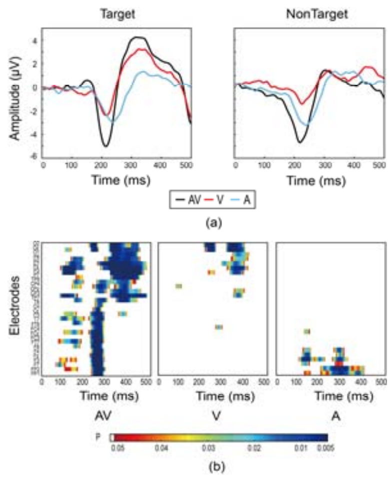

Figure 1. *(a) Average ERP waveforms in each stimulus condition from the "Pz" electrode for all subjects. (b) Point-wise running t-tests compared the target responses with the non-target responses in multisensory and unisensory stimulus conditions across all subjects for 30 electrodes. Significant differences were plotted when data points met an alpha criterion of 0.05.*

This system was then applied to detect the awareness of seven DOC patients in the second experiment. Each patient first performed a calibration run of 10 trials. The test run contained five blocks, each of which was composed of 10 trials and was conducted on separate days because the patients were easily fatigued. In the seven patients involved in our experiment, the online accuracies for five patients (1 VS and 4 MCS) were significantly higher than the chance level. For each of the five patients, the ERP waveforms measured at the electrodes "Fz" and "Oz" showed a robust P300 response elicited by the target stimuli. Our experimental results demonstrated the presence of command following and residual number recognition ability in the five DOC patients.

Discussion: In this study, we designed an audiovisual BCI for awareness detection in DOC patients. Our results for healthy subjects indicated that improved target detection can be achieved by integrating multiple sensory modalities. That is, the audiovisual BCI performed better than the corresponding visual-only or auditory-only BCI. The underlying mechanism is: multiple ERP components including P100, N200 and P300 were enhanced by audiovisual stimuli, and this enhancement was associated with audiovisual integration. There seldom reported similar results for online audiovisual BCIs in existing references. As a clinical application, this hybrid BCI was successfully used for awareness evaluation in patients with DOC.

Significance: To our knowledge, this study is the first attempt to test an audiovisual BCI in this challenging patient population. Furthermore, no results from other groups indicated that VS patient could use an online BCI system with a significant accuracy, and the online accuracy rates for VS and MCS patients in our study were higher than those reported in the existing references.

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Classification of motor imagery with distractions

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Introduction: In order to be operative in everyday life situations, BCI research needs to leave the very controlled lab environment and be adapted to real world scenarios. Therefore, we recently conducted a systematic motor imagery-based BCI study where participants not only had to imagine left and right hand movements but also had to deal with five different distraction tasks, simulating a pseudo-realistic environment. Since standard CSP analysis led only to poor performance rates, we now propose a 2-step approach where we want to find out first which distraction task was applied in a particular trial and then apply a classifier trained on the respective distraction task to determine whether a left or right hand motor imagination was conducted.

Material, Methods and Results: We recorded 16 healthy participants and used the best 8, who reached performance above chance level, for further analysis. The volunteers performed left and right hand motor imagery (MI) tasks while also watching a flickering video, searching the room for a particular number, handling vibro-tactile stimulation, listening to news or closing their eyes. Detailed description of the study can be found in [1]. The experiment was divided into 7 runs, the first containing pure MI tasks without any distractions which we used for calibration. After basic preprocessing, we used Common Spatial Patterns (CSP) [2,3] for feature extraction (3 per class) and used the first run to train an LDA-based classifier [4]. Testing on the remaining 6 runs (containing MI+distraction) only led to low performance results. One reason for that might be the major feature shifts between training and testing due to the different distraction tasks [1]. Performance rates already increased when we computed one classifier for each distraction such that training and testing data contained the same tasks. After further analysis, we discovered that one can easily separate the tasks where participants were searching the room (numbers) from the remaining tasks (1 CSP filter per class). Muscle artifacts resulting from turning the head are one of the main reasons for that. Therefore we used a 2-step approach where we first tried to determine in which of both groups the trial was conducted and then used one of two classifiers, trained on the respective group, to decide whether a left or right hand MI had been carried out. Classification rates for this 2-step approach can be found in Table 1. Comparing those results to our original approach, the overall classification rates increased by around 9%. In Figure 1 we plotted performance rates in both groups for our original approach against the ones for the 2-step approach. Except for smaller deviations the 2-step approach clearly outperforms standard CSP analysis. Alternative grouping scenarios led to lower performance rates.

	csp	od	njy	njz	nkm	nko	nkq	nkt	obx	overall
	overall	94.91	70.60	77.08	69.68	83.53	71.40	77.55	87.50	79.03
1st step	**cond**	99.31	94.68	96.06	79.40	94.87	98.59	97.69	99.07	94.96
2nd step	**numbers**	83.56	45.33	66.67	59.70	75.64	47.83	70.31	75.00	65.51
	not numbers	97.21	75.91	79.06	71.51	85.27	75.90	78.80	90.00	81.71

Table 1. *Classification rates for all 8 participants: 'overall' contains weighted average classification rates of the 2nd step, 'cond' marks the 1st step to separate the data into numbers and not numbers tasks. Results for the 2nd step are represented in the last two rows.*

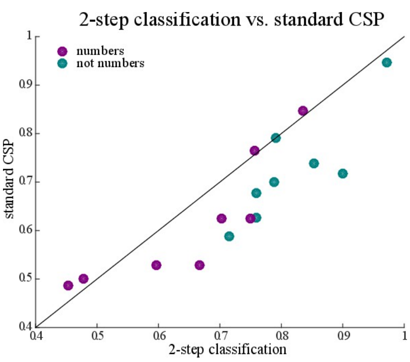

Figure 1. *CSP vs. 2-step approach*

Discussion: Bringing BCIs out of the controlled lab environment and into the real world presents one of the main challenges in BCI research. The study itself already revealed interesting and important findings. Boosting the classification results to a level where we can assume actual BCI control by adding more information to the classification process should encourage the BCI community to continue its path on building reliable BCI systems.

Significance: This new approach marks an important step towards using BCIs in real-world environments. It shows that it is possible to expose a participant to different distortion scenarios within one experiment and still classifiy the data succesfully.

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Cognitive workload BCI in the maritime environment

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Introduction: The human factor plays the key role for safety in many industrial and civil every-day operations in our technologized world. Human failure is more likely to cause accidents than technical failure, e.g. in the dangerous job of tugboat captains. Here, cognitive workload is crucial, as its excess is a main cause of dangerous situations and accidents while being highly subject and situation dependent. However, reliable subjective ratings are hard to obtain while objective ratings remain a necessity for training as well as control, port and operation design – leading to a high general interest in online cognitive workload indicators.

Material, Methods and Results: In a 10-subject simulator study, we recorded electroencephalographic data from a realistic tugboat scenario with professional captains (subj. 8 excl.: sickness). The experiment had 3 phases (approx. 40mins each), where phases 1&3 were identical. While in phases 1&3, the cognitive workload was modulated by the sailing task itself in combination with changing weather conditions, we increased it in phase 2 by an additional task (2-back task [1]) and kept sailing constant (Phase 1&3: 2 blocks 6mins low/12mins high workload. Phase 2: 10 blocks of 4mins high/low). The measurement epochs were designed to lead to similar behavioral patterns. The blocks were subdivided into epochs of 1 min for classification. The classifier was based on regularized shrinkage linear discriminant analysis (rsLDA) [2] after different preprocessing steps. We used 1Hz high-pass filtering alone (**R**), in combination with MARA [3] (**C**), an Independent Component Analysis (ICA) based automatic artifact reduction, as well as manual ICA artifact reduction (**CM**). Then, we built different spectral band power based features. In addition, we performed Common Spatial Pattern analysis (**CSP**) [4] in different band combinations with the logarithm of the variances as features. We evaluated the different classification designs within phases as a block-wise cross-validation (cv) as well as between phases to test for generalization. The results suggest a basic feasibility of binary workload classification with lowest cv-loss in phase 2. For the auditory n-back task (phase 2), higher workload seems connected to increased high visual alpha while results are less clear for the bow-to-bow condition (phase 1&3). Here, we often found an opposite visual alpha effect.

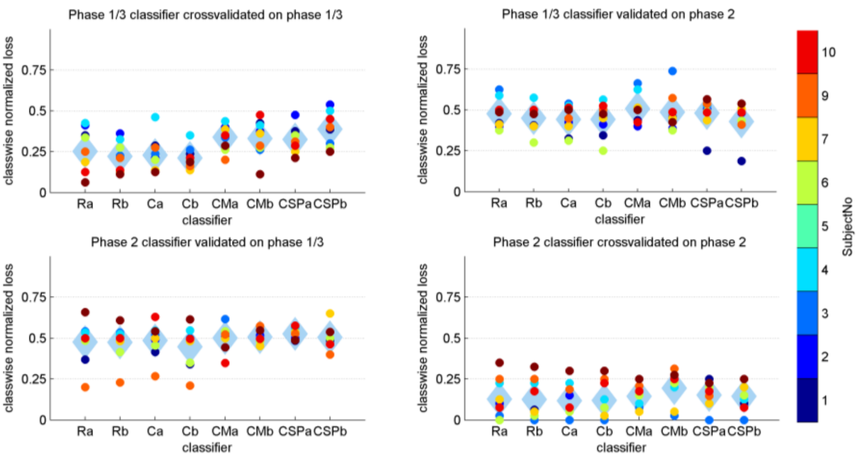

Figure 1. ***Classification matrix for different features:*** ***<u>R</u>*** *<u>HP(1Hz),</u>* ***<u>C</u>*** *<u>MARA,</u>* ***<u>CM</u>*** *<u>manual artifact removal:</u>* ***a*** *1-Hz bins 1-20Hz,* ***b*** *sum α-(8-12Hz) & θ-band (4-7Hz).* ***<u>CSP</u>:*** ***CSPa*** *α & θ-band,* ***CSPb*** *α, β, γ & θ-band. Circles: sinlge subject. Diamonds: mean across subjects.*

Discussion: Classification within phases is in general successful while it works least well in phase 1 which we account to the little familiarization with the simulator and equipment settling time. However, classifiers from different experimental settings work at chance level on others, which could be caused by the task differences: n-back is auditory and thus increasing the visual alpha due to the shift of attention, while in the realistic bow-to-bow task there is a variety of stimuli and senses involved. Different subject specific cognitive strategies in the realistic task could additionally lead to the variances of the results as there is more behavioral freedom. Therefore, a general classifier probably has to be based on more than one setting, more data and more subjects.

Significance: A measure of workload can be derived from spectral features of EEG in a complex maritime scenario, but neural patterns differ from a 2-back task - often used in laboratory studies. Online feedback of the workload level to trainer and trainee her/himself is expected to facilitate tugboat and other captains training.

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Combining Methods To Predict Accuracy of Individual Brain-Computer Interface Selections

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Introduction: Brain-computer interfaces (BCIs) provide a direct communication pathway between a user's brain and an external device to enable communication for people with severe motor impairments [1]. This study used off-line analysis of recorded data from a letter-by-letter spelling P300 BCI [2].

BCI accuracies average 77-90% with speeds of (1.4-4.5 char/min) [1]. Performance can be improved by abstaining selections that do not meet a predetermined P300-Certainty threshold [3]. However, there are multiple ways to predict the accuracy (correct or incorrect) of individual BCI selections. Monitoring attention through the power in the EEG alpha band (8-13Hz) [4] can also predict the accuracy of selections [5]. BCI selection accuracy can be improved by applying an alpha threshold for subjects that exhibit high alpha variance. This study used off-line analysis to examine the potential of combining the P300-Certainty algorithm and alpha-band monitoring of BCI data to improve BCI performance.

Materials, Methods and Results: Off-line data from 16 subjects (exhibiting high alpha variance) was used in this analysis [2]. Figure 1 shows the raw BCI accuracy of each subject and the improvement in performance from using either the P300-Certainty algorithm, an alpha-based threshold, or a combination. The mean accuracy for raw BCI performance, only P300-Certainty, only an alpha threshold, and both P300-Certainty and an alpha threshold were 85.38 ± 5.79%, 89.38 ± 3.44%, 89.69 ± 4.03%, and 92.13 ± 2.99%, respectively. Using a t-test, all methods produced statistically significant improvements over the raw BCI accuracy with P300-Certainty alone ($p = 0.026$), an alpha threshold alone ($p = 0.021$), and the combination ($p = 0.0004$).

Discussion: Both P300-Certainty and an alpha threshold increase accuracy by abstaining erroneous selections. However, combining both methods improves accuracy more than using either method alone.

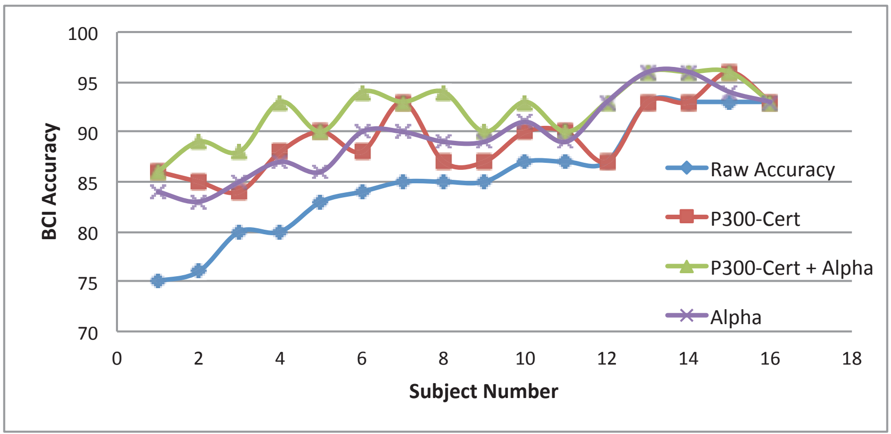

Figure 1. *Potential improvement of accuracy using P300-Certainty, an alpha threshold, and P-300 Certainty + an alpha threshold*

Significance: A BCI that can abstain erroneous selections that are "uncertain" (P300-Certainty) or that exhibit low attention levels (alpha) creates a BCI that is resilient to wandering user attention. Ultimately, a BCI using both methods allows users to type with a higher accuracy and at their own pace.

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Detecting Drowsiness in RSVP Keyboard™ BCI Users with SSPI

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Introduction: EEG measures of vigilance have been studied in fields concerned with driver and pilot alertness, as well as for effect on performance during cognitive tasks [1,2]. Given the importance of alertness and motivation on the P300, it follows that detection of drowsiness is critical to ensure maximal response. The necessity of integrating these fields becomes most evident in populations such as those with severe speech and physical impairments (SSPI), where individuals may not be able to communicate drowsiness or entirely control an alert-drowsy transition. P300 communication devices, such as matrix speller or RSVP Keyboard™ [3] are directed to these populations because of the recognizable need for alternative communication. The RSVP Keyboard™ presents a sequence of rapidly flashing letters (200ms in duration), using the P300 and earlier sensory potentials as indications of target letter. The system requires a calibration phase, calculated using a machine learning algorithm, that is used to identify target letters based on the EEG evidence 500ms following each letter presentation. This study looked at measures of drowsiness as a possible indication why participants might score poorly on these calibration sessions after eliminating the possibility of noise or other interference.

Material, Methods and Results: Participants included four individuals with SSPI who were subjects in our RSVP Keyboard™ BCI studies. For each participant, study sessions with good and poor BCI performance (as measured by area under the curve [AUC] for calibration session) were selected, and EEG recordings analyzed for drowsiness. Participants self-rated for drowsiness on the Stanford Sleepiness Scale (SSS) [4]. EEG was recorded at 256Hz using a 16 channel g.tec system with standard 10-20 coordinates. Data were bandpass filtered from 2-60Hz with a 60Hz notch filter. Drowsiness detection was done using power measurements in the theta (4-8Hz) and alpha (8-13Hz) bands (using channels Fz, Cz, P1, and P2), and persistence of eye-blinks (using an average of Fp1 and Fp2) in the epochs. Power estimates were calculated prior to letter presentation, and epochs following this were screened for a 30% increase in both frequency bands, as well as a 50% increase in these bands' contribution to total power (power in band/total power). The epochs were formed by dividing the dataset into 4 second intervals, FFT applied, and resulting power calculated using MATLAB (v. 2015b). The power and eye-blink calculations were used to determine levels of drowsiness, outputting a score ranging from 0[not drowsy] -4[very drowsy] based on the percent of epochs that satisfied those drowsiness conditions (stepping from 20% to 100%). To eliminate the cause of noise on AUC, only files with more than 80% clean data (free from muscle or other high frequency activity above 6e-12uV) were included in the analysis. The drowsiness detection was more sensitive to within performance differences than the SSS (see Table 1), but neither score fully explained user performance.

	Best Perform. (AUC)	Drowsiness Est.	SSS	Worst Perform. (AUC)	Drowsiness Est.	SSS
Part. 1	0.8311	0	1	0.6845	0.5	1
Part. 2	0.9591	0	5	0.8032	2	1
Part. 3	0.8168	0.5	1	0.5354	1	3
Part. 4	0.6418	0.5	2	0.5925	2	2

Table 1: Best and Worst session performance for participants (part.'s) with SSS and Drowsiness Estimate

Discussion: While this study took a modest approach to the detection of drowsiness, we demonstrated possible drowsiness implications on performance in a P300 based BCI system. Further studies should incorporate lateralized eye movements and optimize channels for calculation of power measurements to make a more sensitive and accurate detector. While neither score was closely related to performance (AUC) in this small sample, automated drowsiness detection is more practical for BCI in this or any population, and further developments will likely result in improved sensitivity.

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Significance: The significance of this exploratory study is in creating potential avenues to improve performance on P300 based BCI systems by considering the impact of drowsiness on the underlying event-related potentials.

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Development of a Real Time Speech Synthesizer Based Brain Computer Interface.

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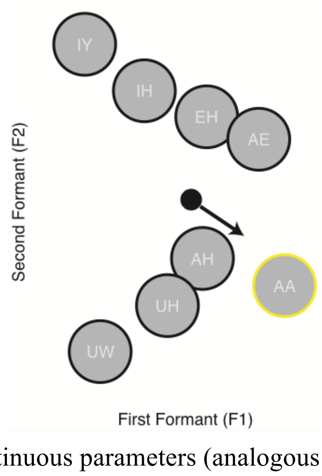
Introduction: In the present study, we investigate an EEG-based BCI that directly controls a speech synthesizer for instantaneous acoustic speech output. Specifically, the BCI decodes modulations of the sensorimotor rhythm (SMR) in a motor imagery protocol for controlling two continuous parameters in a manner similar to 2D cursor control. However in this study, instead of defining graphical positions, the cursor defines the first two formant frequencies of speech, which can be used for instantaneous synthesis and auditory feedback [1] of as many as 8 vowel sounds in American English, though in the present study we only examine the production of 3 vowels.

Material/Methods: Three participants without neuromotor impairments have been recruited to participate in the study, with additional recruitment ongoing (21 participants are targeted). Participants are asked to complete a vowel imitation task that includes an initial training session followed by four sessions of online BCI control. During training, visual and/or auditory representations of vowel sounds are presented to the participant for four seconds depicting one of three target vowels (/aa/ [hot], /iy/ [heat] or /uw/ [hoot]). Our full participant pool will be separated into those receiving visual feedback only, auditory feedback only, or combined audio-visual feedback to test whether the auditory feedback leads to improved BCI performance. Visual stimuli are represented by the 2D formant position displayed as a cursor on the screen. Auditory stimuli are synthesized for both the training paradigm and online BCI feedback using a formant frequency synthesizer (Snack Sound Toolkit, KTH Royal Institute of Technology). Participants are instructed to imagine moving their left hand for /uw/ sounds, right hand for /aa/ sounds and both feet for /iy/ sounds. Model weights are then estimated for a Kalman filter decoder and used for online BCI control. In the control task, participants are presented with the audio and/or visual representation of a target vowel sound (20 trials per vowel) for 1.5 s and instructed to perform the appropriate kinesthetic limb motor imagery tasks to control the SMR-based BCI, which then outputs the continuously varying 2D formants from the center of the formant plane (the neutral vowel) to the target vowel (similar to the well-known center-out task). Instantaneous visual (cursor movements) and audio (synthesized vowel sounds) feedback is provided to the participants in the 6 s response period. All EEG data were recorded via 62-channel acquisition system (g.HIAmp, g.tec) at a sampling rate of 512 Hz. The sensorimotor rhythm was obtained using a fourth order low pass butterworth filter from 8-14 Hz, and the bandpower was calculated using the Hilbert transform.

Results: Trials were labeled correct when the predicted formants entered into the appropriate vowel region, and incorrect if they did not. Offline analysis of Kalman filter model weights show the sensorimotor regions contribute most to neural decoding, which is expected based on previous SMR studies of cursor control via limb motor imagery [2]. The mean vowel production accuracy from our preliminary study is approximately 70%.

Discussion & Significance: The advantage of the BCI described in this study its novel approach to decoding in formant frequencies of speech rather than attempting to use discrete classification of vowels. While motor imagery is not suitable for discrete classification of speech sounds (e.g., there are only 3-4 detectable motor imagery classes for 8 vowels and 30 consonants), it is suitable for low degree-of-freedom systems that use continuous control (e.g., 2D cursor control [2]). In the present study the trained sounds define the outer boundary of all vowel sounds in English, therefore, it is possible to produce all of the other vowels (e.g., /ih/ hid, /uh/ hood, /eh/ head, etc.) through combinations of imagined movements. For instance, the vowel /uh/ lies between /uw/ and /aa/ in the 2D formant plane, therefore, combined left and right hand movements will generate the appropriate formant frequencies to produce /uh/ without additional training. The successful completion of this project will provide the necessary data to proceed to test all 8 vowels, as well as to develop a new BCI in which users control a low degree of freedom articulatory synthesizer capable of producing all 38 phonemes in American English through use of just 3 or 4 continuous parameters (analogous to a cursor in 3D space).



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Effects of Stimuli Relevance on Auditory BCI

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Introduction: Individuals with locked-in syndrome (LIS) typically lose the ability to reliably direct their eyes, in addition to other motor skills, forcing a reliance on covert attention when using many well-established visual processing based EEG-brain computer interfaces. In contrast, auditory processing remains largely unaffected in many cases of severe paralysis (progressed ALS and upper spinal cord injury patients) leaving an opportunity for BCI control via auditory evoked neurological responses [1 2]. At present, most auditory brain-computer interfaces (aBCI) employ sounds designed to optimally stimulate the auditory system (e.g., pure tones) and require a visual interface. Some recent efforts have focused on speech and environmental stimuli, though few studies have eliminated visual support in the aBCI paradigm [3 4]. In this study, we employ speech stimuli and investigate two characteristics, semantic and spatial relevance, hypothesized to affect BCI performance. A positive result of this research validates the benefits of task relevant spoken word stimuli that will simplify user control, promote intuitive learning, and help maintain motivation for users of a purely auditory BCI.

Material, Methods and Results: Approximately 25 participants are being recruited to participate in an auditory BCI task that will move a cartoon icon to a target location by attending to serially presented spoken words corresponding to the desired direction (Fig 1). Decoding intended direction is accomplished through a P300 focused classification using step-wise linear discriminate analysis (SWLDA) classifier as in previous research [1 5]. Condition 1 groups semantically relevant stimuli, while Condition 2 stimuli have no lexical congruence with the direction they represent. Additionally, the stimuli 'skill' and 'care', 'left' and 'right' will be presented over loud-speakers with inter-aural level differences (ILD) and inter-aural time differences (ITD) to provide relevant spatial cues to the participant. Stimuli 'up', 'down', 'joy', and 'while' will be devoid of ITD or ILD cues and will serve as spatial relevance controls. In this way both semantic and audio-spatial relevance are evaluated. Trials consist of ten presentations of each stimulus in a condition and results in a aBCI decision to move the cursor. Eight trials (80 targeted presentations) of training data will be collected for each stimulus at the beginning of each of three experimental sessions, which includes 64 trials of real-time BCI control per stimulus in a condition. The third session will include dynamic stopping of trials [4] in order to estimate the optimal information transfer rates (ITR). The order of completion of conditions will be balanced across participants.

Condition	Stimuli
1	'up', 'down', 'left', 'right'
2	'joy', 'while', 'care', 'skill'

Table 1 – Spoken words used in Conditions 1 and 2.

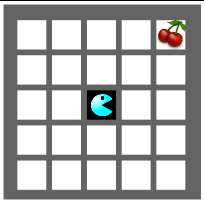

Fig. 1 – User interface screen provides target sound and BCI feedback. Blue icon's position on the grid is controlled by the BCI system. The task is to move this icon to the {cherry} target corner.

Results of BCI performance (ITR and percent trials correct) over multiple sessions will be used to determine the importance of semantic and spatial relevance to an auditory BCI. Participants will also complete questionnaires, as previously utilized [5], to estimate task workload, ease of use and preference of stimuli in our task.

Discussion: Spatial relevance and semantic meaning of words allows stimuli to be immediately associated with the BCI task choices, facilitates high initial BCI performance and improvements in BCI user experience. The visual feedback is used here for motivation but provides no visual ERP for BCI use. Reduction of cognitive workload and increase in user motivation over previous BCIs are the expected outcomes for this system.

Significance: This study's results will validate the feasibility and benefits of spoken word stimuli, allowing future studies to eliminate any visual component. Future developments of auditory-only BCI for users with neuromotor and cognitive impairment will benefit from our results on the relative importance of semantic and audio-spatial features of task relevant stimuli. Thus, taking another major step toward creating a clinically effective communication system.

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Error-Related Potentials for EEG-based Typing Systems

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Introduction: RSVP Keyboard™ is a speller that employs rapid serial visual presentation (RSVP) and uses Bayesian MAP inference based on event related potentials (ERP) fused with language models (LMs) to detect user intent [1]. Here, we study the potential benefits of additionally fusing feedback related potentials, a form of error-related potentials (ErrP), in a Bayesian fashion. By appending a prospect symbol (e.g., the top candidate in the alphabet according to the current posterior) to some or all presentation sequences, we expect to induce an EEG response that may be indicative of that prospect's correctness. Existing BCIs that attempt to use ERP/ErrP jointly typically fall into one of these categories: a flag by the ErrP classifier results in (a) the deletion of the last selection made using the ERP classifier [2,4,5,6]; (b) replacing the last selection made using the ERP classifier with the second ranking option [2,3,7]; (c) presenting more stimuli to gather additional ERP evidence, but not use the ErrP to update symbol probabilities over the alphabet [3]. A language model is not fused with ERP evidence in these particular examples, but has been suggested for boosting both ERP and ErrP evidence assessment. Unlike these early attempts to use ErrP evidence, which tend to make hard decisions based on ErrP classifier outputs, we seek Bayesian fusion of ERP, ErrP, and language evidence using probabilistic generative models. The envisioned (and already implemented) system automatically decides to select a letter to type or proceed with more ERP/ErrP evidence collection in a probabilistic fashion. We present simulation based results that suggest this Bayesian fusion process may outperform existing alternatives in the literature. This framework is also applicable to the Matrix Speller [1].

Methods: EEG data to calibrate ERP/ErrP models are acquired using the RSVP Keyboard™ copy-phrase task. Assuming the ERP/ErrP features are not identically distributed, their distributions are calibrated separately (with a process similar to that in [1]). A 6-gram symbol language model (LM) is used for MAP inference with EEG/ErrP gathered from sequences presenting the 14 most probable symbols in the alphabet (of 28 symbols) according to the latest posterior distribution [1]. When the top candidate becomes *somewhat* probable, it is appended to the end of the sequence as a prospect. ERP/ErrP evidences are extracted from the 500ms windows following regular and prospect presentation trial onsets. A decision is made when the top candidate exceeds the required confidence threshold or the number of maximum allowed sequences is reached (time-out); these thresholds are set to 0.9 and 8, respectively. All parameters can be adjusted to optimize performance on an individual user basis (e.g. using simulations).

Results: Results of 25 Monte Carlo simulations of a copy-phrase task with 10 predetermined sentences for which the language model contribution ranges from friendly (correct letters are likely compared to competitors) to adversarial (competitors more likely) were performed as in previous work [1]. These preliminary results summarized in Table 1 demonstrate that, as expected, Bayesian fusion of all evidence (ErrP, ERP, LM) yields faster typing speeds in all participants (without compromising accuracy). The use of ErrP in a suboptimal fashion as has been done in the literature (by allowing ErrP decisions to override ERP) also improves speed relative to not using ErrP at all.

AUC for [ERP,ErrP]	ERP/LM fusion (No ErrP)	ErrP overrides ERP/LM fusion	Bayesian fusion of ErrP/ERP/LM
[0.845,0.865]	531s, *1.00*	454s, *1.00*	421s, *1.00*
[0.846,0.804]	546s, *1.00*	514s, *1.00*	461s, *1.00*
[0.840,0.786]	589s, *1.00*	530s, *1.00*	467s, *1.00*
[0.821,0.777]	542s, *0.99*	519s, *0.99*	497s, *1.00*
[0.775,0.813]	913s, *0.96*	838s, *0.97*	834s, *0.99*

Table 1. Monte Carlo simulation results (expected time to complete task in seconds, *probability of completion*) for five users, using synthetic EEG features from models calibrated with real ERP/ErrP EEG data. Calibration estimate of AUC for ERP/ErrP class-conditional density models (Column 1); average time and probability of completion for no ErrP case (Column 2), typical ErrP application in literature where single ErrP evidence can discard all ERP evidence for last symbol (Column 3; red), and proposed Bayesian fusion of all evidence (Column 4; green).

Significance: As literature suggests, using ErrP evidence may improve performance. However, preliminary results indicate that Bayesian fusion of ErrP with ERP, not treating the former as a de facto superior form of evidence, may yield better outcomes. We will present details and experiment results in a future paper.

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Features reduction for P300 Spellers

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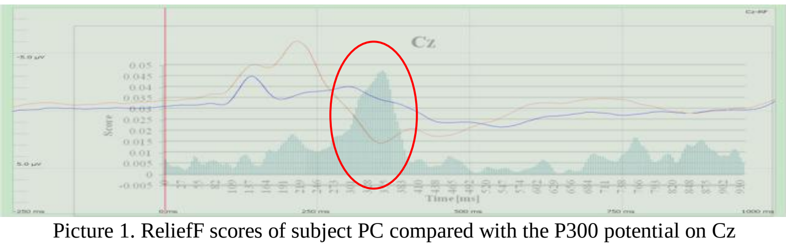
Introduction: The detection of brain state changes plays a fundamental role in the neuroscience research field because it can dramatically improve the comprehension of cerebral functioning. In this field, it may result extremely useful the support of machine learning based automatic tools able to correctly classify different brain responses. The performance of these tools depends on both the features and the classification algorithm employed. In order to select the most appropriate classifier for a given BCI system it is essential to single out a subset of significant features from the original data set, due to the poor signal-to-noise ratio [1] of the EEG signal, and to the small number of training data compared to the number of features. It is well known that distinguishing relevant features is fundamental to improve the predictor's performance. More importantly, it can provide a better understanding of the underlying cerebral processes that generated the data. The aim of this study is twofold: on the one hand to choose the most appropriate features selection strategy in order to maximize the predictor's performance applied to a visual evoked potential based BCI. On the other hand, we aim at showing how the features ranking can be used to support scientific hypotheses or diagnoses.

Material, Methods and Results:
Data were recorded during several training sessions from nine healthy subjects using the P300 Speller paradigm. EEG was recorded using a cap embedded with 19 electrodes according to the 10-20 International System, sampled at 256 Hz and averaged for 800ms after the visual stimulation. Five features selection methods were analyzed: IG, CFS, ReliefF, Consistency and 1RR [2]. All of them belong to the class of filter methods for feature selection. A support vector machine with Gaussian kernel (RBF SVM) was used as classifier for several reasons: first, it is able to handle high dimensional data sets; second, it has few hyper-parameters that need to be defined by hand; third, it has already been successfully adopted in BCI providing very good results [1]. Grid Search was used for hyper-parameters optimization. The data processing was carried out with Weka. All feature selection methods were able to select smaller subsets of features improving the quality of the results. The range of features reduction was between 62 % (IG) and 99.78 % (Consistency). Table 1 shows the classification results in terms of accuracy and Cohen's Kappa on test sets for each subject, using ReliefF [3] which turned out to be the best among the five methods. We compare our result with CFS-FLDA, the embedded feature selection method implemented in Weka that is closer to the SWLDA, a common approach for P300. CFS-FLDA is a correlation based feature selection method embedded into a Fisher's Linear Discriminant Analysis. The results show how ReliefF outperforms CFS-FLDA since the mean value of accuracy is 88.5%, which is significantly better (paired t-test < 0.5) than the one of the LDA method (79.6%) and the Kappa is almost always higher or comparable.

Subjects	**PC**	**LQ**	**FG**	**VP**	**MA**	**LB**	**NL**	**ZI**	**IG**
CFS-FLDA: A(%)/K	93.4/0.78	89.9/0.67	87.92/0.62	84.25/0.53	75.1/0.33	71.82/0.25	77.92/0.43	56.52/0.006	70,66/0.25
ReliefF-RBF SVM: A(%)/K	95.35/0.83	93.02/0.73	91.35/0.66	88.69/0.57	88.67/0.37	88.24/0.48	84.59/0.42	83.41/0	83.21/0

Table 1. Prediction result

Discussion and significance: The most important result is that the subset of selected features is physiologically correct: ReliefF was able to detect physiological components elicited during the protocol either in space (e.g. Cz, Pz, O1, O2, ..) or in latency (e.g. P300). As an example, in Picture 1 we draw the scores assigned by ReliefF versus the evoked P300 potential on Cz, showing how the scores follow the signal behavior. This kind of information may furnish relevant insights to identify which brain areas and when are involved during certain cerebral activities, thus improving the comprehension of brain functioning.



Picture 1. ReliefF scores of subject PC compared with the P300 potential on Cz

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Fusion of P300 and Eye Tracker Data for Spelling Using BCI2000

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Introduction: The P300 speller, an EEG-based Brain Computer Interface (BCI) [1] and various eye-trackers [e.g. 2] have been used individually as communication aids for people with ALS. The work presented here explores the efficacy of combining EEG and eye tracker data to improve P300 speller performance.

Material, Methods and Results: In this work, a Bayesian update classifier [3] has been adapted to combine EEG and eye-tracker inputs probabilistically in order to estimate the probability that a character is the target character. Eye tracker data was assumed to be well modeled by a two-dimensional Gaussian distribution centered on the target character, and independence between the EEG and eye tracker probabilities is assumed. The *a priori* variance of this Gaussian distribution can be static or learned during training – both types were considered in this work. To assess the potential benefit of utilizing this type of bimodal system, data will be collected from 20 non-disabled individuals using the updated Bayesian classifier to select characters in real-time. Data collection is currently ongoing, but preliminary results from seven subjects are shown below.

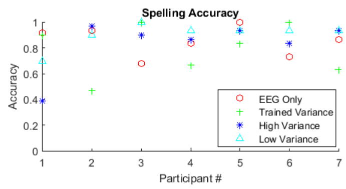

Figure 1. *This figure shows the spelling accuracy given the four different configurations of the Bayesian update classifier.*

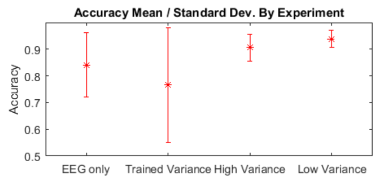

Figure 2. *This figure shows the average number of flashes to spell a character given the four different configurations of the Bayesian update classifier.*

Figure 1 shows the spelling accuracy given four different configurations for the Bayesian update classifier: EEG without eye gaze, EEG with eye gaze variance learned during training, and two static eye gaze variances. The trained variance is very low for all participants, so this configuration is almost identical to eye-gaze only. Using only EEG or the trained variance configuration is always the worst performer except in the case of participant 1, showing that the use of the multimodal system provides robustness to the speller. Figure 2 confirms this observation and shows the mean and standard deviation of the spelling accuracy given the four different configurations of the Bayesian update classifier. The results show that given a broad enough gaze variance, the speller performs with higher accuracy and more robustness than using EEG or the trained variance configuration.

Additional offline simulations were performed to consider eye gaze challenges that might occur in the target population. These simulations included the addition of variance and bias to data collected from non-disabled participants as well as random fixations towards incorrect characters. As with the online accuracy, the classifier was robust given a large enough *a priori* variance.

Discussion: The probabilistic combination of EEG and eye tracker data is fairly robust to large variance in gaze fixation. Although promising, results from online testing with the ALS target population will be necessary to assess the true potential for a bimodal spelling system. Even though the Gaussian distribution for non-disabled eye gaze is appropriate, it is possible that a more complex statistical model will need to be used for eye gaze collected from an ALS patient.

Significance: This work shows that combining information from the P300 and eye-gaze data is a promising research avenue.

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Improving Motor Imagery BCI with User Response to Feedback

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Introduction: It is well understood that feedback affects subject performance in motor imagery (MI) BCI [1]. However, there is still little evidence about how the response to feedback changes the MI signal, and whether the feedback signal can be used to classify MI more accurately. In this work, we show that feedback response and MI signals are both carried in similar frequency bands and investigate ways to improve MI classification.

Methods: EEG data were collected from 7 subjects asked to control a cursor with right and left hand motor imagery who were shown sham cursor movement as visual feedback. The cursor moved every 600 ms based on a pre-determined movement pattern *unrelated* to subject performance. The sham feedback (of which the subjects were unaware) is critical to examine the role of visual feedback on user's MI. Since the sham feedback is independent of the MI, any relationship between the MI signal and the visual feedback is due to a causal effect of the user's response to visual feedback on the read MI. A total of 6 spatial filters (3 per class) were chosen through common spatial patterns (CSP) [2] and the log power of the filtered signals were classified with linear discriminant analysis (LDA) trained with 10-fold cross-validation.

Results, and Discussion: Figure (1) shows classification results and standard error of classification rate for four of our subjects (including 3 of our best) the cyan line shows the significantly above chance level ($p = 0.05$) based on the number of trials [3] and the green line indicates 0.5 level. RvL indicates classifying between right versus left MI. GvB indicates classifier performance for a classifier trained to distinguish whether the last cursor movement was in the desired (Good) or non-desired (Bad) direction. Notice that GvB classification was successful in similar frequency bands as RvL classification [4] meaning that the information about whether the subject "liked" the movement or not may be confounded with the computer's read out MI signal. We hypothesize that a state-of-the art CSP feature extraction and LDA classification - i.e., solid black line on figure (1) - is in fact affected by feedback and there is potential to improve the standard procedure. We applied logistic regression to the output of GvB and RvL classifiers where we trained two distinct classifiers for when the cursor moves to the left or to the right; that is, to directly take into account the observed cursor movement. Results are shown with magenta line on figure (1). The combined classifier is able to improve the RvL in the frequency bands that GvB classifier is above chance level (~ for p<0.1, * for p<0.05 and ** for p<0.01). Subjects received no training with real feedback (only the unrelated sham feedback), which may explain the overall low accuracies.

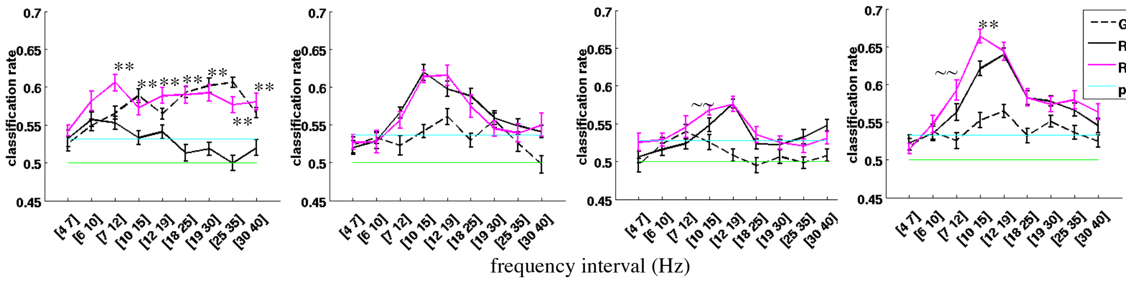

Figure 1. *Figures show correct classification rate versus frequency band for four subjects. Note that the RvL and GvB classifiers have above chance performance in similar frequency bands.*

Significance: The work shows that feedback response and MI signals are present in the same frequency bands that are used for MI classification. We proposed to apply logistic regression to combine RvL and GvB classifiers as a potential way to alleviate the effect of visual feedback. As GvB classification is more robust to non-stationary distributions [5], future work will investigate more sophisticated methods for combining these signals (Supported by NSF grants IIS 1219200, SMA 1041755, IIS 1528214).

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Examination of auditory brain-computer interfaces using virtual sound by shortening stimulus onset asynchrony

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Introduction: A brain-computer interface (BCI) is a system that can operate several devices using only brain signals. It has been actively studied in recent years. There are many studies using event-related potential (ERP), which is a brain signal that occurs in relation to some event. The use of the virtual sound sources using out-of-head sound localization has been suggested as a possibility to estimate the intention direction [1]. In this study, we propose a BCI system for estimating the intended sound source direction of the user by using EEG (P300) when out-of-head sound localization is used. By changing stimulus onset asynchrony (SOA), the accuracy of the auditory BCI using virtual sound sources we examined was improved.

Material, Methods and Results: This study was approved by the ethics board of the Nagaoka University of Technology. Nine healthy people (8 males and 1 female, mean age 22.5) participated. All subjects were given information on the experiment and signed consent forms.
In this study, we used an oddball experiment using virtual sounds [1]. The sound image was located at six different directions (30°, -30°, 90°, -90°, 150°, -150°) with 0° being the direction facing the user directly. We changed the SOA for every task, that is 1100, 800, 700, 600, 500, 400, 300 and 200 ms trials were considered for comparison. The EEG data was sampled at 256 Hz, filtered using a Butterworth band-pass filter (0.1 to 8 Hz) and classified using Fisher discriminant analysis (FDA) to estimate the parameters for the particle swarm optimization (PSO) algorithm [2].
Fig.1 presents the identification rate of direction. Fig.2 shows results of ITR at identification rate of direction.

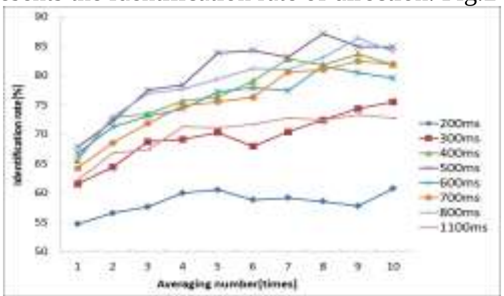

***Figure 1.** Classification accuracy*

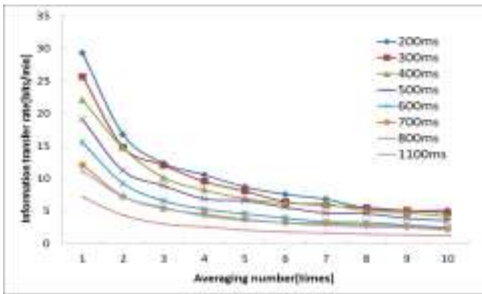

***Figure 2.** Information transfer rate*

The direction identification rate was 87.1% for the SOA of 500 ms averaged 8 times, 86.3% for the SOA of 800 ms averaged 9 times and 84.9% for the SOA of 500 ms averaged 9 times.
The max ITR is 29.31 bits/min at SOA of 200 ms averaged 1 time. The ITR is 1.22 bits/min at SOA of 1100 ms averaged 10 times, which is 24 times slower than that observed in the best scenario. However, the increasing of ITR is higher when the number of averaged times decreases. These results alone can be misleading if identification rate is not considered as well. We determined appropriate identification rate when results were higher than 70 %. Fifty six results met this condition. Under this condition, max ITR is 14.72 bits/min at SOA of 400 ms averaged 2 times.Compared to it, the SOA of 1100 ms averaged 10 times is 12 times slower.

Discussion: For direction identification rate, the SOA of 1100 ms averaged 10 times was used as base for comparison with the SOA of 400 ms averaged 2 times, because it has more than 70 % identification rate and the maximum ITR. As a result, it can be observed that the ITR is around twelve times higher in the SOA of 400 ms and its required estimate time is about a twelfth of that in the SOA of 1100 ms.
As the increasing of identification rate is always pursued, in order to build an improved BCI system, for future work it is being considered the application of different algorithms for classification as well as changing the time used for direction estimation.

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Incorporating neuroscience priors into brain-computer interfaces to detect attentional state

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Introduction: There exist a number of open challenges facing brain-computer interfaces (BCIs) for both clinical and commercial applications. In electroencephalography (EEG) based BCIs, several of these issues stem from analyzing recorded data in the sensor space (i.e., the surface of the scalp) where the electrodes are placed. Here, we focus on two of these obstacles: First, inclusion of priors from neuroscience (e.g., localization of brain regions associated with particular tasks) is difficult when analyzing data in the sensor space as the vast majority of neuroscience operates in the cortical domain. Second, the bulk of BCI research has focused on three canonical paradigms: P300, motor-imagery, and visually evoked potential BCIs all of which are well developed, but presumably, there remain many more brain regions useful for control that could advance the field as a whole [1].

Materials and Methods: Source imaging is a method for estimating cortical sources of activity from non-invasive recordings [2]. We modeled the entire cortex using ~7000 distributed current dipoles each of which represents a small patch of cortex. Using the MNE-Python library, we solved the inverse problem allowing estimation of cortical activity at each dipole from (non-invasive) EEG data. Source imaging also provides a principled path to include neuroscience priors from other research – particularly, from neuroimaging. To this point, the right temporoparietal junction (RTPJ) was recently discovered to be significantly more active when switching auditory attention compared to maintaining it to a single sound source [3]. We hypothesized that a source-based approach incorporating this knowledge (by targeting activity from only this region) would provide significantly better single-trial classification accuracy compared to a naive sensor space approach.

We tested our hypothesis by comparing a sensor-based and a source-based BCI approach both attempting to classify (offline) if a subject switched or maintained attention in an auditory task (previously conducted in the laboratory) [3]. Briefly, subjects listened to one of two talkers and were instructed to either maintain attention to one throughout a trial or switch halfway through. For both approaches, we employed different dimensionality reduction techniques: principal component analysis (PCA), independent component analysis (ICA), and common spatial patterns (CSP) using an identical range of parameters for each. Support vector machines were used to classify the resulting signal and we employed 10-fold cross validation to obtain a stable accuracy estimate.

Results: We found that the source-based approach significantly outperformed its sensor-based counterpart (p=0.003; corrected 2-way repeated-measures ANOVA) conferring a 5.2% absolute accuracy increase between the best sensor- and source-based strategies. Interestingly, the relative difference between the dimensionality reduction techniques appeared to diminish once in the source space.

Discussion: These results suggest that the source space provides an avenue to target more informative signals for classification by incorporating neuroscience priors. The absolute accuracy attained here may not be robust enough to be useful for immediate use; however, the significant gains relative to a sensor approach gives credence to the notion that neuroscience priors can provide a significant performance gain across multiple signal processing strategies. Importantly, this work also demonstrates that activity from a region not associated with the canonical BCI paradigms can be objectively targeted to provide a useful control signal. Note that source imaging is not amenable to all BCI studies; the additional time and cost required to obtain a structural MRI scan will be prohibitive in some cases. That said, there are simplified source imaging techniques that require only 3D localization of electrodes and a generic head model. Future research will evaluate the necessity of MRI information by testing these simplified techniques.

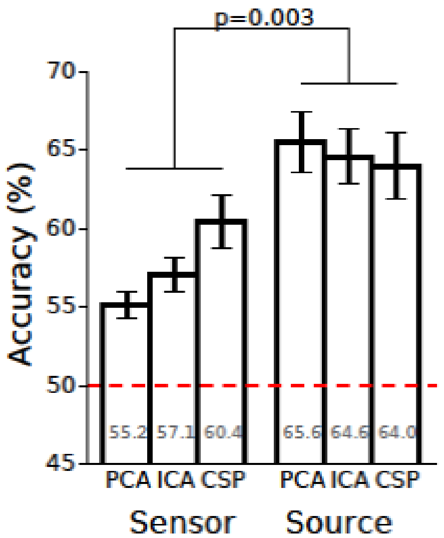

Figure 1. *Accuracy of sensor- and source-space approaches (using 3 dimensionality reduction techniques) when predicting a switch in attention. Source space yields significant improvement. Bars indicate mean (± SEM) and the red line represents chance.*

Significance: In this study, we found that leveraging neuroscience priors via the source space provides a significant increase in classification accuracy and seems to reduce the dependence of this accuracy on the dimensionality technique chosen.

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Initial evaluation of an auditory P300 brain-computer interface for the Japanese Hiragana syllabary

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Introduction: Degenerative diseases that lead to the complete locked-in state (CLIS) also affect gaze control [1]. This calls for a possibility of gaze independent communication and lead to the development of auditory BCIs [2, 3]. In this study we addressed the case of a BCI system for communication with the Japanese Hiragana syllabary. A two-step selection procedure is commonly for the Hiragana alphabet [4, 5]. We investigated a two-step design using stereo headphones, stimuli with spatial cues and a training period of three sessions.

Material, Methods and Results: Six healthy participants (5 male, average age 32.6 years) and one end-user (male, age 43 years, C3/C4 spinal cord injury) participated in the study. Electroencephalography (EEG) was recorded with 16 electrodes. Stimuli were presented using stereo headphones. Classification was performed offline using shrinkage linear discriminant analysis and online with stepwise linear discriminant analysis. All participants performed three sessions on separate days and selected 25 syllables in each session.

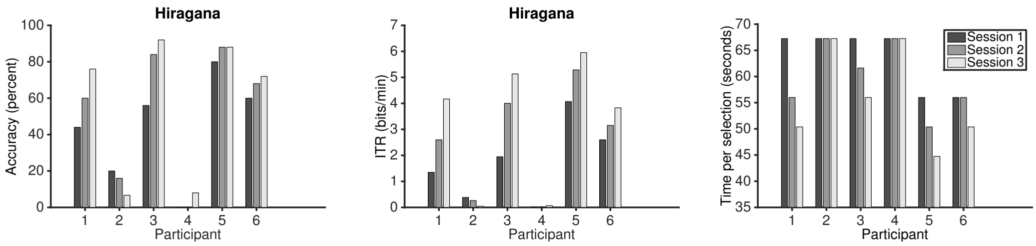

Figure 1. *Selection accuracy (left), information transfer rate (middle) and time per selection (right) of the six healthy participants.*

Offline Hiragana syllable selection accuracy in session one was 43% (SD 29, range 0 to 80), in session two 53% (SD 36, range 0 to 88) and in session three 57% (SD 39, range 7 to 92). In four out of six participants, there is a clear trend to increase of accuracy with session (see Figure 5 top row). Information transfer rate (ITR) of Hiragana selection was in session one 1.7 bits/min (SD 1.5, range 0 to 4.1), in session two 2.6 bits/min (SD 2.1, range 0 to 5.3) and in session three 3.2 bits/min (SD 2.6, range 0.1 to 6). The motor impaired end-user achieved an accuracy of Hiragana selection of 12% in the first session, 28% in the second session and 56% in the third session. Corresponding ITRs in sessions one two and three were 0.2 bits/min, 0.7 bits/min and 2 bits/min.

Discussion: Four out of six healthy participants reached accuracies above 70% in session three, which would make the use of the BCI system for communication possible. The ITR is comparable to what was achieved in other studies [4] but falls behind compared studies using a lower number of choices, e.g. for the Latin alphabet., Due to the larger number of stimuli, a longer training period may be needed.

Significance: We were able to show that healthy controls and one end-user were able to control an auditory BCI with a high number (50) of possible choices using stimuli presented with stereo headphones. Training increased performance both for the healthy controls and the end-user.

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Novel SSVEP-BCI Setup Evaluation During Emotional State Elicited by Unpleasant Sounds

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Introduction: Emotional states can induce changes in biological signals [1]; such as, electroencephalographic signals (EEG); in this sense, the performance of non-invasive BCIs based on EEG could be affected when an emotional state arises. For instance, it was reported the decreasing of the accuracy of the recognition of SSVEP-BCI commands are related to the loss of attention [2]. It causes frustration, fatigue and upset that generates a vicious circle of poor performance of the BCI. In the present work, the performance of a SSVEP-BCI when a subject is unpleasantly stimulated is evaluated. Unlike conventional SSVEP systems that demands gaze movements; the novel SSVEP-BCI setup proposed by [3] is employed. It demands a more meticulous selection condition, in which users must shift their eye focus to select the target stimulus instead of executing muscular movements, due to two stimuli are presented together in the center of his field of view but at different distances.

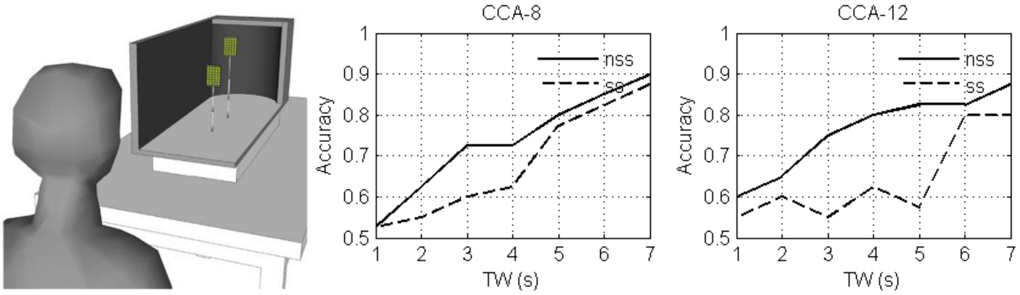

Figure 1. *(Left) The novel SSVEP-BCI setup; Accuracy for TW from 1 to 7s for CCA-8 (middle) and CCA-12 (Right) detection methods. Solid line: Accuracy during **nss** experiments. Dashed line: Accuracy during **ss** experiments.*

Material and Methods: Preliminary experiments were conducted with a healthy male subject. Sixty trials of 9s (2s of rest and 7s of task) were recorded wherein half of them had sound stimulation. Five unpleasantness sounds with approximately 70-80 dB of sound pressure level that were reported in [4] were randomly presented during the selection tasks. The novel setup consists of two 5×7 green LED arranges (13×18 mm) with frequencies of 5.6 and 6.4 Hz, and placed at 30 and 50 cm from the user (Fig. 1 - left). EEG signals were acquired from channels P3, P1, Pz, P2, P4, PO7, PO3, POz, PO4, PO8, O1, Oz, and O2 at sampling rate of 200 Hz, with biauricular reference and grounded at AFz. Canonical Correlation analysis (CCA) was performed for SSVEP detection.

Results: Middle and rightest insets of Fig. 1 show the accuracy of CCA-8 and CCA-12 for time window (TW) from 1s to 7s, respectively. Suffixes 8 and 12 indicate the number of channels. As expected, the accuracy without unpleasant sound stimulation (nss) is higher than with sound stimulation (ss), in both cases for all TW.

Discussion: Although only one subject was considered in this study, results of sixty trials and seven TW indicates that the BCI performance is affected by unpleasant sounds. Hence, due to the focus shift is a more meticulous task, the decreasing of the performance can be attributed not only to the BCI but the loss of the will of the user.

Significance: Currently, hybrid-BCIs that detect emotional states and adapt the BCIs operation are being proposed. However, the user contribution to the reduction of BCI performance (due to their unwillingness) is rarely considered. Finally, after validate these preliminary results with a statistically valid number of users and experiments, a mechanism to avoid or overcome user unwillingness could be added to BCI systems.

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Optimizing the face Paradigm for BCI systems with the modified Mismatch Negativity paradigm

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Introduction: The modified mismatch paradigm could evoke significantly larger N200 and N400 components compared to the traditional P300 paradigm. Based on previous studies, inverted and upright faces with different expressions were used to design the mismatch inverted face pattern (MIF-pattern). The visual stimulus modality elicits a visual mismatch negativity (i.e. the vMMN). Consistent with the auditory MMN, the vMMN elicits an N200 [1, 2]. Our hypotheses are that the MIF-pattern could yield significantly higher classification accuracy and information transfer rate than the inverted face pattern (IF-pattern).

Material, Methods and Results: In the IF-pattern, an inverted woman's face with negative emotion (i.e., deviant) was presented pseudo-randomly above each of the 12 items (Fig. 1B). The MIF-pattern was the same as the IF-pattern with one exception. When the inverted woman's face was flashed above one of the items, a woman's face with positive emotion (standard) flashed in gray above the other 11 items (Fig. 1C). Several standard stimuli (flashing gray face) appeared before the deviant stimuli (an inverted woman face), thereby producing a "visual mismatch" [3]. Ten subjects participated in this study. The inter-stimulus-interval (ISI) of the stimulus was 100ms and the stimulus onset asynchrony (SOA) was 300ms in both patterns, which was same for the flickering background used in the MIF-pattern.

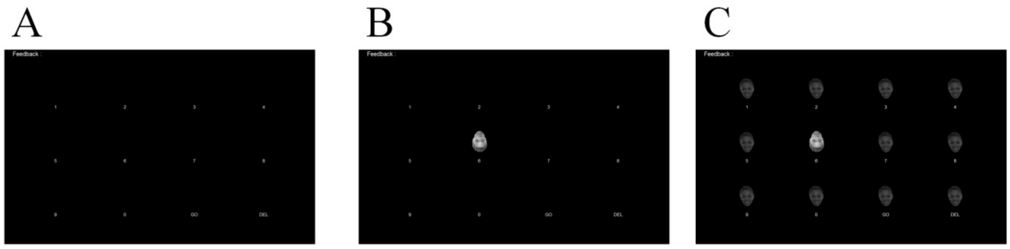

Figure 1. *The interface that was shown to the subjects. A) The stimulus matrix without stimuli. B) An example of the IF-Pattern. C) An example of the MIF-Pattern. The feedback appeared on the top of the screen in the online session.*

The mean classification accuracy is 97.08% (IF-pattern) and 99.58% (MIF-Pattern), the mean information transfer rate is 25.66 (IF-pattern) bit/min and 27.78 bit/min (MIF-Pattern), and the mean trials per average is 2.19 (IF-pattern) and 2.13 (MIF-Pattern). Since the classification accuracy did not meet the normal distribution, a non-parametric Kendall test was used to show the difference in classification accuracy between the IF and MIF patterns. The classification accuracy of the MIF pattern was significantly higher than that of the IF pattern ($p<0.05$). A paired samples t-test was used to show the differences between the MIF-pattern and IF-patterns in bit rate. The raw bit rate of the MIF-Pattern was significantly higher than that of the IF-pattern ($t=-2.7$, $p<0.05$).

Discussion: A mismatch negativity (MMN) was elicited when a stimulus was incongruent with the sensory memory of a standard stimulus. The result showed that higher classification accuracy and information transfer rate could be obtained from the MIF-pattern on health patients. We will further verify this paradigm on patients in future research.

Significance: The new approach introduced in this study could improve the performance of a visual P300 brain computer interface. Results could also be adapted to auditory or other modalities.

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Re(con)volution: accurate response prediction for BBVEP-based BCI

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Introduction: Evoked potentials can be subdivided in three classes: transient, steady-state, and broad-band responses. The extent to which these responses reflect qualitatively different types of neural activation is still debated. Here, we employed the superposition hypothesis, which states that the response to a sequence of events is a linear summation of the transient response to each individual event. We modeled EEG responses to rapid visual stimulation to be the summation of overlapping time-shifted versions of basic transient responses to a flash. The transient responses were estimated from data, using deconvolution. Modeled responses were generated by convolution of the estimated transients with a signal, representing the onset times of the flashes. This linear framework is called reconvolution as it combines both deconvolution and convolution.
With reconvolution, evoked responses to flash sequences can be predicted accurately given relatively small amounts of training data. Therefore, this technique is suitable as a framework for Brain Computer Interfacing. In a visual matrix speller, we have achieved high classification accuracies with short single-trials, resulting in fast and robust communication rates. Additionally, because of the availability of a generative model and optimized stimulation, pilot results reveal the possibility for high-class BCI, zero-training BCI, and asynchronous BCI.

Material, Methods and Results: We presented modulated Gold codes as rapid non-periodic visual stimulation in a matrix speller. While participants gazed at a target, EEG data were recorded from 32 water-based scalp electrodes, amplified by a TMSi Mobita amplifier. A Canonical Correlation Analysis (CCA) based reconvolution was applied, in which single-trials (X) were spatially filtered (XW_X) with a weighting vector over electrodes (W_X), in order to maximize the correlation with the convolution (YW_Y) of a design matrix (Y) and the transient responses (W_Y). This CCA based reconvolution simultaneously learns the temporal as well as the spatial distribution of the transient responses embedded in broad-band responses. This method allows for accurate generation of evoked responses, explaining up to 50% of the variance for bit-sequences used to fit parameters during calibration, as well as for novel bit-sequences. These generated responses can serve as templates in an evoked response BCI. Because of the generative framework, less training data is required to calibrate the classifier, with a retained possibility of using many classes concurrently.
In offline analysis of data acquired in [1], we achieved an average classification accuracy of 88%, with single-trials of 3 seconds (N=12). In online experiments, we have achieved a robust classification accuracy of 95% with single-trials of 1.5 seconds, both using a 6 x 6 matrix as well as using a 5 x 13 matrix speller (N=1).
We investigated the possibility of a zero-training setup by applying CCA based reconvolution to each bit-sequence, on single-trial level. The BCI selected the bit-sequence that revealed highest explained variance in the linear framework. In an online experiment, we found robust classification accuracies (90%) with single-trials starting at 40 seconds, decreasing to 1.5 seconds within approximately 5 single-trials (N=1).
Gold codes are pseudo-random bit-sequences generated in sets, which exhibit a minimized cross-correlation (i.e., the correlation between pairs within the set), as well as minimized auto-correlation (i.e., the correlation of a bit-sequences with a delayed version of itself). Therefore, high correlations would only occur at zero time-lag of a targeted code. This makes Gold codes appropriate for asynchronous BCI, where time-lock information is lost (e.g., in low-end headsets that do not have external trigger inputs to synchronize stimulation and data-analysis). In the asynchronous setup, the number of templates is increased by including time-shifted versions of all templates. In a 6 x 6 matrix speller with 60 time-lags, a classification problem with 36*60 classes is created. Still, the BCI detected the target using 4.2 seconds of EEG data with a classification accuracy of 80% (N=1).

Discussion: The proposed setup allows for high-class, asynchronous, and zero-training BCI. In the case of asynchronous BCI, the calibration phase does require synchronization. An asynchronous zero-training method would overcome this issue, though the methods are not yet combined and rely on results from pilot studies.

Significance: This BCI setup allows robust BCI. Use of low-end headsets is possible, trading signal quality for detection time. Further, only few electrodes are required, no external trigger input for data synchronization is needed, and high classification accuracy is possible even with a high number of classes and short single-trials. This assures to high communication speeds, enabling communication without the need of the peripheral nervous system, with a user-friendly system.

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Recursive Queries for BCIs: SSVEP Shuffle Speller

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Introduction*:* A BCI has two fundamental jobs: classifying the user's physiological inputs (e.g. SSVEP) and finding the meaning of these inputs in the task domain (e.g. letter selection in the spelling task). This work offers a framework for recursively mapping SSVEP stimuli (user symbols) to letters (task symbols) [1]. In particular:

Recursive Framework Feature	SSVEP Shuffle Speller
Performs inference over a task symbol set which is larger than the user symbol set	Selects from among 26+ letters using only 6 SSVEP stimuli
Leverages context prior distributions over task symbols	Uses an N-gram language model to leverage local context
Leverages the varying accuracy of user symbols for inference on task symbols	Letter inference trusts queries whose SSVEP stimulus estimate is typically more accurate than others
Offers a task symbol decision mechanism which is **robust to single classification errors**.	Rarely makes a letter decision mistake when the classifier or user selects a single incorrect SSVEP.

Material*:* The prototype uses MATLAB and g.USBamp.

Methods*:* As a test bed for our framework, we offer the SSVEP Shuffle Speller (Fig 1). A Shuffle Speller query associates sets of letters to each SSVEP stimuli; the user is asked to look at the stimuli closest to their target letter. In decision tree tree style code (Sequential or Huffman) a letter decision is made by successively pruning away all letters which are not associated with the estimated SSVEP stimuli. As a result, any incorrect SSVEP classification necessarily results in a letter selection error. Alternatively, in the recursive style codes (Uniform and Max Mutual Info) no evidence ever precludes the user from selecting a particular letter until a final decision is made. To contrast the two styles of coding 10 neurotypical users typed 5 words using each of the 4 codes.

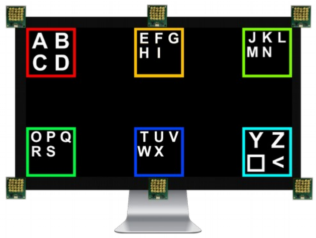

Figure 1: SSVEP Shuffle Speller, see this video.

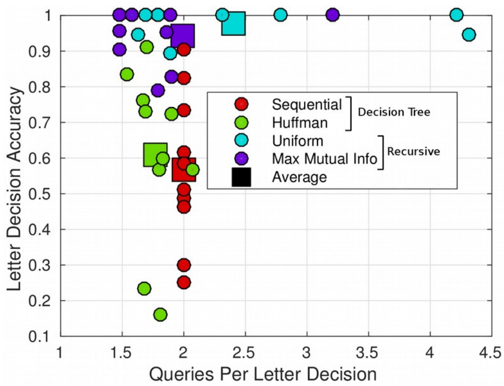

Figure 2: Speed (Queries Per Letter Decision) vs Letter Accuracy, each circle represents a user-code pair. Remember that the classifier was identical across all codes for each user.

Results*:* Recursive codes were more accurate than both decision tree style codes at a modest cost in speed.

Discussion*:* Recursive codes query the user until some confidence threshold in a letter decision is reached (85% for this experiment). This has the effect of adjusting the number of queries to suit the letter difficulty. In other words, it takes fewer queries to select likely letters (via the language model) and more queries to select unlikely letters.

Significance*:* Decision trees are popular within the BCI community; they offer an intuitive structure which BCI users can easily adopt [2-3]. While potentially less user friendly, we suggest that the performance benefits of recursive codes may outweigh their HCI considerations. A live demonstration of Shuffle keyboard which uses keyboard entry rather than EEG, will be provided at the workshop to contrast the performance of different coding schemes.

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Single-trial Classification of Inner Speech and the No-control State Using Electroencephalography

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Introduction: The main goal of brain-computer interface (BCI) research is to provide communication capabilities for people with severe motor impairments who are unable to communicate conventionally. However, a major drawback for most BCIs is the fact that they make use of non-intuitive mental tasks such as motor imagery, mental arithmetic, or mental reaction to external stimuli to make a selection. These control schemes usually have no correlation with normal communication methods making them difficult to perform by the target population. The goal of the work presented is to investigate the reliability of electroencephalography (EEG) signals in detecting inner speech (also known as covert speech or silent vocalization) against an unconstrained "no-control" state. Previous EEG-based inner speech studies have been limited to the silent vocalization of vowels or syllables rather than complete words [1]. To our knowledge, this study is the first report of using EEG measurements to detect covert articulation of a complete meaningful English word. Also, this is the first EEG study of inner speech performed over multiple sessions for each participant.

Material, Methods and Results: The study was conducted on ten able-bodied participants (five males) with a mean age of 26.8 ± 4.1. EEG signals were recorded using 64 electrodes placed across the scalp in accordance with the International 10-20 system. Each participant undertook two sessions, each consisting of 60 trials, on two different days. Each trial starts with a blank screen with a fixation cross in the center which remains unchanged during the trial. In the "inner speech" trials (half of the trials) participants were asked to answer a perceptual yes/no question by iteratively repeating the answer mentally without any vocalization and motor movement. The question was always the same, "Is this word in uppercase letters? word" with a different word every trial but always in lowercase, hence the answer was "no" for all inner speech trials. There were several reasons for choosing the word "no" for the mental speech task including being useful, intuitive and having a nasal letter, "n", and vowel of /o/ both of which have been shown to be detectable with reliable accuracy during imagined and articulated speech using EEG [2]. In the remaining trials, called "no-control" trials, participants were told to allow normal thought processes to occur without restriction, rather than being instructed to control their mental activity in a particular way. The trials were presented in pseudorandom order. The duration of each trial, regardless of their class, was 12 s. However, the first 2 s of each trial was removed for analysis since any reactive brain signal to the visual cue at the beginning of trial is not of interest in this study. Acquired EEG data were preprocessed to reduce the effects of artifacts and noise. Then, autoregressive coefficients and wavelet transform features were used to form the feature vector for each trial. Data collected across two sessions were pooled together for classification, and accuracies were evaluated offline using 100 iterations of 10-fold cross-validation. A fast correlation based filter method [3] was used for feature selection and a support vector machine model with linear kernel was used for classifier training. During each fold, only the training data was used for feature selection and classifier training while the accuracy was calculated and reported based on the test data (Table 1).

Table 1. Per-participant classification accuracies. The upper confidence limit is 66.7% for $\alpha = 0.01$ (confidence level of 99%)

Participant	1	2	3	4	5	6	7	8	9	10	Average
Accuracy	76.1	62.4	68.2	82.5	84.2	78.5	76.8	53.7	51.5	90.3	72.41±13.1

Discussion and Significance: An average classification accuracy (sensitivity, specificity) of 72.41% ± 13.1% (77.4%, 73.1%) between the inner speech and no-control trials was achieved across all participants with 7 participants exceeding 66.7% accuracy (the confidence limit for $\alpha = 0.01$) and 6 participants exceeding 70%, the threshold necessary for effective BCI communication [4]. The results suggest the potential of a two-choice EEG-BCI based on inner speech tasks. The suggested paradigm can be used intuitively by the target population for communication purposes involving yes/no queries regarding to states of pain, hunger and need of help. Also, since this study used an unconstrained "no-control" state as one of the mental tasks, the presented method is suitable for, and will later be used in, an asynchronous BCI with inner speech as an intuitive activation switch.

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Speech envelope tracking using around-the-ear EEG

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Introduction: Envelope tracking can be used to predict the direction of attention to natural speech based on continuous electroencephalography (EEG) [1] and is therefore a useful approach to control hearing devices with neural signals. In our previous work, we showed that this method also works with a small number of electrodes with a minimal decrease in decoding accuracy [2]. Here we compare the quality of speech decoding using around-the-ear EEG electrodes (cEEGrid) [3] connected to a mobile EEG amplifier and high density EEG system and propose an unobtrusive Brain-Computer Interface (BCI) based on continuous EEG signals.

Material and Methods: 18 participants with self-reported normal hearing took part in this study. Participants were presented with two 50-minute long concurrent continuous speech streams and instructed to attend to only one of them. After each ten minutes of experiment, participants answered 10 multiple-choice questions pertaining to the attended story. The EEG was recorded simultaneously with cEEGrid and high-density 84-channel EEG cap (Fig.1A). Decoding accuracy was calculated following the procedure described in [1-2], with 60s training and validation trial intervals. The temporal profile of the neural response to presented speech, temporal response function (TRF), was obtained using a univariate mapping between the stimulus and corresponding EEG [4] in the -200ms to 800ms time lag range.

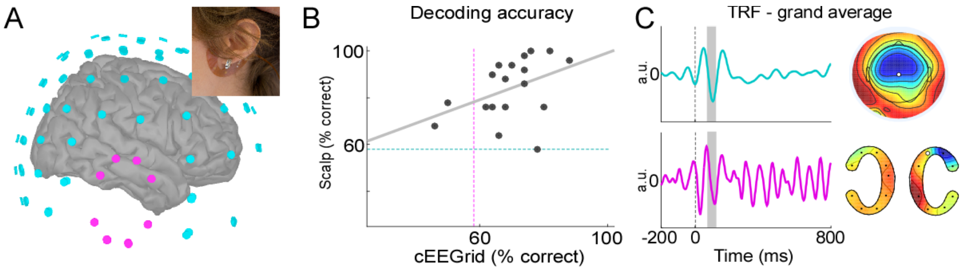

Figure 1. *A) cEEGrid (in the right corner) is a semi-disposable C shaped electrode grid printed on flexible biocompatible material [3]. Recordings were acquired from high density 84 channel EEG (blue) and 18 channel cEEGrid (pink) in parallel. B) Decoding accuracies for scalp and cEEGrid weakly correlate (r=0.43,p=0.07). Dashed lines represent chance level. C) On the left, temporal response functions (TRFs) for scalp Cz and cEEGrid R3 channel are shown. Corresponding channels are indicated in white on the scalp and cEEGgrid topography, shown on the right. The topographies are based on TRF profiles for all scalp and cEEGrid channels at ~100ms time lag (grey shaded area) and exhibit the pattern of N1-P2 AEP component.*

Results: On average, both scalp and cEEGrid decoding accuracy were significantly above the statistical chance level of 59% (cEEGrids 69.4%, scalp EEG 84.5%), as shown on Fig 1B. Only two individuals performed below chance for the cEEGrid. All individuals had above chance questionnaire performance (68% to 100%, mean of 85.7%), validating the attention instruction. No significant correlation emerged between questionnaire performance and decoding accuracy. Both scalp and cEEGrid TRF revealed a temporal and spatial pattern with components also visible in the AEP (Fig. 1C).

Discussion: Electrode placement around the ear is sufficient to indicate the attended speaker in this concurrent speaker paradigm. The usefulness of the cEEGrid data is further confirmed by investigating the physiologically interpretable TRF pattern, which, while showing the negative peak at 100ms for both setups, contains clearer responses for scalp recordings. The decoding accuracy of the cEEGrid recordings is lower compared to the scalp recordings, which might be due to the lower number of electrodes and the lower spatial coverage.

Significance: We show that tracking the auditory attention to continuous speech can be done with an unobtrusive, user-friendly electrode setup located around the ear. Combined with a lightweight mobile EEG amplifier this result is a further step towards controlling hearing devices with a BCI.

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The contribution of counting to neural activity evoked by the oddball paradigm

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Introduction: Research about brain computer interfacing (BCI) has shown that it can be estimated based on EEG data which stimuli a person paid particular attention to (e.g. [1]). In typical BCI experiments that use the oddball paradigm [2], several classes of stimuli are presented in succession and the stimuli of interest *(targets)* are counted while other stimuli are ignored *(distractors)*. The question was addressed if the neural activity evoked by targets is merely a correlate of the silent counting or indeed of the attention itself.
Material, Methods and Results: Three task variations of the oddball paradigm were compared (Fig. 1, left). Only stimuli of the ***target*** colour (indicated at the beginning) had to be counted in condition **T**. In condition **A**, summation had to be performed for ***all*** stimuli (+10 had to be added for targets and +1 for the more frequent distractors). No silent counting was performed in condition **P** where the ***positions*** of the targets on the screen had to be memorised. Thirteen persons performed each task twenty times while EEG signals were recorded with 64 active electrodes. The dynamics of the neural activity evoked by the flashing of targets and distractors were characterised (Fig. 1, center). Support vector machines were trained on the data of each condition to discriminate between single-trial EEG epochs aligned to the flashing of targets vs. distractors using spatio-temporal features and tested on separate data [3]. Training and testing was performed on all possible pair-wise combinations of the conditions (Fig. 1, right). If training and testing condition were the same, cross-validation results are reported.

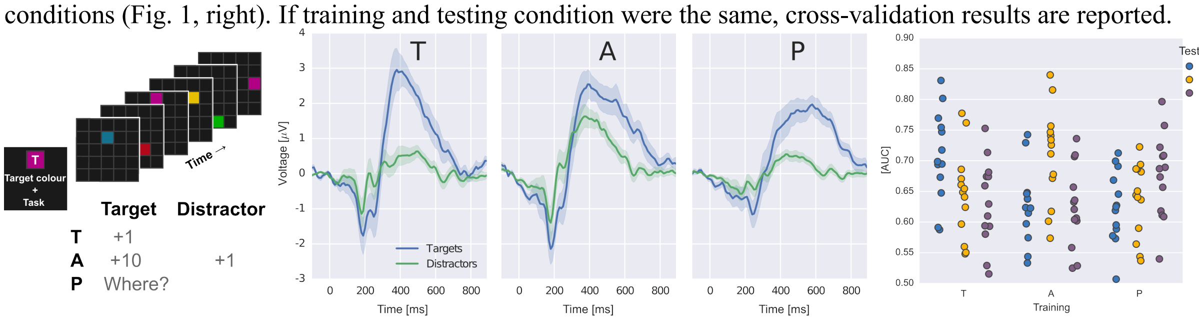

Figure 1. *Left: The stimuli were the same in the three task variations T, A and P of the oddball paradigm. Squares of different colours flashed for 500 ms each, interleaved by 500 ms blank screen, in a 5 x 5 grid in pseudo-random order (short example). Center: EEG responses to targets and distractors at the exemplary electrode Pz (averages over all epochs of all subjects). Right: Classification performances of all subjects (dots) as area under the curve of the receiver-operator characteristic.*

Discussion: Targets evoked a larger late positive component than distractors in all three experimental conditions in particular at parietal and central electrodes (Fig. 1, center) – as it can be expected in the oddball paradigm [2]. Classification performance was better than chance (AUC of 0.5) for all combinations of training and testing condition and every subject (Fig. 1, right). Discrimination based on EEG data was also possible when both targets and distractors required silent summation (A) or when no counting was performed (P) and, therefore, counting only targets (T) was not a necessary prerequisite to elicit the characteristic neural response. The successful transfer of the classifiers between the experimental conditions suggests that the neural processing is similar. Apparently, a substantial part of the neural activity evoked by targets is indeed a correlate of the attention itself and not of the silent counting.
Significance: Background of the study is the objective to widen the range of application of BCI and to transfer the technology to relevance detection in human-computer interaction (HCI). EEG data could be used to predict to which items displayed on the screen a user paid special attention to. This information about the user interest could serve as additional input to computer software. Transferring BCI to HCI is presumably most useful and convenient for the user if the relevance information is inferred implicitly. For this reason, it is crucial for realistic HCI application scenarios that relevant items do not have to be counted (while in most BCI applications silent counting would be legitimate to enhance performance). We could show that counting is not necessary to detect the stimuli of interest. While single stimuli popped up in succession here, the combination of EEG with an eye tracker would allow to relate the neural activity to each of several items displayed in parallel on the screen [4].
Acknowledgements: The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 611570. The work of BB was additionally funded by the Bundesministerium für Bildung und Forschung under contract 01GQ0850.

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Toward a Brain Interface for Tracking Attended Auditory Sources

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Introduction: Auditory-evoked noninvasive electroencephalography (EEG) based brain-computer interfaces (BCIs) could be useful for improved hearing aids in the future. This work investigates the role of frequency and spatial features in building an auditory based BCI specifically for the purpose of detecting the attended auditory source in a cocktail party setting. An initial closed loop design for possible EEG-augmented hearing aids has been tested. Two cross correlation and signal modeling based features which use EEG and speech envelope is shown to be useful to discriminate attention in the case of two different speakers. Results indicate that, on average, for speaker and direction (of arrival) classification, the presented approach yields %91 and %86 accuracy, respectively. Accuracy of correct classification in online setting yields %65.

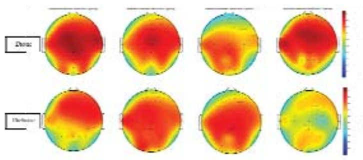

Figure 1: Topographic scalp map for the classification accuracy (measured with AUC) for EEG-based estimation of attended speaker.

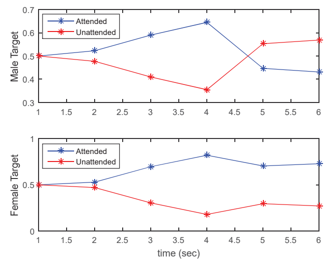

Figure 2: Online weight controlling of subject for attended and unattended speakers.

Material, Methods, and Results: Two sets of experiments have been designed and conducted to test source detection feasibility in an offline setting, and to test an initial online auditory attention classification setup. In the first set of experiments, based on findings reported in the literature on cortical entrainment of EEG measurements to the temporal envelope of speech [1], crosscorrelation between EEG and speech envelope is used to extract features to classify auditory attention. Classifying sources as attended or unattended, based on their frequency or direction of arrival were also attempted, via diotic and dichotic sound presentation paradigms [2]. To localize selective attention responses, single channel classification analysis was performed using a Regularized Discriminant Analysis (RDA) classifier. Discriminant scores from RDA were used to estimate ROC curves and area under the ROC curve (AUC) as a measure of potential classification accuracy. Figure 1 shows scalp topography maps of AUC for both diotic and dichotic auditory presentations. The estimated AUC for the RDA classifier that attempts to detect the attended speech source ranges between 86% and 95% in diotic and dichotic cases, respectively. For the classification of the direction of attended speech, AUC values between 82% and 89% were obtained for female and male narrators, respectively. In the second sets of experiments, the user was asked to amplify a target speech by paying attention to it. To enable this, we designed a closed loop system, which adjusts the convex linear combination parameters of two speech sources presented to the user, based on the estimated probability of each sound being desired (attended) given recent EEG evidence. These estimated probabilities of intent to attend were calculated using class conditional distributions calibrated based on supervised EEG data obtained in a preceding calibration session. RDA scores were used as one dimensional EEG features, and converted to class conditional likelihoods using kernel density estimation. In the on-line session, the convex linear combination weights of sound sources were dynamically adjusted every 10 seconds to be proportional to the posterior probability of each source being attended. Posteriors were updated recursively using Bayes rule. Users attempted to amplify the designated target speech with their auditory attention using this brain interface in 20 one-minute-long trials. Figure 2 shows the average weights (over 20 trials) of attended and unattended speech over the course of one minute, for male and female narrators. While for the female target narrator, users were able to increase the weight of this sound source through this brain interface, for the male target narrator, initial good task performance was followed by incorrect amplification of the nontarget female narrator towards the end of the trials. We suspect, this was due to distraction of subject to the female voice as he confirmed that female sound was catching his attention because of her intonation. In future experiments we take the role intonation factor into account in order to remove attention biases of sources which might occur.

Discussion: We investigated the feasibility of online classification of auditory attention using EEG. Initial experimental data presents mixed, but motivating results for further research on EEG-guided sound modulation.

Significance: This is a step towards hearing aids that use EEG evidence to estimate user auditory attention.

Acknowledgements: This work is supported by NIH 2R01DC009834, NIDRR H133E140026, NSF CNS-1136027, IIS-1149570, CNS-1544895. For supplemental materials, please see http://hdl.handle.net/2047/D20199232 for the CSL Collection in the Northeastern University Digital Repository System.

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Toward improved covert attention application using shifting stimuli

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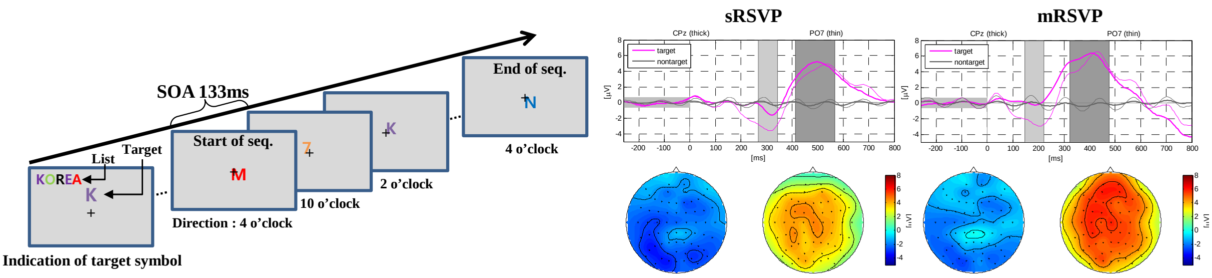
Introduction: Most of P300-based brain-computer interface (BCI) spellers primarily use matrix layouts. These spellers are of limited application value for paralyzed patients with severe oculomotor impairments [1]. Recently, a gaze-independent BCI speller was proposed using rapid serial visual presentation (RSVP) [2], one limitation of which is that it is difficult to recognize targets due to the rapid presentation of characters. The fundamental objective of this study was to increase the perceptibility of target characters by introducing motion stimuli presented inside foveal vision, thereby fundamentally enhancing the performance of a RSVP speller.

Material, Methods and Results: We developed two event-related potential (ERP)-based BCI spellers using RSVP with motion and non-motion stimuli, respectively. Figure 1(a) illustrates an example of the sequence of motion RSVP (mRSVP), where all of 36 characters randomly presented for 133 ms (stimulus onset asynchrony) and moved into one of the six directions (2, 4, 6, 8, 10, and 12 o'clock). We evaluated the effect of the two different stimulation conditions on ERPs and its performance with seven able-bodied subjects. Figure 1(b) depicts grand-average ERPs for two representative channels (CPz and PO7) and topographical maps for standard RSVP (sRSVP) and mRSVP across all subjects. Both stimulation methods show typical P300 responses for targets, but their averaged maximum peak amplitudes are higher and latencies are shorter for mRSVP than sRSVP (latency: 562±68 ms for sRSVP vs. 482±34 ms for mRSVP; peak amplitude: 4.38±2.0 μV for sRSVP vs. 5.0±2.8 μV for mRSVP). The P300 could be affected by stimulus evaluation and response production. The mean classification performances of sRSVP and mRSVP spellers were 84.1±10.5% and 90.5 ±7.1% (chance level: 2.77 %), respectively.



(a) (b)

Figure 1. *(a) Motion RSVP paradigm. (b) Grand average ERPs for targets (magenta) and non-targets (gray) at CPz and PO7(upper panel), respectively, and topographical ERP maps in the two selected time intervals (lower panel).*

Discussion: The mRSVP method showed not only stronger ERP responses but also shorter latency than the sRSVP, from which it can be thought that motion stimuli could be more easily recognized than static ones from the neurophysiological point of view. In this study, moving directions of visual stimuli were randomly designated for mRSVP. We will design and test another mRSVP method in which a motion direction is pre-defined and fixed during visual stimulation.

Significance: Our results revealed that the performance of a conventional RSVP speller can be improved by combining dynamic motion to the conventional stimulation method, demonstrating the feasibility of the mRSVP stimulation method.

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Towards an Auditory BCI for Binary Communication in the ICU

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Introduction: Brain computer interfaces (BCI) provide means of communication for people with severe speech and motor disabilities. Visual paradigms are broadly employed for noninvasive EEG-based BCIs due to their high classification accuracies. However, they cannot be utilized for users with visual impairments. Auditory presentation techniques can be adopted as a viable alternative for this population [1-3]. We aim to develop a multisensory ERP-based BCI for binary selection to communicate in the intensive care unit (ICU). While designing a paradigm that is intuitive and comfortable for the user is important, physical constraints of the ICU setting must also be considered. Furthermore, we aim to design a paradigm that is applicable with both auditory and tactile stimulation. For the auditory stimulation based realization, we primarily focus on using words as the stimulus, since their meanings are intuitive and we expect them to be less irritating than tones, based on literature on auditory BCIs [1]. We report results for several pilot studies that makes the system suitable for binary communication in the ICU.

Method: EEG signals were acquired using a g.USBamp amplifier. PCA was used for dimensionality reduction, regularized quadratic discriminant analysis (RDA) was employed for feature extraction and a MAP classifier was implemented for classification. We tested the following paradigms using words and tones, each with 100 sequences that contain 16 trials distributed according to:

a) **Random:** Each sequence contains 10 distractors (D) (e.g., *Wait*), 3 *Yes* (Y) and 3 *No* (N) stimuli randomly shuffled. An inter-symbol interval (ISI) of 300ms is used for words and 150ms for tones.
b) **Deterministic with fixed ISI:** Each sequence consists of [D Y D N D Y D N…] with an ISI as in (a).
c) **Deterministic with random ISI:** Each sequence is constructed as in (b) with random ISI chosen in the interval [300,450]ms for words and [150,250]ms for tones.
d) **Simultaneous with fixed ISI:** Two sequences play simultaneously, a *Yes* sequence [YYY..] into the right ear, and a *No* sequence [NNN...] into the left ear, with an ISI as in (a).
e) **Simultaneous with random ISI:** Simultaneous sequences as in (d) with random ISI as in (c).

Results: The results for the different paradigms are summarized in Table 1. AUCs are calculated for 10-fold cross validation. The ERPs corresponding to the target, non-target, and distractor stimuli in paradigm (a) row-2 are shown in Fig. 1.

Paradigm	Stimuli	AUC
(a) Random	Y(R), N(L), D(LR)	[0.74, 0.79]
	Y(R,M), N(L,F1), D (LR,F2)	[0.79, 0.82]
	Y (R,M), N (L,F1), 9 Ds (LR,F2)	[0.64, 0.70]
	Y(2kHz,R), N(1kHz,L), D(440Hz,LR)	[0.75 ,0.77]
(b) Det. fixed ISI	Y(R), N(L), D(LR)	[0.63, 0.67]
	Y(R,M), N(L,F1), D(LR,F2)	[0.76, 0.79]
	Y(2kHz,R), N(1kHz,L), D(440Hz,LR)	[0.63, 0.65]
(c) Det. rand. ISI	Y(R), N(L), D(LR)	[0.75, 0.76]
	Y(R,M), N(L,F1), D(LR,F2)	[0.75, 0.78]
	Y(2kHz,R), N(1kHz,L), D(440Hz,LR)	0.72
(d) Sim. fixed ISI	Y(R,M), N(L,F1)	[0.55, 0.58]
	Y(2kHz,R), N(1kHz,L)	0.60
(e) Sim. rand. ISI	Y(R,M), N(L,F1)	0.59
	Y(2kHz,R), N(1kHz,L)	0.55

Table 1. Offline classification results in terms of area-under ROC curve (AUC) for different subjects. R/ L are right/left ears, M/F1/F2 are male/female1/female2 voices.

Discussion: The best results were achieved with the random paradigm. Playing each stimuli from a specific side (right ear for *yes* and left for *no*), helps the user focus on the target, ignoring the non-target and distractors. Using different voices has the same effect. Observing the ERPs for this paradigm, we can see more separability for the target and non-target stimuli. We also notice that the ERPs for the *yes* and *no* stimuli are different. Hence, our approach for online classification will use a joint classifier that fuses a *yes* classifier (trained only with *yes* stimuli) and a *no* classifier (trained only with *no* stimuli).

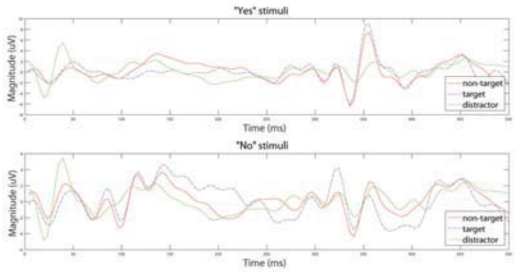

Fig. 1. Averaged EEG signals at Cz for the random paradigm with different voices (a) row-2.

Significance: This pilot analysis provides guidance for the development of binary communication BCIs for use in the ICU. A promising paradigm for auditory (and tactile) stimulation that satisfies ICU constraints and considers user experience is identified.

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Visual and audiory P300-BCI: psychological predictors of performance in healthy subjects

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Introduction: Predictors of BCI performance would be valuable to estimate the likelihood of successful BCI operation. Even more so, if specific predictors could be identified dependent on the input signal for BCI. To date, studies on predictors of P300-BCI performance are sparse. In a sample of severely motor impaired patients (N=11) and another of healthy subjects (N=40) the N2 amplitude during an auditory oddball was highly correlated with later P300 BCI performance of a web browsing task and a visual and auditory P300-BCI spelling task [1,2]. In a sample of healthy participants, a relationship between heart rate variability and BCI performance (visual P300 BCI) was found [3]. Motivation was positively and empathy negatively linked to performance [4,5].

Material, Methods and Results: To further elucidate potential predictors of visual and auditory BCI performance we investigated a sample of 40 healthy BCI novices (21 male, mean age 25.8, SD 8.46 years). Participants' task was to spell 3 times the words "BRAIN POWER" with a visual and an auditory P300 5 x 5 spelling matrix. Visual matrix was standard. In the auditory mode numbers coding rows and columns were presented by a male voice. First the numbers of the rows (1 – 5) and then the numbers of the columns (6 – 10) were presented for selection. On a separate day, participants were presented with a battery of performance, personality, and clinical tests. EEG was recorded with Ag/AgCl electrodes in a 128-channel cap (Easycap GmbH), 67 channels (of these 4 electrooculography) were used during the P300 BCI, sampled at 500 Hz with a band-pass from 0.05 to 200 Hz. Statistical analysis: First, in every subgroup of tests a variable selection procedure was performed by correlating the correct response rate of spelling and all independent test variables. Predictors were selected according to the following rule: Variable X gets selected if (I.) it correlates significantly with the CRR and (II.) it is not inter-correlated with other tests of the sub-group.

Average visual and auditory P300 BCI accuracies were M = 94.5% (SD 14.9) and M= 64,3% (SD 37.4), respectively. In the visual P300-BCI the ability to learn (non-verbal learning test = NVLT; performance) was positively and emotional stability (B5PO, personality) negatively correlated with performance, but not significant after Bonferroni correction. Logistic regression of the two variables on visual P300 BCI performance explained about 24% of the variance ($R^2 = .24$; $F_{2,36} = 5.74$; $p < .05$). Emotional stability was also negatively correlated with auditory P300-BCI performance, but again not significant after Bonferroni correction. Logistic regression explained 8% of the variance, but was not significant.

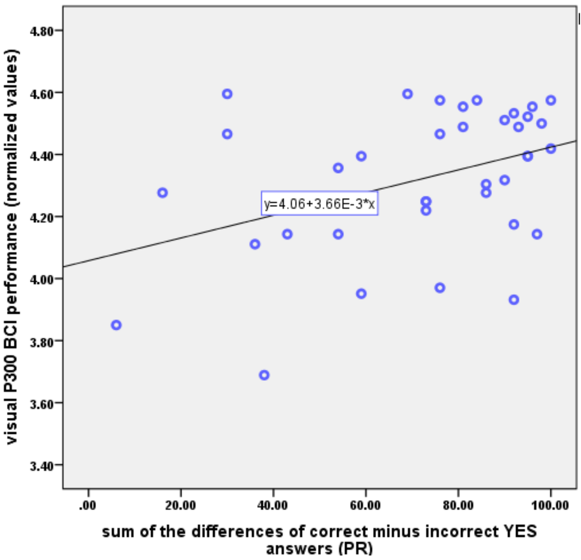

Figure 1. *Correlation between "sum of the differences of correct minus incorrect YES answers (NVLT=learning) and the visual P300 BCI performance after excluding of two outlier values.*

Discussion: Results of only one performance (learning) and one personality (emotional stability) test predicted visual, but not auditory P300-BCI performance. Albeit the P300 is elicited by external stimulation and it is argued that not much learning is involved in controlling a BCI based on event-related potentials, it has been shown that training can improve P300-BCI performance [6]. The contribution of emotional stability was low (results not shown) in the visual and not significant in the auditory P300-BCI.

Significance: Psychological factors as measured with performance, personality, and clinical test seem to play a minor but significant role in P300-BCI performance.

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Communication Strategies to Involve Potential Users in BCI Research

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Introduction: Brain-computer interface (BCI) research and development increasingly involves potential end users as study participants. For BCIs with habilitative or rehabilitative purposes, end users are typically people with severe disabilities. Many of these individuals experience communication difficulties as a result of their physical, sensory (e.g. hearing or vision), cognitive, and/or language impairments, presenting challenges to BCI researchers when obtaining informed consent, giving instructions, requesting and receiving user feedback, and involving people with disabilities in user-centered design and participatory action research. Simple, proven techniques from the field of augmentative and alternative communication (AAC) will help researchers to communicate effectively with these individuals. Pairing these techniques with International Classification of Functioning, Disability & Health (ICF) [1] codes and qualifiers for performance restrictions will present guidelines for more effective communication strategies that could be used for obtaining consent.

Strategies for Communicating with People with Disabilities: People with communication impairments have a diverse range of needs and abilities. They may use AAC strategies ranging from unaided (e.g. eye blinks, gestures, natural speech) to high-tech (e.g. speech-generating devices) [2]. Researchers must understand how these methods are used and plan interactions accordingly. Table 1 presents strategies for communicating with people with various types of impairments, described using ICF codes. These strategies have been used successfully with a total of 18 individuals with disabilities for obtaining informed consent [3-6], participant screening [3], providing task instructions [4], qualitative interviews [5], and soliciting user feedback [6].

ICF code(s)	Communication strategies
b3: Voice and speech functions and/or b7: Movement-related functions	• Learn the participant's yes/no responses. Ask him to "show me your *yes*" and "show me your *no*". • Ask questions with clear yes/no answers. "Did you prefer setting A or setting B?" is not a yes/no question. • Use partner-assisted scanning [2] for multiple-choice questions. Present options one at a time, preferably using multimodal input (see below), and wait for a signal to indicate the participant's selection.
b1: Mental functions (cognition)	• Use spaced retrieval and/or errorless learning [2] in experimental tasks. • Provide verbal and/or written cues.
b2: Sensory functions	• Use multimodal input [2], e.g. both written and spoken words, when sharing information or asking questions.
b167: Mental functions of language	• Use multimodal input (see above). Writing down key words is often helpful. • Keep instructions and questions simple, and rephrase them if necessary. • If open-ended questions are difficult, offer response choices.
Any of the above	• Schedule study visits to allow adequate time for communication. • If longer responses or additional information are required, provide questions in written form and allow time before or after study sessions for the participant to compose responses. • When possible, have two researchers present during each study visit. One can focus on system setup, software operation, etc., while the other focuses exclusively on communicating with the participant. • Ask what behavior the participant expects from you as a communication partner. • Ensure that communication aids, glasses, hearing aids, or other sensory aids are available when applicable. • Establish a signal participants can use to indicate when they need a break to rest or receive medical care.

Table 1. *Suggested strategies for communicating with individuals with physical, cognitive, sensory, and language impairments.*

Discussion: Communication strategies should be chosen based on an individual's specific needs and abilities, using functional descriptions and severity qualifiers consistent with the ICF [1]. Family members or care providers can suggest other methods for optimizing communication.

Significance: Simple AAC techniques support effective interactions between BCI researchers and people with communication impairments who have relatively spared cognition, aiding in the inclusion of potential end users in research tasks, such as giving informed consent, providing user feedback, and decision making.

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An Improved Cognitive Brain-Computer Interface for Patients with Amyotrophic Lateral Sclerosis

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Introduction: Brain-computer interfaces (BCIs) are often based on the control of sensorimotor processes, yet sensorimotor processes are impaired in patients suffering from amyotrophic lateral sclerosis (ALS) [1]. Previously, we devised a novel paradigm that targets higher-level cognitive processes to transmit information from the user to the BCI [2]. The current work describes a refined version of this paradigm. We instructed five ALS patients (table 1) and eleven healthy subjects (6 female, mean age 28 years ± 7.5) to either activate self-referential memories by thinking of a positive memory, or to focus on a mental subtraction task, while recording a high- density electroencephalogram (EEG). We argue that both memories [3] and mental calculations [4] are likely to modulate activity in the default mode network (DMN) without involving sensorimotor pathways.

Table 1. ALS Patient Data

Patient	P1	P2	P3	P4	P5
Age	75	54	NA	51	59
Sex	M	M	M	F	F
ALS-FRS-R[1]	42	48	33	12	0

[1] Revised ALS Functional Rating Scale [5]

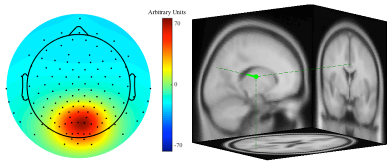

Figure 1. Topography of sources that represent the precuneus

Material, Methods and Results: Subjects performed four experimental blocks in a single session. Each block consisted of ten trials in which they were asked to continuously subtract a small number from a large number, and ten trials in which there were asked to think of a positive memory. The command appeared in the center of the screen and was simultaneously read out by a text-to-speech engine. For the subtraction trials, both the large number and the small number were randomly chosen. Each trial began with 5.5±0.50 seconds rest and ended after 35 seconds. ALS patients were only asked to perform two blocks. We restricted our offline analysis to the α-range of the spectrum, as this band is associated with self-referential processing [5]. We removed EMG confounds by employing independent component analysis. By using the topography in figure 1, we aimed a linearly constrained minimum variance beamforming algorithm [6] at the precuneus region, the hub of the DMN. The α-bandpower of the beamformed signal was then used in a leave-one-trial-out cross-validated support vector machine with a linear kernel to estimate the accuracy in discriminating the activity-patterns. Table 2 shows the classification accuracies for ALS patients and healthy subjects.

Table 2. Classification Accuracies for Patients and Healthy Subjects.

P1	P2	P3	P4	P5	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11
97%	60%	90%	43%	77%	100%	75%	100%	40%	85%	35%	85%	85%	80%	65%	50%

Discussion and Significance: The current study aimed to show that healthy subjects and ALS patients in various stages of the disease are able to use a cognitive paradigm for BCI control. Using a linear classifier, we were able to successfully distinguish a self-referential from a non-self-referential condition, with an average decoding of 73%, separately for both healthy subjects and ALS patients. A one-tailed Wilcoxon signed-rank test rejected the null-hypothesis of a median classification accuracy on chance-level (50%) at p = 0.0015 for the combined subject groups. The presented work could serve as a novel tool which allows for simple, reliable communication with patients in late stages of ALS.

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Analyzing the Performance of Dry Electrodes for P300 Brain-Computer Interfaces in Participants with ALS

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Introduction: P300-based BCIs typically utilize gel-based "wet" electrodes for EEG recording that require a substantial amount of time and expertise to set up. Although dry electrodes are much faster and easier to apply, reduced signal-to-noise ratios impede their widespread use. Without a stabilizing gel layer to keep the electrodes in good electrical contact with the skin, dry electrodes may be more susceptible to motion artifacts. We present a performance comparison between wet and dry electrodes for the P300 speller in participants with ALS, and investigate two artifact detection techniques to measure the difference in possible motion artifacts between the systems.

Material, Methods and Results: Eight participants with communication disabilities (ALS=7, PLS=1) completed this study. Each participant completed two P300 speller sessions; one using a passive wet electrode system and one using the g.Sahara dry electrode system. The average spelling accuracy was 87.9% using wet electrodes and 42.8% using dry electrodes, and the differences in accuracy were statistically significant ($p < 0.01$). Power spectral density estimates revealed an increase in low-frequency noise for dry EEG recordings, which suggest that transient voltages, such a motion artifacts, may be negatively impacting dry system performance. To measure artifact noise, two techniques were used to detect large transient voltages in EEG recordings during the periods between characters (no stimulus flashing, eliminating the possibility of inadvertently detecting P300s). The first technique used an autoregressive model. Given that transient artifacts are non-stationary phenomena, the model detected a large error (exceeding a given threshold) when an artifact may have occurred. The mean number of artifacts detected for a set of thresholds were averaged across the eight participants and the results are displayed in Figure 1a. The second technique used wavelet analysis. Peaks in the wavelet approximation coefficients above a certain threshold were measured as artifacts. The results were averaged across participants and are shown in Figure 1b. The results in Figure 1 show that for thresholds above 30μV, both techniques detect a larger number of possible artifacts in the dry electrode recordings when compared to the wet electrode recordings.

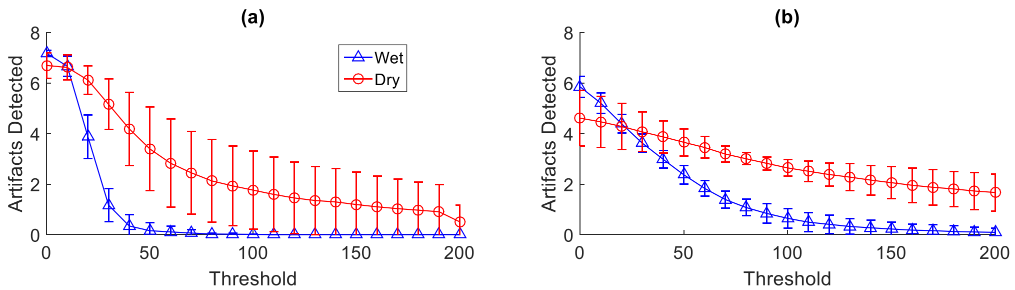

Figure 1. *Two techniques were used to detect possible artifacts during interstimulus durations: (a) autoregressive modeling and (b) wavelet analysis. The results in both plots were averaged across eight participants with communication disabilties. Each plot displays the number of possible artifacts detected (y-axis) for a threshold (x-axis) in the dry electrode recordings (circles) and the wet electrode recordings (triangles)*

Discussion: Two transient artifact detection techniques (i.e., autoregressive modeling and wavelet analysis) revealed an increased number of possible motion artifacts for the dry system when compared to the wet system. This indicates that decreased dry system BCI performance may be the result of artifacts incorrectly classified as target signals.

Significance: Dry electrodes would reduce set-up time and complexity for the P300 speller. However, dry systems often realize lower classification accuracies than conventional wet systems and the differences in performance are statistically significant. The results from this artifact detection study indicate that transient removal techniques may be needed to improve dry system performance.

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Articulatory gestures are insensitive to within-word context

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Introduction: A brain-computer interface for communication that uses speech-related signal as input could drastically improve efficiency and potentially be more intuitive for users [1]. Previously, we have demonstrated patterns of activity within speech motor cortex that represent phoneme production [2]. However, phonology suggests that the basic units of production may be articulatory gestures, such as the tongue closure at the back of the teeth to produce the /t/ phoneme [3]. We therefore investigated speech motor cortex to determine representation of articulatory gestures using electrocorticography (ECoG). Moreover, cortical representation of phonemes varies significantly if the phonemes are at the beginning or the end of a word [4], which poses challenges in speech decoding. If representation of articulatory gestures is independent of context within a word, it would be easier to decode them from speech motor cortex for use in a brain-computer interface. We therefore also analyzed the context-independence of gesture representation, comparing gestures at the beginning of a word to gestures at the end of a word.

Methods: Five subjects undergoing high-density ECoG monitoring during tumor resection participated in our study. Subjects read words aloud at a rate of 1 every 2 seconds. We estimated articulatory gesture onset times by using acoustic-articulatory inversion [5], using microphone-recorded audio synchronized to ECoG recordings (BCI2000). High gamma band activity (70-200 Hz) was z-scored relative to each electrode. We investigated one electrode at a time, decoding the contextual position for any gesture that exhibited some degree of high gamma representation on that electrode. We decoded the position of each gesture in the word (start vs. end of the word) using short time windows (-100 ms to +50 ms) around gesture onset to isolate signal directly related to production. We used linear discriminant analysis to classify the instance of each gesture as either at the beginning or at the end of a word. Cross-validation (90% train, 10% test) was randomized and repeated 100 times. The 95% confidence intervals of resulting decoding accuracy values were calculated. This same process was repeated using randomly shuffled labels to calculate chance performance. Decoding accuracy relative to chance performance revealed whether context could be decoded using gesture information. These results were compared to previous phoneme context decoding during word production [4].

Results: Average high gamma activity for each gesture for each relevant electrode demonstrated a consistent, robust increase in activity irrespective of gesture context in a word. These results differ from phoneme decoding, which reveal substantial differences in high gamma activity related to contextual position in a word. Further, decoding of contextual position of gestures was not significantly different from chance performance using shuffled labels ($p < 0.05$). In contrast, the context of phonemes in a word could be accurately decoded from the high gamma activity ($p < 0.05$).

Discussion and Significance: These results provide evidence that the signals associated with articulatory gestures are more context-independent than those associated with phonemes. Further, these results indicate that articulatory gestures may be the more fundamental building blocks of speech motor cortex activity, largely due to the context-independence across those gestures for which we could determine a relevant electrode with representative information. Accordingly, future speech brain-computer interface devices using ECoG from motor cortex may perform better if they decode articulatory gestures instead of phonemes, as gestures have a more consistent cortical signature. These findings have significant implications outside of brain-computer interface research, as they advance our understanding of how speech is generated from motor cortex activity.

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Attentional processes during P3-based Brain Computer Interface task in amyotrophic lateral sclerosis patients

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Introduction: To be available for a wide range of end-users a brain-computer interface (BCI) should be flexible and adaptable to end-users' cognitive strengths and weaknesses. People's cognitive abilities change according to the disease they are affected by, and people suffering from the same disease could have different cognitive capacities. We aimed at investigating how the amyotrophic lateral sclerosis (ALS) disease, and two different cognitive attentional aspects [1] influenced the usage of a P3-based BCI.

Material, Methods and Results: Thirteen participants with ALS diagnosis and 13 healthy participants, matched for age and years of education, participated in the study. Both groups performed a P3-based BCI task (P3-speller [2]) and were screened for attention substrates by means of a rapid serial visual presentation task (RSVP; [3]).
Aims of the statistical analysis are listed in the following. *i)* First, to investigate ALS influence on BCI usage, by comparing the two groups in terms of BCI performance (ITR scores), amplitude and latency of N2 and P3 ERPs. Furthermore we calculated the influence on ITR scores, of the coefficient of determination R-square estimated within N2 wave interval (N2-Rsquare) and within P3 wave interval (P3-Rsquare). We assumed that the two variables mostly reflected the contribution of N2 wave and of P3 wave respectively, on performance in BCI control. *ii*) The second aim was to investigate whether attentive subprocesses measured with the RSVP (T1%= index of participants' temporal attentional filtering capacity; T2%=index of the capacity to adequately update the attentive filter) were predictors of the BCI control (ITR). *iii*) Third aim was to compare the two groups in terms of T1% and T2%.
Results showed that i) ALS had an influence on BCI usage: participants with ALS had lower ITR scores ($p<.05$) and longer P3 latency ($p<.05$) in comparison to healthy participants; no differences between the two groups were found in N2 and P3 wave amplitudes and in N2 wave latency; in participants with ALS, N2-Rsquare -but not P3-Rsquare- was significantly predictive of ITR scores with a Beta of 0.59 ($p<.05$). *ii*) T1% -but not T2%- was a predictor of ITR scores ($p<.05$) and P3 wave amplitude ($p<.05$) and *iii*) T1% was compromised in participants with ALS ($p=.01$).

Discussion: Results showed that ALS affected the capacity to accomplish the P3-speller task (ITR scores) and the latency of the P3 wave. We speculate that the disease affects attention modulation, when perception (reflected by N2 wave) was complete, by delaying the storing of the target in working memory and the context update processing stage (reflected by P3 wave latency). ALS also influenced another temporal aspect of selective attention i.e. the capacity to temporally filter a target stimulus within a stream of stimuli (T1%), which was related to BCI control (T1% correlate with ITR). Moreover N2-Rsquare significantly predicted BCI performance: we therefore identify the temporal aspects of attentional processing as a limitation for successful interaction between people with ALS and BCI. Conversely N2 modulation (which was not influenced by the disease) could be further exploited for classification, thus improving BCI control.

Significance: Our data partly clarify cognitive features influencing P3-based BCI control in people with ALS. The temporal aspect of the stimulus processing is a crucial point to be taken into account when developing BCI devices which should be specifically designed considering the cognitive characteristics of end-users.

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Beyond the control: idle state detection in human intracortical Brain-Computer Interfaces

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Introduction: Brain-computer interfaces based on intracortical recordings (iBCI) have allowed people with tetraplegia to reliably control a computer cursor on a screen and perform actions with a robotic limb [1, 2]. Long-term goals of this technology include the detection of a user's intention to control the interface, allowing automatic switching between volitional neural control of assistive technologies and idle time. Idle state detection has been examined in EEG-based BCI [3] and in intracortical BCI with monkeys [4, 5]. Here, we report the ability to distinguish motor cortical activity in task-related blocks from idle inter-task periods in an individual with tetraplegia using an iBCI.

Methods: The participant in this study (T9) was a 52-year-old man in the BrainGate2 trial with amyotrophic lateral sclerosis. During research sessions, neural signals were recorded from two 96-channel microelectrode arrays (Blackrock Microsystems, Salt Lake City, UT) implanted into his motor cortex. Multi-unit spike rates were extracted (20ms bins) for each channel during centered-out-and-back radial-8 task blocks and during inter-task periods from five sessions in April and May of 2015. Classification performances were computed using linear discriminant analysis with a 10 fold cross-validation. First, on dataset 1 (first 10min of the session), we determined the optimal neural history (T) using the cost function CF below, constrained to a false positive (FP) rate of less than 1%. We then applied the value T on a second dataset and evaluate the positive predictive value (PPV) and negative predictive value (NPV).

$$CF(T) = max\ \frac{TP(T)}{T\ x\ FP(T)^2 + 1}, \quad \text{with } FP(T) < 1\%$$

Results: Optimal neural history (T) ranged between 2.86 (session E) and 3.90 (session B) seconds (mean±std: 3.30±0.38 seconds). Across all 5 sessions incorporated into this study, linear classification could distinguish idle intertask from cursor control/task periods with a positive predictive value (PPV) and a negative predictive value (NPV) above 98.5%.

Conclusion: In an individual with tetraplegia, idle state could be distinguished from a user's active engagement with high accuracy. Implementing this neural switch online could allow a user to turn the system on and off based on their neural activity only, without the assistance of a caregiver or expert technician. This would also remove undesirable cursor movements on the screen during user's idle periods, providing greater independence and utility for people with severe motor disabilities using iBCI communication.

Significance: We demonstrated that a few seconds of multi-unit spike rates activity could be used to distinguish idle from control periods during intracortical recording in a participant with tetraplegia.

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Blink Artifact Rejection Reduces P3 Speller Accuracy but May Prevent Unintended Blink-Based Control

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Introduction: The P3Speller, first proposed by Farwell and Donchin [1], relies on the P300 brain response. The P300 is well-studied in various application domains and recording standards are available [2]. These standards are not followed by most brain-computer interface (BCI) systems, mainly for reasons of speed. One recommended technique is blink artifact rejection. Of available techniques, we focus on FORCe [3], a recent artifact rejection methods designed for BCI that works on 1 s electro-encephalogram (EEG) segments.

Material, Methods and Results: This study uses recorded data from [4], [5], where participants used a BCI on three separate days to produce three sentences per day, with one extra training file on day one. Data is from the first 33 participants to complete the protocol. There were 10 participants with amyotrophic lateral sclerosis, 9 age- and gender-matched neurotypical controls, 4 with neuromuscular dystrophy, and 7 additional controls.

We used 1 s EEG segments starting from 100 ms pre-stimulus to capture the 0-800 ms window used in our online studies. Each EEG datafile was segmented, passed through FORCe, and decimated by a factor of 13 prior to least-squares classification. The results were compared to an identical processing chain without FORCe or any other artifact rejection. Separate classifiers were trained and tested on their own processing chains.

Of the 297 sentences analyzed, using FORCe decreased BCI accuracy in 204 sentences, had no effect in 48, and increased accuracy in only 45. Assuming a binomial distribution, the 95% confidence bounds on FORCe producing strictly lower BCI accuracy are 0.63 to 0.74. However, a small subgroup of participants did not follow the overall trend, including one participant whose FORCe accuracies were all greater than or equal to those without FORCe (probability by chance estimated at 1 in 1000).

Discussion: For some participants, the grand average waveforms show no large structural changes aside from an overall decrease in amplitude (figures on poster). However, for the participant whose accuracy was most reduced by FORCe, blink artifact appears to have overlapped the P300 Event-Related Potential complex, and thus been used for online BCI operation. This participant appeared to withhold blinking until target flashes, and tended to blink after targets. In contrast, the participant who was helped most by FORCe seemed to blink immediately after all stimuli, rather than showing target/non-target differences. The overall downward trend is more difficult to interpret – not all participants showed obvious blinking trends or changes in morphology. Notably, the finding of blink rejection reducing accuracy are not in accord with [6], possibly due to differences in the methods used.

Significance: The results indicate that blinking patterns may be used unconsciously by participants to boost P3 Speller performance. In some cases this fact may be obvious under inspection, leading to an enjoinder for all BCI researchers to inspect P3 waveforms rather than rely on algorithmically-set weights. Further, BCI labs working with P3 spellers are encouraged to revisit their blink detection algorithms, or begin using them if not doing so already. While BCI accuracy may be reduced by these algorithms, failure to use blink rejection may lead to false conclusions about the performance of the BCI.

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Brain Computer Interfaces as a New AAC Access Modality for Individuals with Advanced Paralysis.

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Introduction: Amyotrophic lateral sclerosis (ALS) is a progressive degeneration of upper and lower motor neurons, and the frontal cortex, with limb and/or bulbar muscular weakness [1]. Disease progressions can lead to a state of near-total paralysis including akinetic mutism, but with intact cognition and sensation, known as locked-in syndrome (LIS) [2]. Without voluntary control of the speech and motor system, individuals with ALS may lose all forms of interpersonal communication. In these cases, augmentative and alternative communication (AAC) devices can be used via a range of access methods including direct selection and eye gaze (among others) for an individual to make communication interface selections. However, there are no current clinical AAC device access methods available for individuals who do not possess overt voluntary control of limb, or eye movements [3]. The aim of this investigation is to develop a hybrid brain computer interface (BCI) method for individuals with advanced ALS to access a commercially available clinical AAC device [e.g., 4], utilizing the contingent negative variation (CNV). The CNV is a negative deflecting event-related potential that has been previously shown to precede the onset of overt and covert motor movements, beginning as early as 1.5 seconds prior to a movement cue [5].

Material/Methods: One individual with ALS (additional recruitment underway), and 4 healthy participants, used the BCI to select communication icons on an AAC device. Selection was made through performance of covert movements (e.g., imagine ‘making a fist’), performed via kinesthetic (first person) motor imagery. Icon selections were made from a Tobii-Dynavox C-15 speech generating AAC device. A preprogrammed Tobii-Dynavox page display was used, and communication icons were displayed via the row-column scan setting, with visual highlighting and spoken word feedback of each icon sequentially every 2.5 seconds. The participants were given a randomized target to select on the device for each set of trials. Online data signals were recorded via 62-channel electroencephalography (EEG) at a sampling rate of 512 Hz (g.HIAmp, g.tec). The EEG signal was bandpass filtered from 0.5 to 8 Hz to obtain the frequency range containing the CNV. An online linear discriminant analysis decoder was used to generate a binary decision (select icon versus don’t select icon) based on the presence or absence of the CNV. EEG data was decoded based on the average amplitude from -0.2 s to 0 s relative to the onset of the auditory highlighting presentation. An offline data collection of 80 covert imagery trials using the participant’s dominant hand, were preformed to train the BCI online decoder. Following training, another 80 covert trials were performed in which participants selected icons on the Tobii AAC device. Percent accuracy was calculated as the number of trials/total trials, in which the BCI correctly identified the participant’s selection. For both the training and decoding portions, a structured break was given after 20 trials to reduce fatigue; however, the participant could request a break at any time.

Results: Preliminary results for healthy participants indicate that the neural decoder was able to predict covert limb movements during AAC BCI tasks with 68.14% accuracy (healthy), and 62.62% for the individual with ALS (data collection ongoing).

Discussion: BCIs may be used as an access modality by individuals with advanced paralysis to make selections on an AAC device via row-column scanning. Performance is expected to increase in both populations with additional AAC-BCI exposure as participants learn to control the device.

Significance: Brain computer interfaces are set to revolutionize the field of communication by offering a new access method for people with advanced paralysis to communicate. BCIs access may allow an individual with advanced paralysis to continue to use their current AAC device, even if worsening paralysis has rendered their current method inefficient or ineffective.

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Estimated Prevalence of Severe Paralysis With Loss of Communication in The Netherlands.

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Introduction: Brain computer interfaces (BCI) can be used to replace, improve, restore, enhance and study brain functions. One of the main topics in the *replacement* field is communication. The target population for this kind of BCI is commonly referred to as locked-in syndrome (LIS) patients [1]. According to BCI-researchers this population encompasses all patients with severe communication impairment due to severe paralysis regardless of the etiology. Medical professionals, on the other hand, define LIS as lesions in the ventral pons, and not by the level of functioning [2, 3]. This results in an underestimation of the number of people that benefit from the same kind of care and therefore poses an impediment for stakeholders such as developers of communication BCIs, caregivers and policy makers. These stakeholders stand to benefit from a more inclusive definition of the patient population for care, information and assistive technology development.

In the current study we argue that the target population for communication BCIs can therefore be best described and quantified using the more inclusive definition that includes all patients that *function* on the level of LIS (fLIS), disregarding etiology. Quantification of LIS has been done before, but these studies used the more constrained definition or only a subset of the population [4, 5].

Method: In the Netherlands all people are obliged to have a general practitioner (GP). Within 1 year we sent out 2 letters to all, 8865 GPs, covering the Dutch population (16.829.289; Statistics Netherlands, 2014) and asked them to report any patients with severe paralysis and communication problems. The GPs who responded affirmative where subsequently approached by telephone and asked to complete a questionnaire consisting of 22 items on the level of functioning of the patient, the cause of paralysis and the type of care and assistive technology used. After completion of the questionnaires two independent raters labelled the patients with LIS, incomplete LIS (iLIS) or not LIS according to the criteria stated in Snoeys et.al. [5]. In addition, as a result of recruitment efforts and media publicity for the Utrecht Neural Prosthesis project (UNP) another subset of patients was brought to our attention, not among the patients reported by the GPs. These patients were also given the questionnaire.

Results: 51 GPs were contacted by telephone and asked to fill out the questionnaire. 41 GPs cooperated. After screening by the two raters this resulted in 19 LIS, 7 iLIS and 16 neither LIS nor iLIS. Of the 53 patients brought to our attention through other channels 16 were rated with LIS or iLIS, leading to 42 patients in total confirmed. Extrapolation of the 26 patients, found among the GPs that replied to one of the two letters (22.3%), to the whole population results in a number of 117 patients in the Netherlands. The number of patients with fLIS living in the Netherlands can thus be estimated between 42 and 117, which gives a prevalence in the Netherlands between 0,00025% and 0,0007%. Furthermore, the questionnaire showed that the cause of fLIS is very diverse, for example, cardiovascular accidents account for 26% and amyotrophic lateral sclerosis 33%.

Discussion: The current research shows that there is a significant population in the Netherlands that functions on the level of LIS. However many of them are not labelled locked-in. This leaves a big number of people outside the scope of researchers and assistive technology developers. We hope that classifying people on the basis of level of functioning will prevent this in the future.

Significance: This research has quantified the target population for communication BCI in the Netherlands. Also it poses a new way of classifying people with paralysis.

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Home use of an electroencephalographic-based BCI by people with amyotrophic lateral sclerosis (ALS): use of impedance to judge system readiness.

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Introduction: We are studying long-term independent home use of a P300-based BCI by people with amyotrophic lateral sclerosis (ALS) ([1] and Heckman et al., this meeting). Successful electroencephalographic-based BCI use requires reliable EEG recording. At home, the quality of the EEG depends on environmental conditions and a trained System Operator (SO) (e.g., the primary caregiver) who must place an eight-channel electrode cap on the home user before starting the BCI system and ensure that it functions properly. Thus, reliable BCI home use requires a robust easy-to-use BCI system and a properly trained SO. The goal of this study is assess the effectiveness of a tool that provides SOs with information about impedance prior to system startup. And the reliability of impedance as a predictor of BCI performance of an EEG-based BCI as well as

Material, Methods and Results: Set up for the Wadsworth BCI Home System begins with the SO logging onto diagnostic software (DS). The DS guides cap selection and placement, and provides the SO with information about hardware connections, cap use, impedance, and signal quality. After placing the electrode cap and before starting the system, the SO is shown color-coded impedance values on a dynamic display of the electrodes on the head: red (attention required, >40 KΩ), yellow (<40 KΩ, acceptable) and green (<20 KΩ, excellent). When the SO views any yellow-green combination, s/he inspects the filtered analog signal (HP=.5Hz, LP= 30Hz) for artifacts. Obvious artifacts are corrected with routine procedures (e.g., noticeable 60 Hz requires attention to the ground). Intractable artifacts may reflect a problem with a cap, for example, and result in a support call to the Wadsworth. Once the DS routine is complete, the SO may start the system. We looked at 1325 10-selection copy-spelling records recorded over 17 months from fifteen male home users with ALS who needed assistance with written and/or spoken communication (Ave age=58.3+11.6; Ave ALSFRS=17.4+12.3));. Ninety-two percent of the 10599 impedance measures were in the yellow-green range (<40KΩ), $\bar{x}$=22(SD 75). An ANOVA demonstrated that impedance values of under 40 KΩ remained a source of significant variance in BCI performance, and that some of that information was subject specific.

Discussion: SOs used the DS guidelines most of the time, indicating such tools can assist in regulating signal quality in the home setting. Further analysis of these data recorded in the home may reveal easier and more significant ways to impart information about the EEG. Understanding the relationship between impedance, signal quality and successful BCI use will assist investigators and developers in evaluating their methods, and, ultimately benefit the home users.

Significance: Quality control of the EEG in the home can be supported by the use of simple diagnostic tools. However, impedance alone may not be sufficient as an indicator of data quality. Additional and concurrent information may be necessary to ensure greater EEG-based BCI reliability.

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MindBEAGLE: An EEG-based BCI developed for patients with disorders of consciousness

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Introduction: Patients with disorders of consciousness (DOC) maintain a circadian sleep-wake cycle, but suffer from severe awareness deficits, ranging from complete unawareness (vegetative state/ unresponsive wakefulness syndrome patients) to minimal awareness (minimally conscious state patients). By definition, these patients are unable to communicate. A third group of patients (emerged from the minimally conscious state) could functionally communicate or use objects, but suffer from severe mental and physical disabilities. At present, diagnosis is mainly based on behavioral assessment. Impaired cognition, sensory deficiencies, aphasia, sleep, and awareness fluctuations, are some of the possible causes of misdiagnosis [1]. Misdiagnosis could mean that a patient is mistakenly considered unconscious and incapable of communication. Patients may thus be ignored by friends, family and medical staff who might otherwise interact with them about issues including environmental preferences (as temperature, music, and bed position), or important life decisions. Here, we aim to detect objective signs of consciousness in DOC patients, measured by auditory (AUD) and vibrotactile (with two stimulators, VT2) P300 responses, and to establish binary communication by employing the VT P300 with 3 stimulators (VT3). These paradigms have been proven successful in a group of locked-in patients who are completely conscious, but behaviourally unable to demonstrate consciousness [2].

Material, Methods and Results: 11 patients (4 unresponsive patients, 5 minimally conscious patients, and 2 patients emerged from the minimally conscious state, all diagnosed through profound clinical evaluation) were evaluated with the mindBEAGLE (Guger Technologies OG, Graz, Austria). Patients were assessed with the AUD P300 and the VT2 P300. Whenever a significant difference between the target and non-target responses was found, the VT3 P300 was tested, intending to establish communication (as described in [3]).
A P300 (AUD or VT2) to target stimuli was observed in 3 patients (one unresponsive and two minimally conscious). More importantly, a patient in the minimally conscious state attained a median accuracy of 70% in the VT3 paradigm (Fig. 1). We are currently advancing the efforts to establish communication.

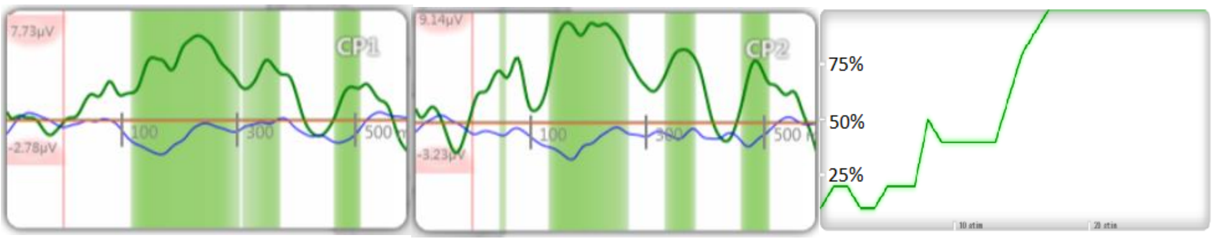

Figure 1: *The P300 in the left and right hemisphere (left and middle images) to VT stimulation with 3 stimulators. The green and blue lines reflect activity elicited by target and nontarget stimuli, while green shaded areas show significant differences. Classification accuracy (right image) reaches 100% after about 18 stimulation sequences with 8 single trials each.*

Discussion: The presented work potentially reduces misdiagnosis of DOC patients, improving their treatment and prognosis. Ultimately, it could empower patients to communicate. A limitation of our approach is that the absence of a response does not directly imply the absence of awareness, as the assessment depends on the patient's level of participation, and thus multiple sessions for assessment and communication are often required.

Significance: This is the only plug-and-play BCI developed for DOC patients, a patient group that might benefit considerably from the capabilities it offers.

Acknowledgements: We would like to acknowledge the patients and their families for trust and participation.

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Nationwide survey of 780 Japanese patients with amyotrophic lateral sclerosis: Their present status and expectations from brain–computer interfaces

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Introduction: Amyotrophic lateral sclerosis (ALS) is a progressive neurodegenerative disease that causes eventual death through respiratory failure unless mechanical ventilation is provided. Brain–computer interfaces (BCIs) may provide brain control support for communication and motor function. Based on preliminary results of a small-scale questionnaire survey [1], we performed a large-scale questionnaire survey to investigate the interests and expectations of patients with ALS concerning BCIs supported by the Japan Amyotrophic Lateral Sclerosis Association.

Material, Methods and Results: We conducted an anonymous questionnaire survey of 1918 patients with ALS regarding their present status, tracheostomy use, interest in BCIs, and their level of expectation for communication (conversation, emergency alarm, Internet, and writing letters) and movement support (postural change, controlling the bed, controlling household appliances, robotic arms, and wheel chairs).

Seven hundred eighty participants responded. Fifty-eight percent of the participants underwent tracheostomy. Approximately 80% of the patients felt stress or having trouble during communication. For all nine supports, more than 60% participants expressed expectations regarding BCIs. More than 98% of participants who underwent tracheostomy expected support with conversation and emergency alarms. Participants who did not undergo tracheostomy exhibited significantly greater expectations than participants with tracheostomy did regarding all five movement supports. Seventy-seven percent of participants were interested in BCIs. Participants aged <60 years had greater interest in both BCIs.

Discussion: Communication and emergency alarms should be supported by BCIs initially. BCIs should provide wide-ranging and high-performance support that can easily be used by severely disabled elderly patients with ALS.

Significance: This is the first large-scale survey to reveal the present status of patients with ALS and probe their interests and expectations regarding BCIs.

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Non-invasive detection of neural sources underlying ECoG-based P300 speller performance

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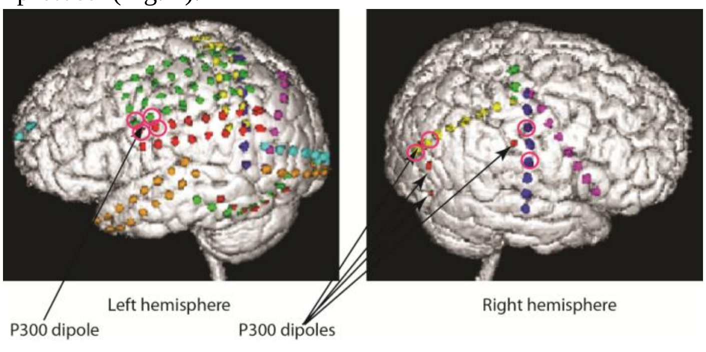
Introduction: There is evidence to suggest that surgically-implanted intracranial BCIs might be more efficient than scalp-based BCIs, especially for severely disabled patients. However, before moving into invasive implantation of BCIs, the important question must be addressed – localization of the areas for implantation, which might vary dependent on the BCIs type used as well as on individual person's characteristics. In our previous study [1], we concluded that specific approaches must be developed to identify and extract the data of interest from intracranial brain signal recordings in order to achieve desired BCI performance. Among several suggested approaches, the most promising has been proposed the use of magnetoencephalography (MEG). Therefore, the aim of our current study was to evaluate possibility for non-invasive navigation of subdural electrode implantation with MEG needed for high accuracy performance of P300 speller.

Material, Methods: The study was performed in a right-handed female patient (17 yo) with intractable epilepsy, undergoing evaluation for epilepsy surgery. We used MEG source localization to navigate the choice of electrodes for using invasive P300 speller.

1.1. Non-invasive localization of P300 generators with MEG. During this test, visual evoked fields were recorded in response to the letter (O and X) stimuli presented in an "odd-ball" paradigm manner, with 76% of NON-TARGET (letter "O") and 24% of TARGET stimuli (letter "X"). Altogether, 76 of frequent and 24 of deviant stimuli were presented. The patient was instructed to count all infrequent stimuli. The source of P300 speller was localized by using equivalent current dipole (ECD) in right central and occipital as well as left frontal and central areas (Fig. 1).

1.2. Merging information from subdural electrode location and MEG results. After the patient was implanted with subdural electrodes, the 3-D-rendered map of cortical patient's surface was created with co-registered and overlaid on it subdural electrodes. The localized P300 ECDs were overlaid with the 3-D-rendered cortical and grid map. Eight electrodes in a close proximity with localized P300 sources were selected for P300 speller protocol (Fig. 1).



Results: The accuracy of intracranial P300 speller was compared for 8 electrodes identified with MEG after creating a classifier with 10 letter phrases. The accuracy of P300 speller for MEG-identified sites was 80%.

Figure 1. *3D-rendered cortical surface of patient's brain with overlaid subdural grids, P300 dipoles localized with MEG. Locations of 8 electrodes selected by using MEG for intracranial P300 speller are presented in cyan circles.*

Discussion: Our preliminary data suggest that neural sources underlying performance of P300 speller can be successfully and non-invasively identified with MEG. Therefore, MEG has a strong potential to serve as a non-invasive tool for navigating electrode implantation of P300 speller-based BCI in patients, who are in need for communication via intracranial P300 speller. Further studies are recommended to explore this approach.

Significance: These results can contribute to clinical application of P300 speller for disabled patients, e.g., those with late stages of amyotrophic lateral sclerosis (ALS) or locked-in syndrome.

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Non-verbal Communication using BCI, Haptic Feedback and Dance

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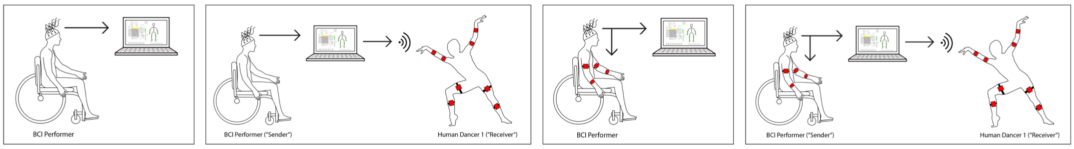
Introduction: Non-verbal communication is an extremely important aspect of our life, sometimes estimated to comprise of 65% to 93% of all communication, and the majority of our feelings and intentions are expressed with the help of non-verbal communication [1]. Nevertheless, this aspect of communication is often overlooked by the brain-computer interface community. Non-verbal communication involves sending and receiving signals with the help of body language, gestures, postures, proximity, haptic and facial expressions. Our over-arching goal is creating a new quality of non-verbal communication between disable and able subjects. Specifically, dance can be considered a form of non-verbal communication, as it plays an important role in sharing strong feelings of togetherness between humans. Previous research showed that observation of dance results in strong activation of motor brain areas, and, importantly, observation of live dance produces significantly stronger motor activity than observation of dance on video [2]. We report about our work in progress research, aimed at exploring the potential of multimodal feedback based on both haptics and live dancers in facilitating BCI performance.

Material and Methods & Results: We have developed a platform that combines several elements: motor imagery BCI (using the OpenVibe platform (Renard et al., 2010) and a gTec (Austria) gUSBamp amplifier), multiple programmable wearable units of haptic feedback, and visual feedback in the form of live dance. This architecture enables systematic exploration of motor imagery BCI enhanced with both haptic feedback and live visual dance feedback (specifically comparing four conditions; Fig. 1), in order to test whether multimodal haptic-dance feedback can enhance BCI learning curve and accuracy in paralyzed patient.



a b c d

Fig 1: Our technical and conceptual frame work allows systematic exploration of several conditions: a) BCI with no feedback, b) BCI with visual feedback only (while transmitting haptic feedback to dancer), c) BCI with tactile feedback only, and d) BCI with both tactile and visual feedback (with haptic feedback to dancer).

We have performed an exploratory pilot study in which one spinal cord injury (SCI) subject performed four practice sessions with binary (left hand vs right hand) motor imagery BCI and two sessions with the full apparatus[1]. The dancer responded to left/ right classes with movement of corresponding limbs to simulate synchronised dance. Each session included 40 triggers of left or right hand imagery, with an equal number from each class, in pseudo random order. Electroencephalography (EEG) was recorded from electrodes placed in 10-20 location C3, Cz, and C4, with reference on the earlobe. The subject has some residual capacity to move both arms, but he was asked to imagine grasping actions, which he cannot perform. The subject achieved beyond chance BCI accuracy: 67%, 63%, 76% and 78% classification in the training sessions, and 74%, 79% classification in the two pilot sessions. Both subjects, BCI performer and dancer, were interviewed using semi structures interview. The interview was transcribed and the results were analyzed in order to design the detailed experiment.

Discussion: The pilot study validated the operation of our technical platform, and established that a meaningful communication took place between the BCI performer and the dancer. The results are encouraging in terms of the reported motivation of the subject as well as the feasibility in carrying out the study under highly ecological conditions. This now allows us moving into the next step: studying whether multimodal feedback, including real human dancers and tactile feedback, can increase BCI learning curve and performance in disabled patients.
Significance: We present the feasibility of our technical and conceptual framework, which includes BCI, multimodal feedback, and dance, in a highly ecological setup.

Acknowledgement: The study was partially supported by Kelim Centre for Choreographic work, Israel.

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Online BCI Typing using Language Models by ALS Patients in their Homes

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Introduction: The P300 speller is a common brain computer interface system that can provide a means of communication for “locked-in” patients, such as those with amyotrophic lateral sclerosis (ALS) [1]. While this system was initially developed almost 30 years ago, it is not widely used in part because typing speed and accuracy are below those desired by the ALS population [2]. Recent studies have shown that performance using the system can be improved by utilizing knowledge of natural language to improve signal classification [3]. The preliminary results have been promising, but they have largely been tested on healthy volunteers in a laboratory setting. The goal of this study was to demonstrate the functionality of the P300 speller system with language models when used by ALS patients in their homes.

Material, Methods and Results: Electroencephalogram (EEG) data was recorded using g.tec amplifiers, active EEG electrodes, and an electrode cap (Guger Technologies, Graz, Austria). The BCI2000 application [4] was used to run the P300 speller experiments with famous faces stimuli [5] and language model integration using a previously published particle filtering algorithm [6]. The hardware was loaded onto a cart, which was then transported to patients’ homes so they could use it in their home environment.

Two ALS patients participated in this study. The first is on a ventilator and uses and eye tracking system for communication, while the second maintains some speaking ability. To form a baseline for comparison, three healthy subjects also participated, using the system in a hospital setting. All subjects consented to participate and the study was approved by the UCLA institutional review board. For each subject, the study consisted of three five-minute calibration phases where the subject would copy a given phrase without feedback. A testing phase followed during which the subjects were instructed to type anything that they chose with the results being displayed in real time. Results were evaluated using selection rate, accuracy, and information transfer rate (ITR).

Both ALS subjects were able to type using the system with 100% accuracy. The first subject typed nine characters in 58.4 seconds for a selection rate of 9.24 characters/minute and an ITR of 47.8 bits/minute. The second subject typed 15 characters in 77.4 seconds, for a selection rate of 11.6 characters/minute and an ITR of 60.1 bits/minute. The three healthy subjects also typed with 100% accuracy, with an average selection rate of 11.7 characters/minute and and average ITR of 60.4 bits/minute.

Discussion: Both subjects performed well above the average previously reported using the particle filtering algorithm (37.3 bits/minute), which is likely due to the inclusion of the famous faces stimuli. The second subject had comparable performance to the healthy volunteers, while the first was somewhat lower. This drop could have been due to the fact that his head was supported by a cushion, which could have affected the connection of occipital EEG electrodes. Future work will involve further testing in ALS subjects to determine if there is a consistent pattern between disease progression and P300 performance.

Significance: The results of this study indicate that the improvements in performance using language models in the P300 speller translate into the ALS population, which could help to make it a viable assistive device.

Acknowledgements: This work was supported by the National Institute of Biomedical Imaging and Bioengineering Award Number K23EB014326 and the UCLA Scholars in Translational Medicine Program.

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P300 Latency Jitter More Likely for People with ALS

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Introduction: Although brain-computer interfaces (BCIs) have been useful for people with amyotrophic lateral sclerosis (ALS), they do not reliably interpret the brain signals of everyone with ALS [1,2]. The reasons for these difficulties remain unknown. P300 BCI [3] configuration is based on the average amplitude, latency, and shape of the subject's P300. Current BCI classifiers assume that the P300 response occurs exactly at the average latency used in the configuration. However, even under tightly controlled conditions, within-subject variations in latency (latency jitter) still occur [4]. We found that BCI accuracy is highly correlated ($r = .744$, $p < .0001$) with latency jitter and that large latency jitter interfere with BCI accuracy [5]. Further, Arico, et al. [6] found decreased BCI performance and increased latency jitter when BCI subjects used covert attention instead of overt attention to operate a Geospell BCI. Thus, understanding for which subjects latency jitter occurs is important.

Material, Methods and Results: Data is from 22 subjects (10 with ALS and 12 age-matched controls). Each subject typed 9 sentences (3 sentences on each of 3 days) [2]. Latency jitter was estimated with our classifier based latency estimation (CBLE) method [5]. Latency jitter differed between sentences and the aforementioned correlation between accuracy and latency jitter holds for all subjects (Fig. 1, left). Sentences were divided into bins by amount of latency jitter and sentence accuracies in each bin were averaged separately for the ALS and age-matched groups. Average accuracy declines with increased latency jitter without relation to ALS (Fig. 1, middle). However, sentences with the highest latency jitter were more common for the ALS group (Fig. 1, right).

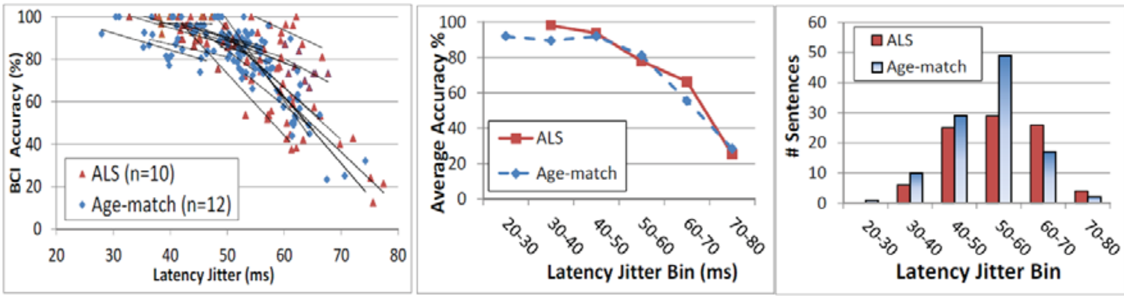

Fig. 1: Relationship between latency jitter and BCI accuracy for individual sentences with regression lines by subject (left), average accuracy by latency jitter bins (middle), and distribution of latency jitter for subjects with ALS and age-matched controls (right).

Discussion: Our ALS group showed higher incidence of latency jitter than age-matched controls despite a relatively minor level of physical impairment. This raises the concern that with increased impairment, the need to use covert attention for BCI operation would further increase the amount of latency jitter and could make a BCI unusable. While the cause for increased latency jitter in the ALS group is not yet known, it is known that latency jitter is greater with impaired attention [4], which is the most common cognitive symptom of ALS [7].

Significance: The high occurrence of latency jitter among people with ALS and its detrimental effect on BCI performance make development of P300 detection methods that are robust to latency jitter a top priority.

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Spelling with cursor movements modified by implicit user response

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Introduction: Typically, BCI systems are controlled via invoking asynchronous commands or by strategically attending to task-specific stimuli. We explore an approach defined by implicit control [1] which uses error-related responses [2,3] and targets the user's innate task-relevant processing.

Materials, Methods and Results: The cursor was the BCI’s primary task element as it navigated through a 7x7 grid, moving in one of eight potential directions (cardinal or diagonal neighbor) every step until reaching a corner. Each corner of the grid was assigned a subset of the alphabet, pruned after each corner hit. The probability distribution of the next cursor movement was modified by the user’s response with a Bayesian update rule. Thus the cursor movement was both the primary task and the probe stimulus.

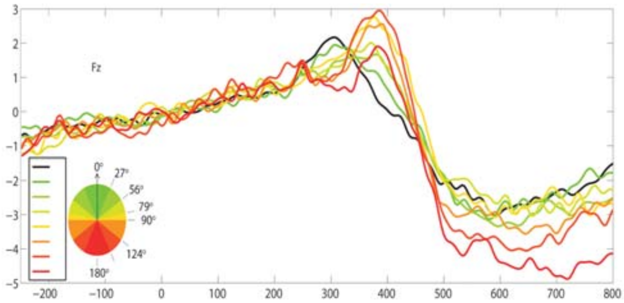

Fig. 1: Grand average plot of voltage for the 8 angular groups. Based on cursor movement’s angular deviance from target corner direction.

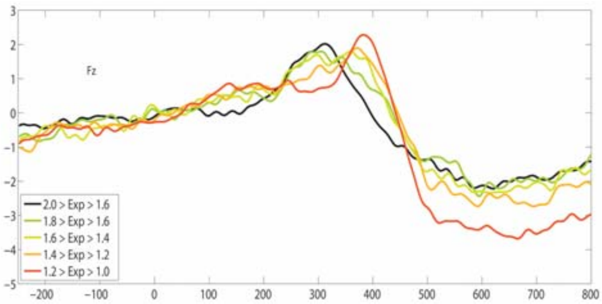

Fig. 2: Grand average plot of voltage for 5 expectation groups. Reflects distance from hyperplane distinguishing classes, with 1.5 lying between.

Participants were instructed to evaluate each cursor movement as "good" or "bad", with respect to reaching the letter they wanted to select. For classification, movements were grouped by angular deviance from the direct path to the target corner (0^{o} deviance “good”; > 135^{o} “bad”.) A regularized LDA classifier was trained on an average of 250 of these trials (from 900) of training data per subject, using BCILAB’s windowed mean’s paradigm (150-700ms epoch, 11 windows of 50ms periods). The participants' response patterns varied systematically relative to angular deviance (Fig. 1). Additionally, the trained classifier was sensitive to this relationship (Fig. 2). For each subject, there was a significant correlation (averaged $R = -.3237$ [± .1003], $p < 1.0e\text{-}7$ for all subjects) between increasing angular deviance and decreasing classifier output. The off-line classifier's per jump error rate for participants (n=18) was 30.88% (± 6.11%). Analysis entailed a leave one out training scheme for the “good” and “bad” trials; the resulting model was then applied to trials within a more liberal hit class (angular deviance $\leq 30^{o}$).

Discussion: Removing explicit stimuli and replacing them with embedded probes enables an implicit form of control [1]: users are not actively communicating control commands, but instead, are merely evaluating the cursor movements. Their event-related potential reflects implicit evaluation of the degree of mismatch between the system’s activity and the user’s desired end state and presents a new form of human-computer interaction.

Significance: We present a BCI system using an implicit control signal, wherein the user’s evaluation of task conditions informs the system. Interaction is implicit; the subject does not need to perform any discrete action to indicate a target. (Supported by NSF grants IIS 1219200, SMA 1041755, IIS 1528214)

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Subject-Specific Electrode Subsets for P300 BCI: Typically Developing and Cerebral Palsy Populations

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Introduction: An electroencephalography (EEG)-based brain-computer interface (BCI) that uses the P300 response usually collects data from a default set of electrodes with fixed locations. Studies have shown that P300-based BCI performs better when used by healthy participants compared to those with impairments [1,2]. While there are studies on electrode selection and the impact on BCI accuracy [3,4], to our knowledge there is no systematic analysis on electrode selection using data of populations with impairments. Custom electrode subsets could address potential physiological difference among individuals, and thus might be particularly useful for subjects with impairments. This study investigates the effect of a customized electrode subset on P300-BCI accuracy, in particular for subjects with cerebral palsy (CP).

Methods: The selection method is adapted from McCann et al. [4]. In brief, the program uses a forward-search greedy algorithm to search for an electrode subset of size 16 among all the available 32 electrodes (Fig. 1). While there is no guarantee of a global maximum, the same study shows no statistically significant difference in performance between subset results from an exhaustive search and one from a greedy forward search. Best performance is defined as the highest accuracy in identifying a user's intended selections. Performance of the subject-specific subsets is compared to the default 16-electrode subset (Fig. 1).

An offline analysis was performed on data from a four-target selection protocol described in Huggins et al. [5]. Data was from 10 participants with CP (mean age of 19.2 ± 6.07 years), and 9 typically developing participants (mean age of 15.9 ± 4.58 years). In addition, training data of 4 CP subjects who were not able to use the BCI due to low training accuracy or unsuccessful configuration generation were also analyzed.

Results: For all 19 subjects, a significant increase ($p = 0.004$ with a paired 2 sample t-test) in P300-based BCI accuracy after 10 sequences is shown with a mean improvement of 3.24 ± 4.56%. Seven of the most-selected 15 electrodes (CP5, CP2, Pz tie at the 16th position) are not covered in the default 16 electrode subset (Fig. 1). Mean of improvements of the 10 subjects with CP is larger compared to the 9 typically developing subjects and the result trends towards significance ($p = 0.16$). Among the 4 subjects who could not use the BCI, training accuracies of 2 subjects improve greatly with custom electrode selection (12.9% and 15.0%). Of those, one subject reaches above 75% accuracy using the selected custom electrodes subset.

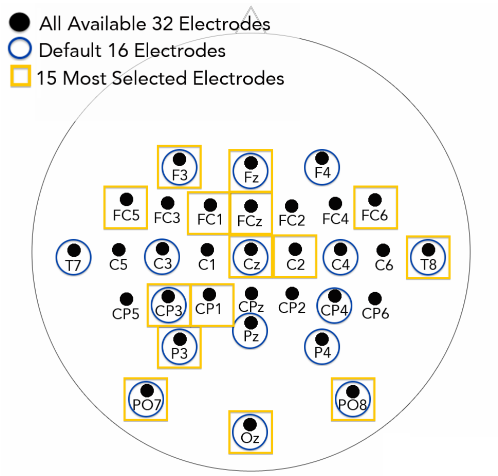

***Figure 1.** Locations and Labels of All Available 32 electrodes, the Default 16-Electrode Set, and the Most Selected 15 Electrodes*

Conclusion and Significance: Subject-specific electrode selection improves P300-based BCI accuracy. The pilot data demonstrates that a custom electrode subset might allow more people to effectively use the BCI, in particular in populations with impairments.

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Using congruent activity from primary motor cortex and the cognitive attention network to improve the specificity of the BCI control signal.

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Introduction: Both primary hand motor cortex (M1) and dorsalateral prefrontal cortex (DLPFC) have been proven to allow for robust BCI control using electrocorticographic (ECoG) signals [1,2]. However, to date no BCI system engaged in long-term 24-hour-a-day use has been reported. Thus, most BCI studies have focused on neural features that are sensitive to modulation when subjects are engaged in BCI control and have not investigated activity patterns when subjects are not actively attending to the control task. One of the most important aspects of a 24/7 BCI system is its ability to remain sensitive to intentionally generated control signals without being susceptible to changes in brain activity when the user is not actively engaged in control. In this work we test the hypothesis that by combining signals from M1 and DLPFC the BCI signal can be made less sensitive to non-task engaged activity (i.e.: false positive (FPs)) without sacrificing BCI performance. We are motivated by the observation that engagement in BCI using M1 leads to increased connectivity from DLPFC to M1 [3].

Material, Methods and Results: This study used ECoG signals from 5 subjects with implanted electrodes for clinical use. The gamma band (65-95Hz) power from bipolar electrode signals (potential difference between nearby clinical grid electrodes, < 3cm center-to-center) was computed for at least one location over both M1 and DLPFC for each subject. The signals were then turned into a series of gamma events by finding instances when the z-scored power remained above a threshold for at least 10ms for M1 and 50ms for DLPFC. Congruent events (CEs) were defined as instances in which an event in DLPFC was followed by an event in M1 within a specific time period. CEs were tested in terms of performance during an overt movement BCI task and number of PFs during a 3 minute rest task and compared with M1 events. The M1 event thresholds were defined on the BCI data files as the lowest threshold that resulted in at least 80% performance. The CE interval was then chosen as the smallest interval for which 80% performance could be achieved using any DLPFC threshold. The DLPFC threshold was chosen as the highest possible value that still resulted in 80% performance given the chosen M1 threshold and interval. Using this strategy the mean z-score thresholds for M1 and DLPFC were 1.48 and 0.47 respectively and the mean interval was 230ms. The difference between M1 and CEs BCI performance was then tested using a paired t-test across parameters settings and data files. The results show that the mean BCI performance for M1 events is just above 80%, as per design, but the CE performance is significantly higher (Figure 1A). As we hypothesized, the number of FPs with CEs was dramatically and significantly lower (Figure 1B).

Significance: Here we present first attempts to use the cognitive network in combination with primary motor cortex to increase the specificity of the BCI signal and thereby reduce FPs and enhance the quality of permanent BCI solutions.

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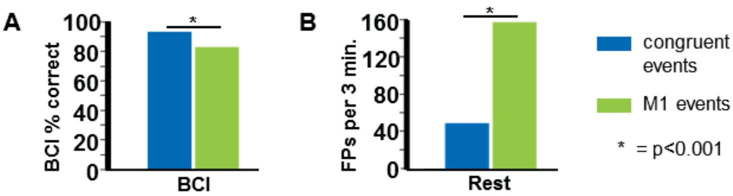

Figure 1: *A: Mean BCI performance. B: Number of false positives (FPs).Blue bars report the results using congruent events. Green bars report the results using M1 events.*

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Detecting and utilizing the idle state in an intracortical brain-computer interface

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Introduction: Much attention in the field of brain-computer interfaces (BCIs) has been devoted to decoding the intended motor output of a neural prosthetic. However, detecting when the user actually desires to utilize the device remains an important yet relatively understudied problem. Our lab has previously demonstrated the differences in intracortical activity that differentiate periods of active physical reaching or holding an arm posture vs. resting one's arm [1]. Similarly, other studies have examined differences in cortical modulation patterns between active task and rest periods in the context of a BCI paradigm [2]. However, these differences have yet to be exploited for the purposes of enabling or disabling a prosthetic device. In this study, we first examine post-hoc analyses of differences between active and resting periods in a BCI task. Utilizing these results, we demonstrate the online implementation of a BCI idle state detection scheme for gating movements of a cortically controlled prosthetic arm. Finally, we examine the differences in idle/active states that arise when monitoring a physical reaching task or a similarly structured BCI task.

Material, Methods and Results: Two rhesus macaques (Macaca mulatta) were implanted with one or two 96-channel intracortical microelectrode arrays. Threshold crossing or sorted unit firing rates from these arrays were used to control the end-point velocity of a robotic arm (WAM Arm, Barrett Technology) to perform 1D, 2D, and 3D reaching tasks. Blocks of "rest" trials, in which the WAM arm and target presentation robot were locked in their home position for ~30-60 seconds, were interspersed between active BCI task blocks.

To investigate the neural changes between active and idle states during BCI operation, we first calculated a discriminability index, d', on individual channels. These analyses showed significant active/idle distribution differences using firing rates as well as LFP power in several discrete frequency bands (8-15 Hz, 15-24 Hz, 30-50 Hz, 70-150 Hz). We extended these offline analyses to a population level by training an idle state classifier using several approaches. For one model, we trained the classifier using labeled periods of arm resting and reaching during a physical reaching task performed just prior to a BCI session. A second approach utilized the rest blocks described above and the reach portion of BCI trials to label rest and active training samples. When applied to test neural data from each task (hand control – HC, brain control – BC), the BC derived model accurately classified idle and active periods with a high degree of accuracy in both HC and BC test sets. When the HC derived model was applied, it did classify BC task and idle states at a rate much better than chance performance, although the overlap of these distributions was much greater than was observed for the BC model.

Finally, we implemented this classification scheme in real-time during a BCI task. When an idle state was detected, brain control of the WAM arm was suspended, and the robot was moved toward its home position. When put into practice, we observed that the idle detector accurately permitted prosthetic movement during BCI task periods and correctly gated movements during rest blocks. In addition, movement was also intermittently gated when a monkey was externally distracted or when his motivation declined toward the end of a session.

Discussion: These results demonstrate the potential utility of several intracortical signal modalities in detecting the intent of a subject to use a BCI device. Not only may classifiers built with these signals be used in real-time to gate the movement of a prosthetic device as demonstrated in this study, they may also be used to identify periods of inattention or low motivation that may be used to exclude data from movement decoder calibration or other analyses. Finally, the differences observed between using HC or BC derived models suggest that these processes likely operate in similar but non-identical neural state spaces.

Significance: We demonstrate a novel implementation of idle state detection to gate the movement of a BCI prosthetic device in real-time. This feature would grant BCI users an additional layer of safety and autonomy over when to enable a prosthetic device as well as the potential to serve as a state classifier for multi-tasking between BCI and other activities sharing similar neural resources.

Acknowledgements: This study was funded in part by the NINDS Training Grant 5 F32 NS092430-02.

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Mirage91: The Graz BCI-Racing Team - making students familiar with BCI research

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Introduction: The field of Brain-Computer Interface (BCI) research [1, 2] is very interdisciplinary as it needs knowledge and expertise from many areas: neurophysiology, anatomy, psychology, neuroscience, computer science, biomedical engineering, electronics, software engineering, machine learning, statistics and so on. Bringing students into the field usually involves disproportional effort, not only for the educator but also for students themselves.

The newly founded Cybathlon [3] tournament will take place in Zürich (Switzerland) in October 2016. This is a championship for end users with disabilities who are using advanced assistive devices. The competitions are comprised of different disciplines which will test the ability of end users to navigate through a series of everyday tasks while using a wearable arm prosthesis, powered knee prosthesis, powered exoskeleton, powered wheelchair, electrically stimulated muscles of the lower extremity and brain-computer interfaces.

One of our strategies to introduce students early into BCI is to offer classes at Master Level in several study programs. As a next step, the BCI Lab of Graz University of Technology has founded the Graz BCI Racing Team Mirage 91.

Material, Methods and Results: During courses in our study programs Information and Computer Engineering and Biomedical Engineering, we announced the idea of the Racing Team and asked for interested students. In October 2014 we started with first informative meetings with interested students; we introduced the idea further, explained the idea of the Cybathlon and were highlighting several tasks to be done in such a team: BCI development, paradigms for training, analysis of the BCI challenge, search for potential pilots, organization of pilot training, website, public relations, sponsoring and team outfit. In this way we were able to form a loose group of students into the Graz BCI Racing Team, named Mirage91 (Motor Imagery Racing, Graz, established 1991, the year when in Graz BCI research started). We already participated in the Cybathlon rehearsal in July 2015 in Kloten (Switzerland), where we were able to test the environment, our BCI, and all infrastructure. This was of special importance, since for the actual tournament in October 2016, we need to know how to organize performance including a tetraplegic end user (see Figure 1).


Figure 1. *Left Photograph: Setup of the system by Team members. Right: Team at the Rehearsal.*

Discussion: So far, our BCI Racing Team consists of PhD students, Master and Bachelor students of study programs Information & Computer Engineering, Biomedical Engineering and Computer Science. The team was announced officially by the University and has its own website (http://bciracing.tugraz.at/).

Significance: With this activity, we were able to attract students to make first experiences with BCI research, to work with end users, and to meet other young scientists in an international setting.

Acknowledgements: Thanks to all actual team members: M. Höller, R. Kobler, K. Statthaler, L. Hehenberger, M. Adamek, J. Steininger, J. Brandstetter, F. Ebner, D. Narnhofer, B. Frohner, T. Limbacher; and thanks for the effort to our ”Pilot” G.

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On the use of ROS as a common infrastructure for robotic BCI driven applications

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Introduction:
The number of Brain-Computer Interface (BCI) driven applications to control actual devices is rapidly increasing, ranging from robotic arms to mobile platforms. However, each research group integrates BCI systems into robot control in different ways depending on their background and their software packages. This makes difficult to propagate open-source software, to share source code and to replicate experimental results. Herein, we propose a common design for BCI driven applications based on the Robot Operating System (ROS) [1], a middleware framework that in the last years became the worldwide standard de-facto in robotics.

Material, Methods and Results:
A ROS implementation is based on four fundamental elements: nodes, messages, topics and services. **Nodes** are stand-alone, independent processes—namely, software modules—that perform specific computations. Inter-nodes communication is provided by message exchange. **Messages** are data structures that support standard primitives as well as custom, user-defined nested typed fields (i.e., C-like structures). Nodes communicate by publishing and/or subscribing to a given topic. **Topics** can be considered as stream channels (peer-to-peer communication based on TCP protocol). Finally, nodes can broadcast synchronous request-response transactions via specific routines named **services**. Although ROS was designed for robotic applications, its infrastructure perfectly matches the basic requirements of any BCI system. In fact, regardless of the unique characteristics of each BCI system, they share the same information flow to implement the BCI loop: acquisition, processing, classification, and feedback modules. In a ROS-based implementation of the BCI loop, each of the aforementioned modules is straightforwardly implemented as a stand-alone node. Each node communicates with the rest of the system by publishing on predefined and standardized topics. For instance, an EEG acquisition device would publish on the */data/eeg/raw* topic, and any EEG processing modules will be notified when new EEG data are available. The same design can be replicate for other modules (e.g., for the classification modules) as well as for additional acquisition devices. The strong competitive advantage of using ROS is the fact that the whole communication framework is provided “out-of-the-box” and thus, researchers can concentrate efforts on the implementation of the own custom modules—if necessary.

Discussion:
ROS shares and extends the main advantages of the most common BCI platforms (e.g., BCI2000, OpenVibe, CIP; see [2] for an extended review). ROS is open-source software released under BSD and GPL license, it is cross-platform, multi-language (e.g., C++, Python) and multi-architecture and it ensures highly efficiency in terms of resources and memory. In particular, one the most important advantage of ROS is its strong modularity: people can design and implement its own ROS package with specific functionalities and thus, distribute it through common repositories. In a BCI framework, this means that it would be possible to easily integrate together several user-contributed, deeply tested packages implementing different steps of the BCI loop (e.g., classification, artifact removal). It is paradigmatic what happened in the robotic community: the impressive number of available packages in the ROS ecosystem (more than 3000 in less than 5 years) demonstrates that such a distributed approach for sharing reliable code definitely works. With respect to the aforementioned BCI platforms, the adoption of ROS infrastructure would allow integrating BCI and control of robotic devices in the same ecosystem. Following the idea of a hybrid BCI and a shared control approach to drive external devices [3], the BCI output signal might be directly used into algorithms for navigation or trajectory generation of prosthetic robot arms, which are already available, tested and widely adopted in ROS.

Significance:
A standard infrastructure is becoming increasingly important to handle the proliferation of BCI driven devices in a common way. A BCI based on ROS would match the fundamental requirements of any BCI system as well as would provide a direct interface for most available robotic platforms. Furthermore, it would allow sharing the same code across different groups, by increasing the reliability and the efficiency of BCI driven applications.

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BCI-based Semi-Autonomous Wheelchair Control using a Human-in-the-loop Cyber Physical System Approach

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Introduction: BCI-controlled wheelchairs have been the focus of innovative research over the past years [2-4]. We propose a HiLCPS design framework that focuses not only on rapid prototype design, but also on the seamless deployment of augmentative and assistive technologies [1]. This framework has three sub-systems: (1) human interaction through physiological signal extraction, user interface, and stimulation, (2) fusion of physiological and non-physiological evidence for intent inference, and (3) interaction of the system with the physical environment. Sub-systems and modules transfer information with each other via a unified communication scheme. The framework's modular design simplifies both upgrading as well as building new extensions; furthermore, forward compatibility has been a guiding design principle in order to support future use-cases. The ultimate goal of this work is to enable developers to build systems that empower locked-in users to move, communicate, and/or control their physical environment. To demonstrate that this framework can benefit researchers, we built a demo that tackles the use-case of semi-autonomous wheelchair control.

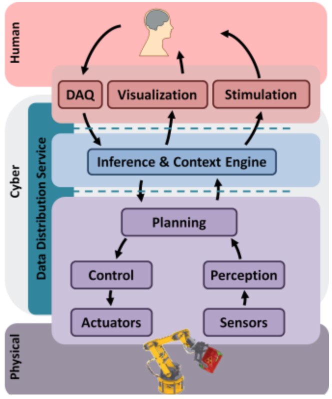

Fig 1: HilCPS diagram.

Materials and Methods: The HiLCPS framework is summarized in Fig 1. The main contribution of this design is its distributed nature. All system modules communicate with each other through OpenDDS, an open source real-time publisher-subscriber networking model. This gives developers the flexibility to add and build new features for BCIs. The inference engine is able to estimate the desired action (intent) using physiological information from the user, as well as non-physiological evidence collected from context. The framework allows the incorporation of sources of information, such as robot sensors that can output position, orientation, and velocity, history from the user, among others. Once a high level option has been selected by the user through the BCI, the intelligent robotics module converts the action into one or several physical commands to control the physical device (semi-autonomous control). This abstraction allows the users to define an action alphabet, leaving the lower level control to the robotics engine. In the wheelchair application, we implemented obstacle and cliff avoidance using a combination of LIDAR, infrared, and ultrasonic range sensors. The BCI driving this application was based on the SSVEP paradigm, using flickering LED arrays positioned around a tablet display. EEG acquisition was performed at 250Hz sampling rate with EEGu, our portable in-house DAQ running on a Beaglebone Black platform. The wheelchair system allowed 4 actions (forward, backwards, left, and right) for step-wise navigation.

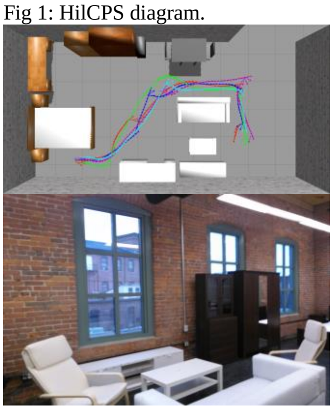
Fig 2: Wheelchair trajectories for 5 users from odometry, displayed in a 3D model (top) of the physical home environment testbed (bottom). The odometry data for the other 5 users were corrupted and cannot be displayed .

Results and Discussion: Fig. 2 shows the wheelchair trajectories for 5 users overlaid on a 3D model of the home environment. Healthy users were asked to navigate from the bed to the living room area and point the wheelchair towards the TV to execute a realistic task. Each subject executed this test 3 times. The results are shown in Table 1. The optimum wheelchair command sequence length for fastest successful task execution was 11 (33sec total with 3sec/action).

Significance: We have demonstrated that the proposed HiLCPS design framework can be successfully applied to BCI-controlled semiautonomous wheelchair navigation. Current system required instantaneous maneuver commands from the BCI. Future work on the wheelchair includes extending the application to navigate via waypoints to a precise destination coordinate in complex indoor environments. With the publisher/subscriber design, it is straightforward to use HiLCPS for environment control or communication.

Acknowledgements: Supported by NSF (CNS-1136027, IIS-1149570, CNS-1544895), NIDRR (90RE5017), and NIH (R01DC009834).

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	Runtime				Number of decisions			Training accuracy	Avg trials per decision
	Run 1 (in sec)	Run 2 (in sec)	Run 3 (in sec)	Avg (in sec)	Run 1	Run 2	Run 3		
U1	104.00	175.00	89.00	122.67	13	22	11	0.97	1.3
U2	97.00	127.00	104.00	109.33	12	16	13	0.91	1.2
U3	192.00	129.00	115.00	145.33	24	16	14	1.00	1.61
U4	216.00	120.00	222.00	186.00	27	15	28	0.79	2.1
U5	117.00	106.00	98.00	107.00	15	13	12	0.97	1.21
U6	99.00	105.00	111.00	105.00	12	13	14	1.00	1.18
U7	385.00	148.00	222.00	251.67	48	19	28	0.70	2.87
U8	141.00	109.00	114.00	121.33	18	14	14	0.87	1.39
U9	114.00	122.00	145.00	127.00	14	15	18	0.85	1.42
U10	88.00	114.00	163.00	121.67	11	14	20	0.91	1.36

Table 1: result of wheelchair application in home environment

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Decoding of two hand grasping types from EEG

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Introduction: Arm and hand movements are essential for performing activities of daily living (ADL). As a result, people with severe motor disabilities would greatly benefit from hand neuroprostheses for restoring grasping capabilities. Non-invasive prostheses mostly rely on EEG correlates of reaching, such as anticipatory potentials for movement initiation [1] or sensorimotor rhythms for movement execution [2]. In this work, we report EEG correlates for two different grasping types and the feasibility of performing reliable detection in single trials.

Methods: Ten subjects (1 female, mean age 27 years) participated in the recording. At the beginning of each trial, subjects rested their dominant (right) hand on a button on the table. Whenever they wanted (but waiting at least 2 seconds after the previous trial), they performed a movement to reach and then grasp the object placed at around 50 cm of distance. The object could be grasped in two different ways: power and precision pinch grasp. The type of grasping was freely chosen by the subject at each trial. After grasping the object, subjects were instructed to lift it, place it back to its original position and move back their hand to the rest position. Every 100 trials, the object was repositioned to a different place in order to avoid any laterality confounds. Subjects were asked to restrain eye movements or blinks during the reaching and grasping states. Approximately 400 trials per subject were recorded (~200 per grasping type). Trials where the rest phase lasted less than 2 seconds (around 5% of the total number) were removed from the analysis. Grasping onsets were synchronized with the EEG by means of hardware triggers generated when the user grasped the object (see Fig 1.a).

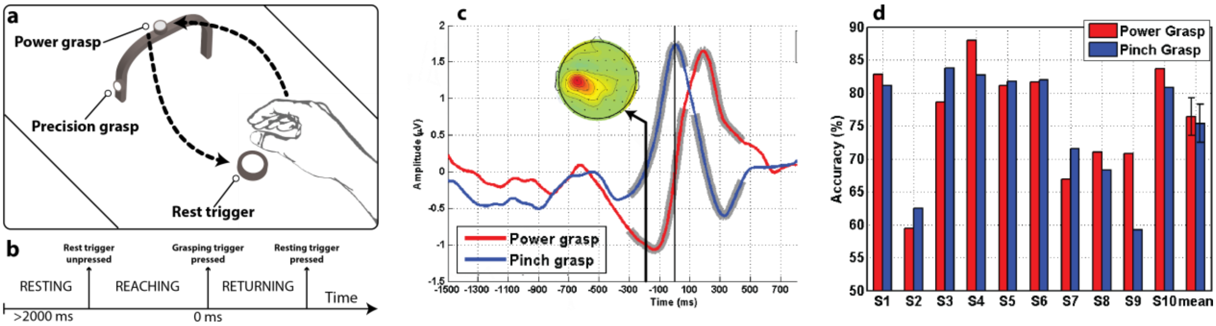

Figure 1. *(a) Schematic illustration of the setup. (b) Timeline of a single trial. 0 ms indicates the onset of grasp. (c) Grand averaged EEG at channel C3 for both types of grasp, where 0 ms indicates the onset of grasping, together with a topographic interpolation of the difference between the two conditions at -200 ms. (d) Ten-fold clasification accuracies of power vs precision grasps across all subjects.*

Results: EEG was recorded using a BioSemi system with 64 electrodes and non-casual filtered in the [1-6] Hz following previous results with ECoG [3]. EOG activity was removed using a regression algorithm 4]. Fig. 1c shows the grand averaged signals across subjects on channel C3 (contra-lateral motor cortex). Signals for the two grasping types were significantly different ($p<0.01$, Bonferroni corrected t-tests) as early as 300 ms prior to the grasping onset, and differences could be found up to 500 ms after grasp. The topographic representation of the difference between the two conditions revealed a very focal activation in the contra-lateral motor cortex, as expected by the nature of the task performed [5]. To discriminate between the two grasping types, a linear discriminant was trained on 8 contra-lateral motor channels using the activity prior to the grasping onset ([-500, 0] ms). Grasping types were detected with an accuracy of 75.90 ± 5.02% on average across subjects (Fig. 1d).

Discussion: We report for the first time the existence of EEG correlates for two different grasping types. Importantly, reported results are in line with similar works using semi-invasive signals [3], yet with slightly lower accuracies. Further experiments will confirm the decoding of these correlates on closed-loop scenarios.

Significance: Decoding of grasping types in single-trials using EEG is possible, which could lead to a new generation of neuroprostheses capable of executing different high-level commands based on the user needs.

Acknowledgements: This work has been supported by the NCCR Robotics and the Marie Curie EPFL Fellows.

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Discriminating goal-directed from nongoal-directed movements and its potential impact for BCI control

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Introduction: Differences in the electroencephalographic (EEG) recordings between the execution of goal-directed and nongoal-directed movements have been recently shown in [1]. Such differences can be of interest for brain-computer interfaces (BCIs) control, when combined with information on the kinematic level (e.g. velocity decoding), since this combination mirrors the hierarchic way one plans a movement. In this study, we show that the time-domain differences between these movements are discriminable in a single-trial classification.

Material, Methods and Results: Ten healthy, right-handed subjects participated in the experiment. Subjects were presented a small red ball on the monitor (*Goal*) or a red screen (*No-Goal*). After 2 seconds and only when the stimuli color changed from red to purple, subjects were instructed to reach-and-touch the ball (*Goal Movement*) or to decide on their own where to touch (*No-Goal Movement*). 72 trials per condition were recorded. EEG signals were recorded using 60 passive electrodes and sampled at 512 Hz.

Independent component analysis (ICA) was performed for artefact removal: components representing eye movements and muscle activity were rejected. To extract relevant low-frequency time-domain features, data were down sampled to 16 Hz, common average referenced and band-pass filtered from 0.3 to 3 Hz with a zero-phase 4th order Butterworth filter. Classification was done using a random forest binary classifier; accuracies were calculated for each time-point and validated using 10x5-fold cross-validation. To score significantly above the chance level, 64.7% had to be reached (p=0.01, Bonferroni corrected for multiple tests over the trial length). Fig. 1 shows the time-course of the classification accuracies when discriminating *Goal Movement* and *No-Goal Movement*. Accuracies rise above the chance level after both first and second cues. After the GO cue (second cue), the average accuracy peaks immediately after movement onset with 67%. Here, 4 out of 10 subjects show accuracies above 80%, and all subjects are above the chance level. Also interestingly, 3 of the subjects show high accuracies even 2 seconds after movement onset.

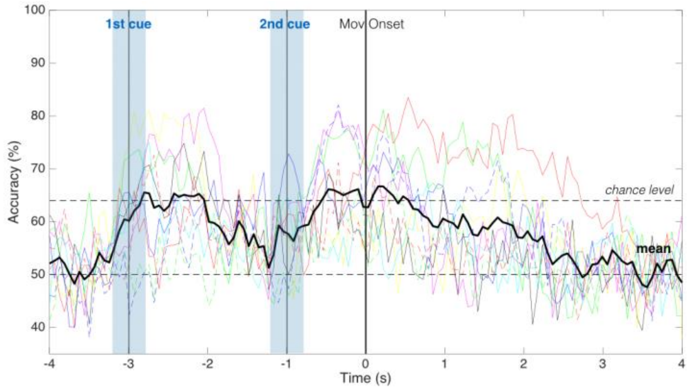

Figure 1. *Classification accuracies when discriminating Goal and No-Goal Movements, time-locked at movement onset (t=0s). The first 2 vertical lines correspond to the average time-points when the 1st and the 2nd cue appeared, in respect to movement onset. The thick black line corresponds to the grand-average accuracy.*

Discussion: Our results show that there are differences between goal-directed and nongoal-directed movements when time-locking at movement onset. Namely, the motor-related cortical potentials – after the second cue- show different amplitudes between conditions. These differences are discriminable in a single-trial classification. Future work will be to investigate whether similar results are obtained with neuroprostheses end-users and movement imagination (MI). If so, this information could be useful to establish activation thresholds, or even by instructing the subjects to imagine the kinesthetic MI associated with a target. We hypothesize that this instruction, combined with movement decoding at the kinematic level, could additionally improve classification accuracies.

Significance: The results contribute to the goal of our research: a naturally-controlled BCI neuroprostheses. Furthermore, we encourage the BCI community to explore the neural correlates behind goal-directed movements and how recent neurophysiological findings in action planning (e.g. [2]) can be of practical interest for BCIs.

Acknowledgements: This work is supported by the EU ICT Programme Project H2020-643955, “MoreGrasp” and the ERC Consolidator Grant “Feel Your Reach”.

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Full Body Spatial Tactile BCI for Direct Brain-robot Control

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Introduction: We present a study of a stimulus-driven tactile BCI, in which somatosensory stimuli are given to the full body of the user in order to evoke P300 responses. Six spatial tactile stimuli are applied to various body locations of the user's entire back. The classified BCI results are employed for an intuitive robot control. The robotic control is designed for paralyzed users who are in bedridden conditions. We define this approach as full body BCI (fbBCI) and we investigate how it could be applied for people in need soon.

Material, Methods and Results: The fbBCI is one of the P300-based stimulus driven paradigms [1], which identify intentional responses to spatial somatosensory patterns. The presented approach is developed in mind for clinical conditions and for locked-in syndrome (LIS) bedridden users, although at the current stage we test it only with healthy participants. For this reason, we develop a tactile stimulus generator applying vibration patterns to a full body of the user's back [1]. Tactile transducers DAYTON TT25-16 are embedded within a mattress in order to generate somatosensory evoked potentials (SEP) with intentional P300 responses to attended stimulus patterns applied to six distinct areas of user's back and limbs (namely the both arms and legs; waist and shoulder areas). NAO humanoid robot is also tested as a practical application of the fbBCI usability of direct brain-robot control. Six robot movements preprogrammed in the robot are mapped to the fbBCI commands (e.g. walk straight, back, left, or right; sit down; and say goodbye). The direct brain-robot control application is depicted in Figure 1.

Figure 1. *The fbBCI user lying on a mattress with tactile transducers embedded. NAO robot depicted seating is controlled using the fbBCI. One of the tactile transducers used in experiments is depicted in the lower left panel.*

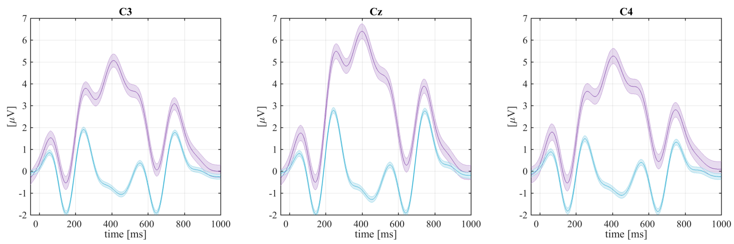

Figure 2. *Grand mean averaged ERP results of all ten subjects for target (purple lines) and non-target (blue lines) stimuli. Electrodes C3, Cz and C4 are depicted with very clear P300 responses, together with standard error intervals, in latencies of 200 ~ 600 ms. Eye blinks have been rejected with an absolute threshold of 80 μV.*

In the fbBCI online experiments, the EEG signals were captured with a bio-signal amplifier system g.USBamp (g.tec Medical Instruments, Graz, Austria) and processed using in house extended BCI2000 environment. The P300 responses were classified using a stepwise linear discriminant analysis (SWLDA) method. Active EEG g.LADYbird electrodes were attached to eight locations of Cz, Pz, P3, P4, C3, C4, CP5 and CP6, as in 10/10 international system. The EEG sampling rate was set to 512 Hz. The high- and low-pass filters were set at 0.1 Hz and 60 Hz respectively. A notch filter to remove power line interference was set for a rejection band of 48~52 Hz. The vibration frequency of the tactile transducers was set to 40 Hz. Ten healthy subjects (five males and five females; mean age of 21.9 years with standard deviation of 1.45) took part in the experiments approved by the Ethical Committee of the Faculty of Engineering, Information and Systems at the University of Tsukuba, Tsukuba, Japan. Grand mean averaged ERPs from the online experiments have been depicted in Figure 2. SWLDA classification accuracies in the fbBCI experiments resulted with 53.67% on average.

Discussion and Significance: In the presented project, which shall be considered as a relatively novel approach, we could successfully apply a full body tactile BCI to realized the concept of direct brain-robot control application [2]. The presented fbBCI results are a step forward in development of a clinical application and the assistive robotic control for bedridden patients.

Acknowledgments: We would like to thank Dr. Andrzej Cichocki and Peter Jurica for support and rental of the NAO robot from RIKEN Brain Science Institute, Wako-shi, Japan.

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Movements of the same upper limb can be classified from low-frequency time-domain EEG signals

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Introduction: Brain-computer interfaces (BCIs) can be used to control neuroprostheses of spinal cord injured (SCI) persons. A neuroprosthesis can restore different movement functions (e.g., hand open/close, supination/pronation etc.), and requires a BCI with a sufficiently high number of classes. However, sensorimotor rhythm-based BCIs can often only provide less than 3 classes, and new types of BCIs need to be developed. Since a couple of years, a new EEG feature has evolved: low-frequency time-domain signals. For example movement trajectories [1] and movement directions [2] were decoded using this feature. In the present study, we investigated whether low-frequency time-domain signals can also be used to classify several (executed) hand/arm movements of the same limb. A BCI relying on the imagination of such movements may be used to control a neuroprosthesis more naturally and provide a higher number of classes.

Material, Methods and Results: We recorded the electroencephalogram (EEG) using 61 channels and movement data from 15 healthy subjects using g.USBamps (g.tec, Austria) and ArmeoSpring (Hocoma, Switzerland). The subjects sat in a chair with the arm supported by the ArmeoSpring. We instructed subjects to execute hand open/close, supination/pronation, and elbow extension/flexion movements according to cues presented on a computer screen, i.e., 6 movement types/classes. In total, 360 trials (60 trials per class) were recorded. We removed independent components contaminated with artifacts and down-sampled data to 16 Hz. Subsequently, we referenced to a common average reference and applied a 0.3 – 3 Hz 4th order zero-phase Butterworth band-pass filter to extract the low-frequency signals. Finally, we time-locked the data to the movement onset and classified the EEG with a shrinkage regularized linear discriminant analysis. To avoid overfitting we applied a 10x10-fold cross-validation. Fig. 1 shows the classification accuracies of all subjects and the average. The average classification accuracy peaked at 0.0625s after the movement onset with a classification accuracy of 37%. Classification accuracies were significant above 24% (p=0.05, Bonferroni corrected for multiple time-points, Adjusted Wald interval).

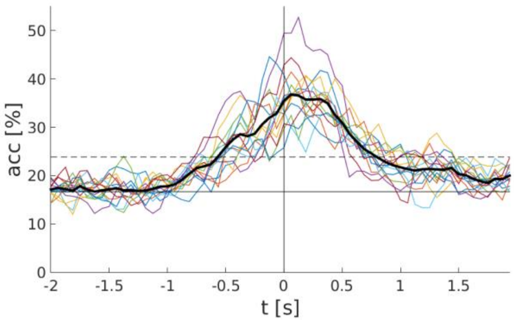

Figure 1. *Classification accuracies of all 15 subjects. Time point 0s corresponds to the movement onset; thick black line is the average; horizontal solid line is the chance level; horizontal dashed line is the significance level.*

Discussion: We have shown that low-frequency time domain signals can be used to discriminate between different movements of the same upper limb. Movement accuracies peak after the movement onset but reach significantly high classification accuracies before the movement onset. This shows that upcoming movements can be classified from the movement planning phase. This is crucial for a BCI applicable for end users with SCI who cannot execute all movements anymore. However, the classification accuracies are rather low and further studies have to investigate whether user training improves classification accuracies.

Significance: Low-frequency time-domain signals contain information about upcoming movements and may serve as a control signals for future neuroprostheses. This would allow more degrees-of-freedom and a more natural control.

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Multiuser Spatial cVEP BCI Direct Brain-robot Control

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Introduction: We present a recently extended by our team spatial code-modulated visual evoked response (cVEP) based BCIs paradigm applied for online control of two humanoid robots NAO in the brain-robot symbiotic configuration utilizing the Internet of Things (IoT) scenario. The presented extension is based on the eight commands BCI paradigm, in which two users simultaneously execute the same movement scenarios. Our previously reported experiments allowed only single user four commands-based BCI [1, 2]. The very encouraging results of two users executing in synchrony the same robot eight-movement-based sequences are a step forward in BCI applications for training and possible artistic performances with healthy as well as handicapped users.

Material, Methods and Results: Brainwave responses in the reported online BCIs, tested with two healthy users in each trial, are captured with two sets of eight active EEG electrodes g.LADYbird connected to two g.USBamp portable amplifiers from g.tec medical instruments GmbH, Austria. The both amplifiers are not synchronized and only digital stimulus series triggers are shared via a g.TRIGbox. The Ethical Committee of the Faculty of Engineering, Information and Systems at the University of Tsukuba, Tsukuba, Japan, has approved the experiments. Direct brain-robot control experiments are conducted with visual steady-state response type of paradigm eliciting cVEP responses [1, 2], classified next with a linear support vector machine (SVM) method. The users are requested to execute only micro eye saccades to gaze directly at one of the eight LEDs flashing 31–bits long m–sequences with eight bits circular shifts applied to differentiate the patterns [1, 2]. The target LEDs are arranged on square frames in front of each user as shown in Figure 1. We apply also 18 single cVEP sequence averaging procedure in online experiments to remove non-cVEP related noise in EEG (each command generated in about 10 s due to slow robot movements). The classified commands are sent to each robot using wireless connection with user datagram protocol (UDP) applied, which realizes the IoT communication scenario. The robots execute pre-programmed commands of walking straight, back, left, right; greeting and saying goodbye; inviting to interact; and stopping without any movement.

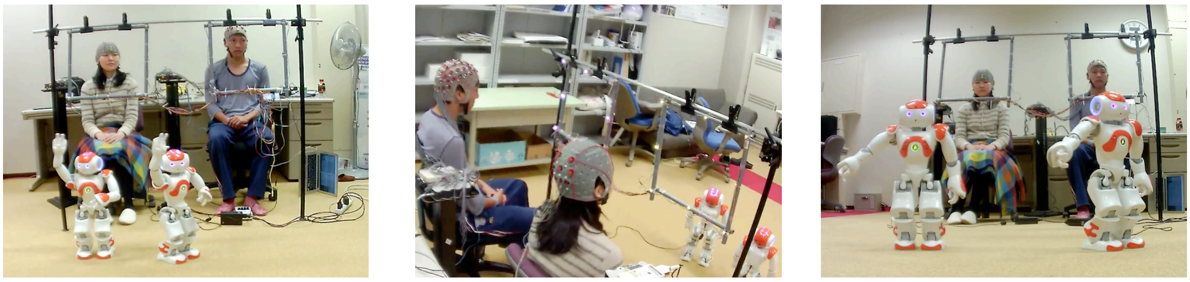

Figure 1. *Three screenshots from a video available online [3] documenting the succesful synchronized control of two robots using eight commands' cVEP BCI scenario.*

Discussion and Significance: In the presented novel project of the synchronous and successful direct brain-robot control (with perfect accuracies) by two users simultaneously we could create the new application with possible broad impact on BCI usage training in a master-apprentice scenario (advanced and naïve users). The multiuser robotic control could be also utilized in artistic performances or healthy with handicapped user interactions. The presented novel and successful cVEP-based BCI robotic application is a step forward in development of creative neurotechnology paradigms. Based on experiences with healthy user teams employing the tested direct brain-robot control scenarios we expect that the multiuser BCI application could have a significant potential also for clinical applications to support the user training (rehabilitation or locked-in syndrome cases) or building competitive teams challenging each other. Based on the conducted study we also could observe that the participating users were more encouraged to practice "to move the machines." The robots, as in real life, not always executed the movements perfectly, which required creative feedback from the users. Some situations were also on a border of a comedy of mistaken movements, which further encouraged the users to perform.

Acknowledgements: We would like to thank Dr. Andrzej Cichocki and Peter Jurica for support as well as rental of two NAO robots from RIKEN Brain Science Institute, Wako-shi Japan.

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NAO race: exploring social context on motor imagery performance

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Introduction: Motor imagery (MI) has been suggested to facilitate motor recovery after stroke. Particularly promising seems the combination of MI and neurofeedback, albeit most feedback implementations are not necessarily supporting MI skill learning [1]. We compared the effect of single player versus multiplayer scenarios [2]. For feedback, foot motor imagery signals were used to control NAO walking distance. Using this feedback we ensured that the imagined action matched to the feedback signal provided, albeit in a discrete way.

Material and Methods: 25 individuals (mean age = 24.9; 14 females) participated in the experiment, comprising 4 experimental blocks (each 40 trials). In the first block, participants physically performed repeated foot movements while sitting. In the subsequent blocks, the same movement was performed mentally. In block two, no feedback was given (training), whereas in blocks three and four, a discrete EEG-based robotic feedback of four different length was provided. Feedback was based on the classification (LDA) output of the power in the 8 to 30 Hz frequency band. In one of these sessions (pseudorandomized across participants), the participant was by himself (solo), while in the other, a race against a confederate steering a second NAO robot was implemented (duet). Intensity and easiness of MI were assessed after each block by means of questionnaires. EEG data were recorded from 24 scalp sites (Easycap, Herrsching, Germany) using a wireless, mobile amplifier (mBrainTrain, Belgrade, Serbia). OpenViBE was used for data acquisition, stimulus presentation and NAO robot (Aldebaran, Paris, France) control [3]. For offline analysis, we followed a previously established procedure [4].

Results: Online accuracy was on average 61.2% (SD = 8.45%). Offline, for each individual, the channel with the strongest event-related desynchronization (ERD), across all MI blocks, was selected (Fig. 1). Significant differences between MI blocks were found in ERD ($F_{2,48} = 6.02$, $p = .012$, $\eta^2 = .20$), intensity ($F_{2,48} = 6.23$, $p = .005$, $\eta^2 = .21$) and easiness ($F_{2,48} = 6.3$, $p = .005$, $\eta^2 = .21$), by repeated measures ANOVA. Follow-up paired t-tests revealed stronger responses during solo (ERD: $t_{24} = -2.78$, $p = .01$; intensity: $t_{24} = 3.18$, $p = .004$; easiness: $t_{24} = 2.65$, $p = .01$) and duet (ERD: $t_{24} = -2.44$, $p = .01$; intensity: $t_{24} = 2.60$, $p = .02$; easiness: $t_{24} = 3.08$, $p = .005$) compared to training. No difference between solo and duet could be observed (ERD: $t_{24} = -.38$, $p = .71$; intensity: $t_{24} = -2.78$, $p = .01$; easiness: $t_{24} = 0.42$, $p = .68$).

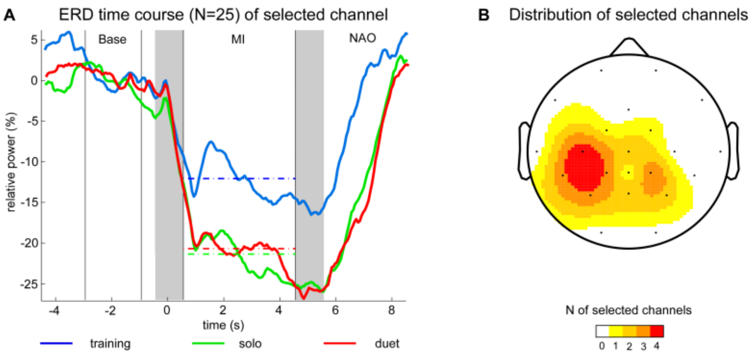

Figure 1. *Grand average of MI induced relative power at the selected channel (A) and the distribution of the selected channel (B).*

Discussion and Conclusions: In line with previous findings, we showed that EEG-based robotic feedback is feasible, as it enhances task specific activity. Our results suggest that this also applies to multiplayer scenarios. However, in contrast to our prediction, MI induced ERD was not enhanced in the multiplayer compared scenario. The type of social context applied, and the discrete feedback signal implemented, may have contributed to this null finding. Further research, specifically with respect to different frequency bands and other EEG components, is necessary to identify potential benefits of social context on neurofeedback performance.

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Noninvasive EEG Based Control of a Robotic Arm for Reach and Grasp Tasks

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Introduction: It is of significance to develop brain-computer interface systems controlling external devices or prosthetic limbs [1]. Noninvasive electroencephalography (EEG) based control of a robotic arm for reaching and grasping targets by motor imagination in real world was explored in this study. Compared with BCI studies in virtual environments [2], interaction with physical device might greatly motivate the subjects to engage into the experiments [3]. We aim to test the hypothesis that human subjects using motor imagination protocol can operate a robotic arm reliably, from sensorimotor rhythms detected from noninvasive scalp EEG.

Material, Methods and Results: EEG data were recorded for six subjects by a 64 channel Neuroscan cap, among which EEG channels over left and right motor cortex were utilized to be the online control signals. Each subject performed eight to eleven sessions of instructed experiments including virtual cursor control and physical robotic arm control. Each subject first performed one to four sessions of virtual cursor experiments as training and then progressed to two sessions of reaching and grasping with four targets via the robotic arm and three sessions of reaching and grasping with five targets via the robotic arm, all while the moving cursor was displayed on the monitor (**Fig. 1a**). Finally, they performed two extra sessions of reaching and grasping via the robotic arm with four and five targets in absence of the virtual cursor movement. All of the protocols were approved by the Institutional Review Board of University of Minnesota. EEG activity from the control channels were spatially filtered and then fed into an autoregressive model to extract the power spectra features. The power activities in the upper mu frequency band over the left and right hemisphere were linearly mapped to the position of the robotic arm. The robotic arm, which is a seven degree of freedoms human-like robotic arm, was mounted on the right side of the subject (**Fig. 1a**). A two-step task was employed to assist the participants' ability to reach and grasp an object in 3D space. The robotic arm moved in a horizontal plane in the first step and moved vertically in the second step.

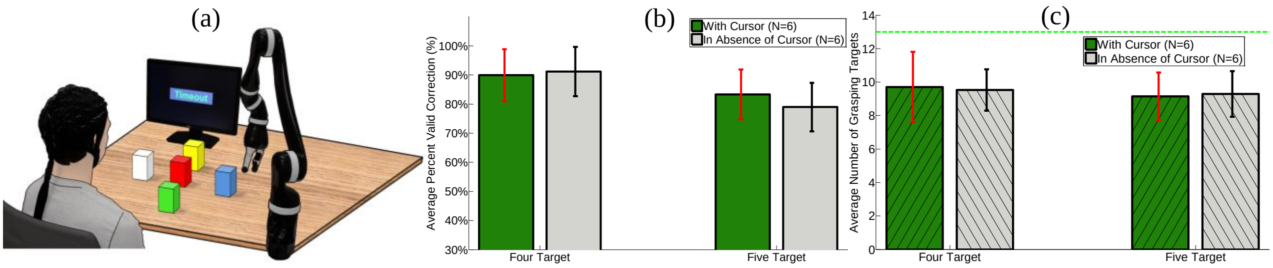

***Fig. 1** (a) Experimental paradigm for 5 targets reaching and grapsing. (b)Group average PVC of 4 and 5 targets reaching and grasping with and in absence of cursor movement. (c) Group average number of blocks grasped for the same two tasks with and in absence of cursor movement.*

Fig. 1b shows the group average percent valid correction (PVC) for the four targets and five targets reaching and grasping tasks on the left side and right side of the plot, respectively. The green bar shows the results of reaching and grasping with the cursor displayed on the monitor and the gray bar shows the same results in absence of cursor movement, in which only designated target to be grasped was shown. The group average PVC for six subjects of reaching and grasping with four targets was about 90%, which was similar to the corresponding results in absence of cursor (~91%). The group average PVC of reaching and grasping with five targets was about 83% and the corresponding results in absence of cursor was about 79%. The group average number of blocks for grasping four targets and five targets in each run are 9.7±2.1 and 9.2±1.4, respectively, where 26 trials in each run were completed in about six to nine minutes and each session consisted of four or five runs. The maximum number of blocks (targets) in each run that can be grasped was 13. The group average numbers of blocks for counterparts in absence of cursor in each run are 9.5±1.2 and 9.3±1.4, respectively.

Discussion: With the motivation of controlling a real robotic arm to accomplish a series of reaching and grasping task, the majority of subjects showed high and consistent accuracies in the relatively longitudinal sessions. The comparison of results between the controlling the robotic arm with virtual cursor and in absence of virtual cursor indicates that there is no significance difference between the two conditions. This implies that controlling a robotic arm by the input of either a remote terminal or subjects' direct visual input would show similar performance.

Significance: We demonstrate the capability for human subjects to control a robotic arm from noninvasive EEG for reaching and grasping tasks in 3D space. Our promising results indicate that noninvasive EEG based BCI is able to provide high precision and efficiency for controlling a robotic arm to finish complex reaching and grasping tasks in a real world. This promising finding indicates potential in future applications of noninvasive BCI for neuroprosthetics.

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Pushing the limits of BCI accuracy: Winning solution of the Grasp & Lift EEG challenge.

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Introduction: To better understand the relationship between EEG signals and hand movements the WAY Consortium has organized the Grasp-and-Lift EEG Detection challenge. It was held in 2015 from 29th June to 31th August on Kaggle, a platform for competitive predictive modeling, and attracted 379 contesting teams. The goal of the challenge was to detect 6 different events related to hand movement during a task of grasping and lifting an object, using only EEG signal. The 6 events were representing different stages of a sequence of hand movements (hand starts moving, starts lifting the object, etc.). True labels were extracted from EMG signal, and provided as a +/-150ms frame centered on the occurrence of the event. Contestants were asked to provide probabilities of detection for the 6 events and for every time sample. The evaluation metric for this challenge was the Area Under the ROC Curve (AUC) averaged over the 6 event types. Finally, the model must be causal, i.e. only the data from the past can be used to predict the events. This abstract presents the winning solution of this challenge.

Material, Methods and Results: EEG data that was provided was recorded with 64 electrodes on 12 different subjects while they were performing around 300 tasks of grasping and lifting an object. In many ways, the formulation of the problem differed from a typical motor imagery BCI problem: 1- The 6 events were representing different stages of a sequence of hand movements and therefore the temporal structure of the sequence had to be taken into account. In addition, some events were overlapping, and some others were mutually exclusive. 2- the events to detect were short timed (300ms) and positives predictions have to be provided for the entire frame. The sharpness of the prediction was critical for achieving optimal accuracy. 3- the predictions have to be provided for every time sample (3 million in total), which represents a considerable amount of data.

As a consequence, most of the current approaches used in motor imagery failed to produce accurate results. For this challenge, we used three different types of features: time domain signal low pass filtered by a bank of filters, covariance matrices estimated on different time window and frequency band, and a special form covariance dedicated to asynchronous detection of evoked potential. In the above context, we employed stacking to build a 3-level classification pipeline described in Figure 1.

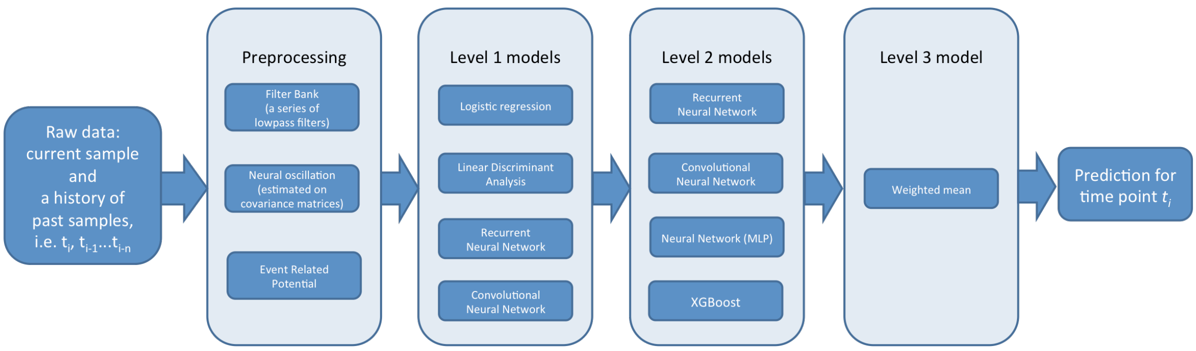

Figure 1. *Overview of the 3-level classification pipeline.*

Level1 models provided support and diversity for level2 models by embedding subject and events specificities using different types of features. A total of 51 level1 models were developed, the best was a convolutional neural network and achieved 0.95 AUC. Level2 models are global models (i.e. not subject-specific) that are trained on level1 predictions. Their main goal is to take into account the temporal structure and relationship between events. 32 level2 models were used, the best being a recurrent neural network (0.98 AUC). Level3 models ensemble level2 predictions via an algorithm that optimizes level2 models' weights to maximize AUC. This step improves the sharpness of predictions while reducing overfitting. The final model scored 0.981 AUC and allowed our team to take the first position of this challenge.

Discussion: Robust features, advanced machine learning methods, and algorithms able to model highly nonlinear relationships were crucial to achieving top performance. The score was gradually boosted with each stacking level, at the costs of increased solution complexity and computation time, without risk of overfitting due to the amount of data and the stability across time. Significant improvements of the score was achieved with the addition of level2 recurrent neural networks to the ensemble, which were able to model relationships between events and the temporal structure of the sequence of hand movements more accurately than other algorithms.

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Scenario screen: P300 speller variation for wheelchair control

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Introduction: The Donchin (or P300) speller is a Brain–Computer Interface developed for enabling people with severe motor disabilities to dictate words to a computer. We propose a variation on the stimulus scheme (also called *scenario screen*) which is a stimulator for controlling wheelchair navigation based on the native OpenViBE Donchin speller, but with dynamically changing image background and asymmetrically arranged stimulation markers. The image is a snapshot of the current navigation scenario and markers are located over relevant landmarks inferred from an automated scene analysis engine. In this work, we focus on the evaluation of P300 detection when the image and marker locations are different from those used for training.

Material and Methods: SCREEN IMPLEMENTATION. Our *scenario screen* is an improved version of the screen described in [1]. This version implements: single marker stimulation mode, green/blue flashes, eight landmark markers, four specific task markers placed on corners, and variable and random Inter–Stimulus Interval in six discrete steps within 125–225 ms. Three different screens (images and navigation markers) namely A, B and C implemented the aforementioned features. ACQUISITION SETUP. Eight passive Au electrodes (Fz, C3, Cz, C4, P3, Pz, P4, Oz), joint reference (A1, A2) and right mastoid reference were used. Acquisition device was a 16 channel g.USBamp with 512 Hz sample rate, passband (1.5–10.0 Hz) and notch (60.0 Hz) filters. EXPERIMENTAL PROCEDURE. Ten body–abled subjects aged 26$\pm$5.5 years participated in this protocol. Two sessions (*S0, S1*) separated between 3 and 15 days comprised the protocol. Both sessions consist on 16 copy mode repetitions of 10 trial each with homogeneous target selection. On *S0* only screen A is presented. *S1* was organized and presented to subjects in four blocks of four repetitions each. Blocks 0 and 3 showed screen A, and blocks 1 and 2 showed screen B or C. PREPROCESSING. EEG signals were filtered (41th order passband FIR, 1.5–10.0 Hz) and segmented in epochs of 307 samples. Each epoch was detrended, z–score normalized and subsampled by a factor of four. Eight channel data were concatenated. FEATURE EXTRACTION. LASSO [2] regression was used for both sparse feature selection and classification as follows. Through the LARS [3] algorithm with 15–fold cross–validation the optimal regression weights and relevant features were computed. Concatenated epochs were labeled for target and no-target respectively. CLASSIFICATION. Reduction to relevant features and projection over weights were performed on appropriately arranged data. The marker that elicits P300 on a given repetition was the minimum of the 12 accumulation of the ten trial regression results.DATA ORGANIZATION. Train data were the first eight repetitions of *S0*. Already calculated weights were directly utilized for classifying the unseen data from three groups: G0 last eight repetitions of *S0*, G1 blocks 0 and 1, and G2 blocks 1 and 2 of *S1*. On each group, sensitivity and specificity were computed as performance metrics. EVALUATION. Kruskal–Wallis H test was computed for sensitivities among the three groups in order to test whether changes on the image background and marker positions impact on the performance detection of P300. A similar test was made for specificities.

Results: There was no evidence to reject that sensitivity is statistically equal for all groups with $p > 0.15$ and medians 1.00, 0.75, 0.88 (IQR = 0.78–1.00, 0.47–0.88, 0.50–0.97). Similar results were obtained for specificity with medians 1.00, 0.98, 0.99 (IQR = 0.98–1.00, 0.95–0.99, 0.95–1.00).

Discussion: As the results suggest, the image and marker location do not impact on the classification performance, even for unseen screens. In other words, LASSO feature extraction and cumulative classification demonstrated to be robust given their tolerance to inter–session time, and image and marker location changes. Additional analysis has to be made on the temporal behavior of the detections since some subjects reach lower performances on the very last repetitions. However, there were subjects whose performance increased on the unseen screens.

Significance: The robustness of the P300 detection gives evidence to the potential application of the *scenario screen* on a real wheelchair navigation task. On the other hand, the results are consistent with the fact that P300 are potentials related to the stimulus perception and not to the screen appearance, however, more research should be made in this sense.

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Single Trial Classification of Neural Correlates of Anticipatory Behavior during Real Car Driving

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Introduction: Anticipation of events such as changes in traffic light signals and preparing to brake or accelerate are critical behaviors during driving. Smart vehicles, equipped with on-board Brain-Computer Interface (BCI), could decode the driver's intention to perform an action from his brain activity, thus, enable a possibility to enrich the interaction between the car and its driver [1]. We investigated on the existence and single trial detection of neural correlates of anticipatory behavior [2] in response to traffic lights during real world driving. This can be beneficial in the prediction of the driver's movement intention through neural correlates of anticipatory behavior.

Methods and Results: The experiment was conducted on 8 drivers over 2 sessions on separate days. EEG was acquired using 64 electrodes along with two EMG electrodes, placed on the *tibias anterior* muscle of the subjects' right leg. Experiments were performed with an *Infinity Nissan* car on a closed road with 6 traffic lights placed at specific locations. These traffic lights were programmed with a fixed timing (3 s of Yellow). The drivers were instructed press accelerator pedal as soon as they see the Green light and press the brake pedal immediately after the Red light. The EEG signal was filtered using the weighted average filter (WAVG) to reduce the spatial noise, then spectrally filtered in the range of [0.1 1] Hz [1]. Cz potentials at 4 equally spaced time-points during the last 2 s before each cue has been considered as the features. The EEG grand averages shows that a negative slope starts around 1 s after Yellow light and peaks around the onset of Green/Red light (see Fig. 1), similar to those observed in closed classical CNV paradigm [2]. For the single trial classification, we relied on QDA classifier with 4 fold cross-validation method and evaluated using the AUC in the ROC space. The average AUC, across 2 recording days, of the 0.63±0.08 for accelerating and 0.64±0.13 for braking has been achieved in an offline analysis. Notably, 4 subjects reached an AUC of 0.70.

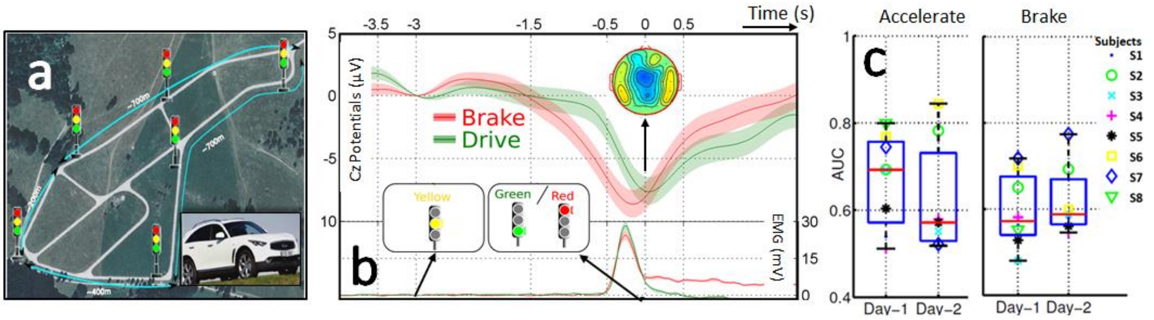

Figure 1. *(a) The map of closed road, inset is Nissan Infiniti vehicle. (b) Grand averages of Cz potentials (shadow represent the standard deviation) and EMG envelopes. Topographic representation of average EEG scalp distribution at t=0 s (the onset of the appearance of Green/Red light).(c) The AUC for Accerelate (Drive) and Brake.*

Discussion: We confirmed the existence of the anticipatory Slow Cortical Potentials (SCPs) in response to traffic lights. Remarkably, we have demonstrated a possibility of detecting these potentials in real world driving, despite large amounts of visual distractions and movement artifacts.

Significance: This study shows, for the first time, the possibility of detecting the anticipatory SCPs in response to traffic lights during real world driving. This will be beneficial for building in-car BCI systems to predict driver's intended action through anticipatory brain potentials. Such BCI systems can provide information in order to achieve the assistance in-line with the driver's intention.

Acknowledgements: The work was supported by Nissan Motor Co. Ltd., under the project 'Research on Brain Machine Interface for Drivers'.

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Time domain classification of grasp and hold tasks

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Introduction: Brain-Computer Interfaces (BCIs) enable its users to interact with their environment only by thought. Earlier studies indicated [1, 2] that BCI might be a suitable method for controlling a neuroprostheses, which could assist people with spinal cord injuries (SCI) in their daily life. One drawback for the end user is that only simple motor imaginations (MI) are available for control e.g. MI of both feet to control ones arm is abstract and in contradiction to an associated natural movement. Therefore we are looking for means to design a more natural control modality. One promising scenario would be to use MI of different grasps to actually control different grasps of the neuroprosthesis. In this study we attempt to classify the execution of different grasp types in low-frequency time-domain EEG signals.

Methods: Fifteen healthy participants from age 23 to 37 participated in the experiment. In a cue guided paradigm (see figure 1), subjects were instructed to perform 3 different reach-grasp-hold tasks on 3 different objects: palmar grasp (cylinder), pincer grasp (needle) and key grasp (key). To introduce a control condition, one spot was deliberately left empty and users were asked to not perform any movement. We recorded 72 trials per condition (288 in total) over 8 runs and varied the position of the objects so that every object was positioned equally often on each position. We recorded 61 active electrodes (g.tec, g.GAMMAsys) as well as data from a data glove (5DT) and a switch button to obtain the movement onset. We rejected artifact contaminated trials and channels using a statistical outlier rejection. We down-sampled the EEG to 16 Hz and applied a bandpass-filter between 0.3 and 3 Hz (4^{th} order, Butterworth, zero-phase) to extract the low-frequency signal. Using 5 fold crossvalidation to avoid overfitting and a random forests classifier [3], we investigated all grasp versus grasp combinations. To score significantly higher than chance level ($p = 0.05$, Bonferroni corrected for multiple comparisons over trial time), the accuracy level had to be higher than 64.7 %. Table 1 displays the results.

Figure 1: Paradigm: Participants were instructed to rest the hand comfortably on a pressure button. At second 0, a cross appeared on the screen to focus users' attention. At second 2, one of the objects was highlighted in white for a random time period. As soon as the highlighting turned green, participants performed the reach and grasp tasks and held the object as long as the green highlighting remained. Thereafter participants returned their hand to the pressure button.

Grasp vs Grasp	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
Pal vs Pin	61.5	**78.8**	61.7	**73.0**	**76.8**	**69.7**	**65.9**	**69.9**	**69.6**	60.6	**71.2**	**68.0**	**74.3**	63.7	**69.2**
Pal vs Key	**70.0**	**74.4**	64.1	**76.9**	63.6	**68.5**	64.6	63.6	**66.2**	**65.7**	**70.7**	**71.1**	**66.2**	**66.7**	**67.5**
Pin vs Key	64.4	**68.9**	63.0	**67.1**	**66.7**	61.3	**66.1**	63.0	**66.9**	65.7	**69.7**	**66.4**	62.2	**70.7**	**69.3**

Table 1: Peak accuracies after movement onset over all trials in percent. (Pal = Palmar, Pin = Pincer, Key = Key Grasp). Bold values indicate performance levels significantly higher than chance.

Discussion: We could confirm that grasp versus grasp classification in the low-frequency time-domain is possible. Fourteen out of 15 participants scored significantly better than chance in at least one combination, whereas 8 participants' performance topped 70%. Peak performances occurred within the first one and a half seconds after movement onset, but different for each subject. We believe this is due to the varying movement speed towards the object. No significant predictions could be made before actual movement onset. So far these results only reflect motor execution of a grasping task – there is still need to investigate whether these results can be achieved with motor imagery. Furthermore it is still unknown whether user can be trained to boost classification to a robust level.

Significance: We could show that executed grasp versus grasp classification is possible. We believe that these findings will contribute to a more intuitive and natural form of control for neuroprostheses.

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Time varying EEG Bandpower Estimation Improves 3D Hand Motion Trajectory Prediction Accuracy

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Introduction: Motion trajectory prediction (MTP) employs a time-series of band-pass filtered EEG potentials for reconstructing the three dimensional (3D) trajectory of limb movements with a multiple linear regression (mLR) block. While traditional multiclass classification methods use power values of mu (8-12Hz) and beta (12-30Hz) bands for limb movement based classification, recent MTP brain-computer interface (BCI) studies report the best accuracy using a 0.5-2Hz band-pass filter [1]. We recently [2] introduced a novel approach for MTP BCIs where the time-series of band-pass filtered EEG potentials were replaced with the time-series of power values of subject specific frequency band(s) prior to the application of mLR. Here we present an analysis of three subjects performing 3D arm movements and comparing the accuracy rates of the standard EEG potential model and the proposed spectrum power based approach.

Material, Methods and Results: The experiment involved two runs with six blocks/run and 15 movements/block (i.e., trials/block), between the home position and one of six target positions (Fig. 1A). Movements were synchronized with an auditory cue. Sixty-one EEG channels and kinematic data (x, y, and z hand position coordinates) were recorded simultaneously with a gHIamp80 (g.tec, Austria) and Kinect camera, respectively.

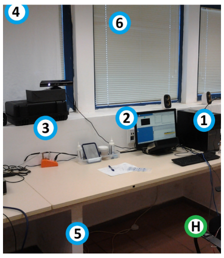

***Figure 1A**. Experimental setup. Home (H) and the six target positions (1-6).*

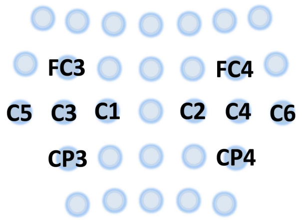

***Figure 1B.** Illustration of the thirty-one Laplace filtered EEG channels from which ten channels (see labels) were selected for kinematic data estimation.*

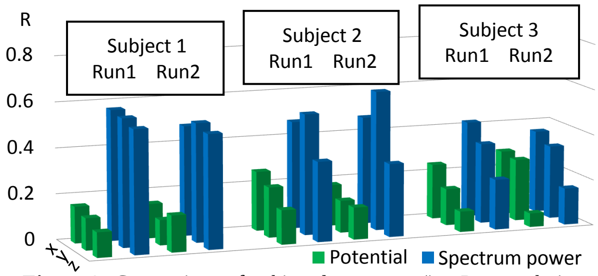

***Figure 2.** Comparison of achieved accuracy (i.e. R: correlation of registered and calculated test velocity trajectory components) for potential and spectrum power models in x, y, and z directions.*

Thirty-one EEG channels were re-referenced with a Laplace filter (Fig. 1B). Data intervals with high level transient noise (>|±300µV|) were removed along with their corresponding kinematic data. A 0.5-40Hz, 8th order Butterworth band-pass filter and independent component analysis (ICA) were applied for removing electrooculographic (EOG), electromyographic (EMG), and noise components. Ten ICA filtered EEG channels covering the sensorimotor cortex (Fig. 1B) were selected. For the potential model, channels were band-pass filtered in six specific bands (0.5-2Hz, 4-8Hz, 8-12Hz, 12-18Hz, 18-30Hz, and 30-40Hz). For the spectrum power model, signal bandpower was calculated in 500ms sliding window to replace the commonly used EEG potential time series. Parameter optimization is described in [2]. Correlation between registered and reconstructed velocity trajectories was assessed in an inner-outer (nested) cross-validation. The time lag, embedding dimension, frequency bands and EEG channels were optimized from the inner fold test correlations. The mean of the outer test fold correlations for the selected best architectures are reported for each subject and for each run (Fig. 2).

Discussion: Although the potential model provided best accuracy (R~0.2) in 0.5-2Hz (low delta) band, the spectrum power model yielded significantly higher accuracy (R~0.4) in the 4-8Hz (theta), 8-12Hz (mu), and 12-18Hz (low beta) bands. The current findings show parallelism with classical sensorimotor rhythm SMR-BCIs result that involve classification of different limbs e.g., left vs right hand movement, wherein the best accuracy is achieved using power values of mu (8-12Hz) and beta (16-28Hz) bands.

Significance: Significant improvements in the accuracy of 3D MTP can be achieved by replacing the time-series of delta band-pass filtered EEG potentials with the time-series of power values of the theta, mu, and beta bands. These bands, which are commonly used in classical SMR BCIs might encode movement trajectory relevant information, which is not accessible by the commonly used potential model [1] as a result of the approach used to time embed time series for the regression models. As the ultimate goal is to decode imagery of motion trajectory for movement-free control with a BCI, which is more challenging than decoding real movements, improvements in MTP approaches methods are necessary.

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Towards Detecting of Walking Intention from Readiness Potentials for a Powered Exoskeleton Control

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Introduction: Readiness potential (RP) is an appearance of cortical contribution to the premotor planning of voluntary movement [1]. Due to its characteristics, RP could be a useful feature for brain-machine interface (BMI)-based gait-rehabilitation using exoskeleton. Our final goal is a development of the RP-based lower limb exoskeleton control system without commands by muscle activation. The system may promote brain plasticity efficiently and can offer shorter response time for generating commands than other BMI paradigms. In this pilot study, we propose a self-paced exoskeleton control system using electromyography (EMG) in order to decode the walking intention-based RP signals. We also investigate the artifact influence in the RP patterns under the exoskeleton operation compared with normal walking (without exoskeleton) because the various artifacts in electroencephalography (EEG) signals can be induced by the powered exoskeleton locomotion [2].

Material, Methods and Results: The proposed system consists of the exoskeleton (REX, Rex Bionics Ltd), wireless EEG, and EMG modules (MOVE, BrainProduct GmbH). The system was controlled by movement onset triggers generated by EMG processing; the onset triggers were transmitted to the exoskeleton and EEG module when amplitude became higher than a threshold that determined by one tenth of the maximum value of EMG. The EMG electrodes were attached on the tibialis anterior and biceps femoris muscles of the right leg [3]. The EMG data were processed in real-time using 2s sliding window size with 100ms shift. The EEG data on 32 Ag/AgCl electrodes were band-pass filtered by 2nd Butterworth filter ([0.5 2]Hz) and were segmented into 10s epoch between 4s before and 6s after the movement onset. Three subjects (age: 26-29, 3 males) were asked to perform half step walking (basic walking function of the exoskeleton) and standing repeatedly with 50 trials in the normal walking and exoskeleton walking sessions.
We acquired the grand averaged RP patterns of normal and exoskeleton walking in Cz. To this end, each trial was baseline corrected in [-4 -2]s, and the amplitude was normalized to [0 1]. The RP patterns were detected approximately from -1000 to 0ms in the both sessions.

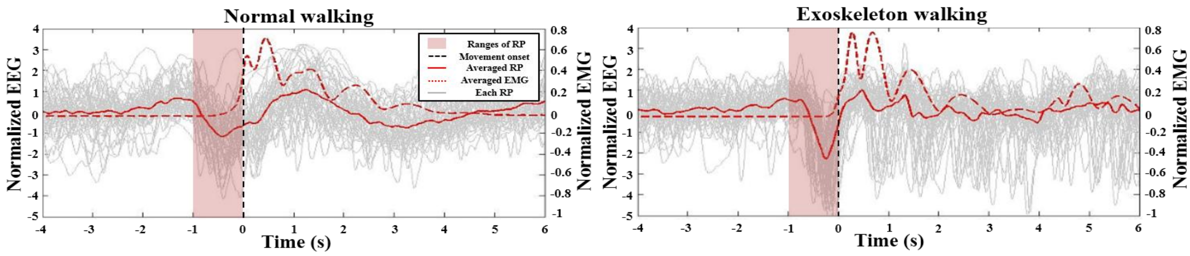

Figure 1. *The grand averaged RP patterns in normal walking (left) and exoskeleton walking (right).*

Discussion: We found the RP patterns in the exoskeleton walking as well as normal walking during [-1 0]s (Fig.1); specifically, negative slope appeared before the movement onset by EMG activation. Also, we confirmed that EMG signals showed similar muscle activation patterns (average and std) in the both sessions. However, the EEG patterns showed large variations in exoskeleton walking ([0 6]s) compared to normal walking in each trial; the exoskeleton operation time requires approximately 6s. For the RP based asynchronous control in the single trial, misclassification of user intention due to artifacts induced by exoskeleton walking should be minimized. Hence, gait-related artifact removal techniques in low frequency will be investigated in our future work.

Significance: We compared the grand averaged RP patterns of both walking sessions through the proposed system. We confirmed artifact influence in the EEG signals during exoskeleton walking. Our results show feasibility of the RP-based powered exoskeleton control system for BMI-based gait rehabilitation.

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Adaptive assistance for BCI: a locked-in syndrome end-user case study

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Introduction: Performance variation is one of the main challenges that BCIs are confronted with, when being used over extended periods of time. Several methods have been proposed to find correlates of performance variation for sensorimotor rhythms EEG-based BCIs [1]. However, they typically focus on assessing performance variations within the same day or session, and do not use this information online. This issue is even more critical for end users, as they usually achieve a limited level of performance [2]. Previously, we proposed that some issues resulting from performance variation could be overcome by providing adaptive assistance based on the users' needs. Therefore, we suggested a method for providing online adaptive assistance (i.e., modulating the timeout to deliver the intended command) based on an estimation of the user's performance (i.e., the command delivery time, CDT, for a single trial) [3]. We previously reported results on able-bodied subjects (N=9). Here, we test the approach with an end-user with locked-in syndrome.

Material, Methods and Results: We conducted several experimental sessions, each on a different day, using a motor imagery (MI)-based BCI in a game. The subject was 53 years old, suffering incomplete locked-in syndrome after hemorrhagic brainstem stroke in 2009. The experiment was performed in two phases: the first one (6 sessions), with no assistance, which was used to build the performance estimator, and the second one (10 sessions), where online adaptive assistance was provided to the user. In order to predict the CDT, trials shorter and longer than 3 s were considered as short and long, respectively. The performance estimator used PSD features in a short time window (1 s) at the beginning of the mental task execution trial and a linear discriminant analysis classifier to differentiate between short and long CDT with a reliable performance (AUC = 0.8). In the next phase, 10 sessions of the experiment were conducted in order to assess the feasibility of providing adaptive assistance based on the estimated performance by modulating the timeout for delivering a mental command. Two conditions were compared: having a *fixed timeout* (3 s) and providing *adaptive assistance* when the user needs it (by providing a longer timeout of 10 s in case the performance estimator predicts a long CDT). Details of the experiment and the methods can be found in [3]. As depicted in Fig. 1, providing adaptive assistance leads to significantly higher success rate (the ratio of correct command delivery to the number of commands) in the MI task ($p<0.005$; Wilcoxon ranksum test) over sessions (S1 to S10).

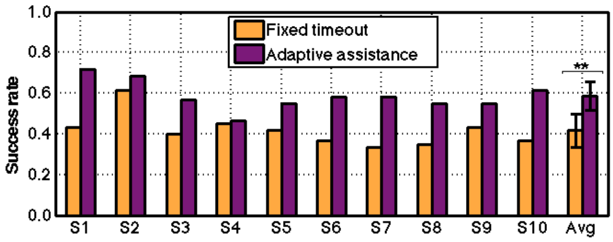

Figure 1. *Comparison of the success rate (ratio of correct command delivery to the number of commands) over 10 sessions (days) in two cases: fixed timeout and online adaptive assistance.*

Discussion: The proposed performance estimator overcomes some limitations of the existing studies on performance variation by taking into account several sessions of online MI experiment for building the estimator and providing a trial-based estimation. In addition, providing online adaptive assistance based on the users' needs at each time is shown to improve success rate.

Significance: This study proposes a method for estimating the performance of an MI BCI on a single trial basis as a mechanism to deal with the performance variability of BCI users, especially severely disabled ones. Importantly, promising results are achieved when providing online adaptive assistance based on this estimation in both able-bodied subjects and an end-user with locked-in-syndrome.

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Can amputees control a brain-computer interface with their missing hand?

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Introduction: One of the main goals of brain computer interface (BCI) research is providing disabled patients with some levels of communication, control of external devices, and mobility. For such patients to use BCI we need to address two major questions: i) can motor brain circuits that have been deprived of input following trauma still be used for controlling BCI? and ii) if so, what happens to these neural circuits after BCI training? We suggest that our real-time functional magnetic resonance imaging (fMRI) BCI paradigm is most suited to address these questions. Unlike electroencephalogram (EEG), or even invasive methods, fMRI provides a highly detailed anatomical mapping of the brain activity, which allows us a quantitative investigation of brain activity during BCI in both healthy and patient population. In this study we addressed the first question by conducting a BCI experiment using real-time fMRI on arm amputees, comparing their brain activity and performance with healthy patients, as well comparing brain activation and BCI performance used to control the amputated arm versus the intact arm.

Material, Methods and Results: Three male upper limb amputees (all 1.5-2 years after amputation) performed cue-based BCI as well as free choice BCI (a complex navigation task) with four classes: left hand, right hand, feet, and rest (null class), and their results were compared with four able bodied subjects. BCI was based on our system for whole brain machine learning classification in real time, described elsewhere [1]. A univariate statistical analysis taking into account subject, condition, and accuracy, indicated that both groups had a very high degree of BCI control (amputees – 95.8%, control – 97.2%), and the difference between the groups was not significant ($p = 0.176$, $F=7.1$). The classification accuracy of the intact hand was the same as that of the missing hand; taking into account the repetition time (TR) with maximum classification yields exactly the same mean accuracy for both groups (96.7%, based on 3 subjects, two runs each). In addition, all subjects controlled an avatar along a trajectory and there was no significant difference between the performances of both groups. Performance was computed by time to reach targets, as compared with navigation of the best run by an experienced healthy subject from a previous experiment; the control group was slower by 38% and the amputee group by 48%.

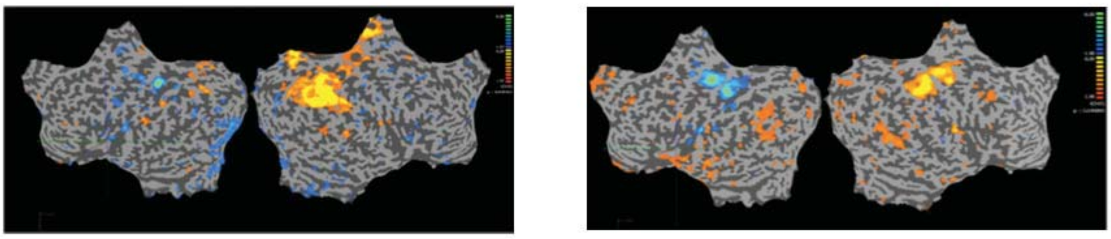

Fig. 1: *Right>left brain activation contrast, during cue-based BCI. Left: Right-hand amputee subject. Right: control subject.*

Discussion: Amputee subjects were able to control a BCI with very high performance, using their missing hand, in both cue-based and free-choice BCI. Their performance with the missing hand was identical to their performance in their missing hand, and their overall performance was nearly identical to that of able bodied control subjects. This performance is possible despite a reduction in the corresponding brain activation; Fig. 1 shows an example from one amputee subject; two others had similar activation patterns.

Significance: The study shows successful BCI, including a complex navigation task, using cortical networks of body parts following amputation. Our real-time fMRI method allows studying residual brain activations systematically in clinical populations, in the context of actual BCI performance.

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Classification of attempted and executed hand movements from ipsilateral motor cortex in amputees

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Introduction: Decoding complex hand movements from the motor cortex is an important strategy for brain-computer interface (BCI) control, with the sensorimotor cortex (M1/S1) contralateral to the moving hand being a natural and successful target for movement decoding using fMRI and electrocorticography (ECoG) [1]. We have shown recently that also *attempted* complex movements can be decoded accurately from this area in subjects with arm amputation [2], suggesting that, despite years of denervation, detailed information remains present. This finding is interesting, since arm amputation is accompanied by reorganization of the motor network [3]. Hand movements have previously also been decoded from ipsilateral M1/S1 in stroke patients [4], suggesting a preserved ipsilateral hand representation in spite of lost hand function. Here, we investigate whether the ipsilateral representation is also preserved in amputees. For this purpose we analysed 7T fMRI BOLD data, which shows good correspondence with ECoG [5], obtained during (attempted) gestures, and tested whether classification is possible from the hemisphere ipsilateral to the amputation side.

Methods: Eight subjects with above-elbow arm amputation participated (age 52 ± 12 y, 1 female, 7 right arm amputation, acquired 16.4 ± 11.5 years ago), as well as 8 control subjects (age 36 ± 18 y, 4 females). All subjects performed a task in which they had to *execute* (controls and intact hand of amputees) or *attempt* (missing hand of amputees) making six different complex gestures. After preprocessing, data from each gesture was contrasted against baseline in a general linear model. We then selected 450 voxels with highest *t*-values over all six contrasts within the left and the right sensorimotor cortex. The BOLD data in the ROIs was detrended and normalised, and the average signal in volume 4, 5 and 6 of each scan was used as feature set for classification. The classification score was obtained by a support vector machine using a cross-validation scheme (20 folds). The overall classification score was calculated as the mean score over all folds. The *differential classification score* (DCS) was defined as the difference between the score from the contralateral minus that of the ipsilateral hemisphere for the left (intact) or right (missing) hand.

Results and discussion: Contralateral cortex decoding yielded significant scores for amputees and controls (M = 73%, $p < 0.001$). Decoding scores for ipsilateral cortex were lower but still significant (M = 46% in controls and M = 62% in amputees, $p < 0.001$). For the left (intact) hand, the DCS was positive for controls (21 ± 11%, $p < 0.01$) and amputees (22 ± 12%, $p < 0.01$), which means that all subjects decoded better with the contralateral than with the ipsilateral side. For controls, also the DCS for the right hand was positive (31 ± 15%, $p < 0.001$). However, for the missing hand in amputees, the DCS was *not* different from zero (-1 ± 10%, n.s.), and direct comparison between the DCS of the missing hand of amputees with the right hand of controls revealed a significant difference ($p < 0.001$, $1 - \beta = 0.99$). Together, these data show that in controls, and for the intact hand of amputees, the classification score is higher when decoded from the contralateral side than from the ipsilateral side, whereas for attempted movements with the amputated hand, the classification scores from the contra- and ipsilateral sides are comparable, and are as high as the contralateral score from the intact hand.

Significance: These results strengthen the notion that information about complex movements is still present in M1/S1 after amputation: not only contralateral, but also ipsilateral to the amputation side. It may be speculated that, if this also applies to people with brain lesions, this might open possibilities for BCI targets in these patients.

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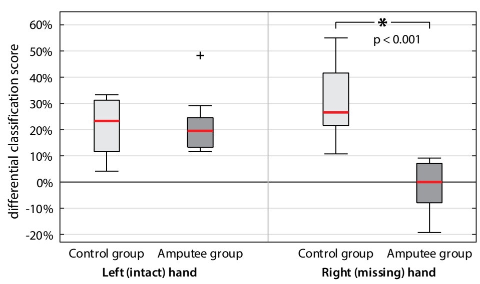

Figure 1. Differential classification scores: scores from the contralateral hemisphere minus the scores from the ipsilateral hemisphere. Left panel: left (or intact) hand differential scores. Right panel: right (or missing) hand differential scores. Red lines indicate the median DCS.

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Classifying force levels of hand grasping and opening using electroencephalography cortical currents

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Introduction: For people suffering from extremity-paralysis due to a stroke, assistive robots that can be an alternative for their hand will dramatically improve their quality of life. This study aims to develop a brain-machine interface (BMI) for controlling a robot hand using electroencephalography (EEG) signals. Especially, we attempt to add functions not only to control opening and grasping its hand but also to change its grip force levels according to users' intension. However, it has been considered that EEG signals do not have spatial resolution enough to extract such detailed information. To overcome the issue, instead using EEG signals as they are, we estimated EEG cortical current signals from EEG sensor signals by a variational Bayesian method with hierarchical priors [1]. EEG cortical current signals are time series signals of vertices that were spatially randomly assigned onto cortical surface. Since they might be theoretically equivalent to electrocorticography signals, we expect grip-force levels can be discriminated from EEG cortical current signals.

Material, Methods and Results: A T1-weighted 3D anatomical magnetic resonance imaging (MRI) image, 32-channel EEG sensor signals, and EEG sensor coordinate position data were used to calculate an inverse filter for estimating EEG cortical current signals by Variational Bayesian Multimodal Encephalography (VBMEG) toolbox [2]. During EEG signal acquisition, five participants performed five isometric hand-movement tasks (i.e., opening or grasping with high or low force, and no-motion) for 1 sec according to visual stimuli. Two-channel electromyography (EMG) signals were recorded simultaneously with EEG signals from electrodes placed over common digital extensor muscle and flexor digitorum superficialis muscle. EEG epochs were extracted in reference to EMG onset defined by Teager-Kaiser Energy Operation method [3], ranged from 1 sec before to 0.5 sec after the onset. EEG cortical current estimation and task-classification analyses using power specter density signals through a sparse logistic regression [4] were conducted by 10-fold cross validation method. As shown in Fig. 1, EEG cortical current showed significantly higher classification accuracies for force levels as well as movement difference than EEG sensor signals.

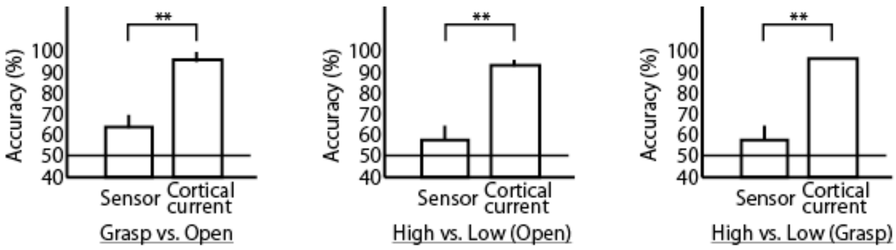

Figure 1. *Comparison of mean binary classification accuracies across participants between EEG sensor and EEG cortical current signals. Left: Grasping vs. opening. Middle: High vs. low forces in opening movement. Right: High vs. low forces in grasping movement. Error bars are standard errors and statistical significances were calculated using paird t-test **p<0.001.*

Discussion: Vertices with high weight values were located in slightly different positions for grasping vs. opening from high vs. low forces classification. Furthermore, when calculating accuracies for different time windows, it was found that accuracies surged just before the EMG onset from around chance level to high values, which were reasonable considering that we used vertices in the primary motor cortex for the analysis.

Significance: This work showed the usability of EEG cortical currents to overcome a drawback of EEG that has been considered not to have enough spatial resolution for extracting force differences. Our findings will expand the possibility of EEG-based BMI.

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Factors and values related to technology acceptance of Brain-Computer Interfaces as assistive technology

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Introduction: This study aims to identify which factors and values are related to the technology acceptance of end-users for Brain-Computer Interfaces as assistive technology (e.g. Alternative and Augmentative Communication or neuroprosthetics). We thereby aspire to facilitate the transfer of BCI technology to society and promote responsible innovation.

Material, Methods and Results: Participants were divided into three groups; neuro-muscular diseases (NM group; spinal muscular atrophy, amyotrophic lateral sclerosis, N = 7); spinal cord injuries (SCI group, N = 9); and Locked-In Syndrome (LIS group, N = 5). Participants in the NM and SCI group were educated about the state of art of BCI via a mini lecture, experienced a BCI demo, and participated in focus group interviews. Participants in the LIS group were visited at home and individually attended the mini lecture, BCI demo and interview. Interviews were recorded on audio and video and transcribed Ad Verbatim. Three coders (FN, AS, EL) coded the interviews three times, using the Noticing, Collecting, Thinking (NCT) method [1], Atlas.ti (version 7.5.6), and the Coding Analysis Toolkit (CAT; cat.texifter.com). Nine codes, based on previous studies [2,3,4,5], were used for the first round of coding. The list of codes was elaborated to 28 codes (see Table 1) in the second round (interrater reliability: Krippendorff's Alpha = 0.236; Fleiss' Kappa = 0.48). During the third round the three coders compared and discussed their codes (Krippendorff's alpha = 0.90; Fleiss' Kappa = 0.86).

Depending on group and type of sensors (invasive or non-invasive) participants were concerned or excited about a range of topics related to the (potential) use of Brain-computer interfacing. For example, invasive sensors were a point of concern for participants with LIS, but not for most participants in the NM and SCI group, who perceived the esthetics of current non-invasive BCI headset as a great barrier for technology acceptance and a direct threat to their value inclusion and dignity.

Category:	Codes:
Medical issues	Progressive disability (19); Situational disability (31)
Technical issues	Effectiveness (51); Efficiency (63); User experience (27); Esthethics (40)
Ethical issues	Agency (38); Responsibility (6); Info from peers (21); Info from professionals (12); Info from media (16); Risks of BCI intervention (32); Risks of BCI use (28); Real or expected benefits (56); Bodily integrity (19); Enhancement (27); Privacy (10)
Policy / Market	Legal issues (28); Economical issues (47); Standardisation (24)
Social issues	Relational issues (22); Societal issues (5); Potential users (70);
Values	Safety (20); Autonomy (21); Self-expression (9); Inclusion (13); Dignity (4)

Table 1. Categories with associated codes (number of quotations per code)

Discussion: While it is relatively easy to identify and count technical, legal, ethical, and societal issues, it is harder to understand the dynamics between issues and resolve conflicts between values and to come to responsible design choices. Compatible with [5] we recommend including end-users in the research and design of new AT and BCI technologies, for example through the use of Value-Sensitive Design.

Significance: These results clarify the main concerns from end-users which must be addressed by BCI developers to increase the wide-spread use of BCIs.

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Magnetoencephalography-based Real-time Control of a Prosthetic Hand in Paralyzed Patients

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Introduction: Real-time control of prosthetic limbs based on brain-machine interface (BMI) technology may be a new treatment option for severely paralyzed patients. A previous study revealed that electrocorticography of paralyzed patients was capable of controlling a prosthetic hand in real time by not only detecting the intention to move the paralyzed hand, but also by inferring the type of attempted movement [1]. Notably, our previous study demonstrated that magnetoencephalography (MEG) in healthy subjects also conveyed enough motor information to control a prosthetic hand [2]. However, it was not evident whether severely paralyzed patients could control the prosthetic hand with the motor information extracted from these non-invasively measured signals.

Subjects and tasks: Eight severely paralyzed patients with brachial plexus root avulsion and 1 amputee participated in this study. All patients joined 1 open-loop session; 5 patients joined 1 closed-loop session after the open-loop session. In the open-loop session, the patients were presented visually with the types of movement to perform, and were instructed to attempt to grasp or to open their paralyzed hand once, at the time an execution cue was presented. In the closed-loop session, the patients were shown a prosthetic hand and a monitor that displayed alternating instructions every 7 s to grasp or open the prosthetic hand. The patients were instructed to control the prosthetic hand at arbitrary times using the same attempts performed in the open-loop session.

Prosthetic hand control: A 160-channel MEG recorded the neuromagnetic activities of the patients in real-time. The MEG signals from 84 parietal sensors were averaged within a 500-ms time window, and normalized to form a slow magnetic field (SMF). A real-time decoder was trained using the SMFs in the open-loop session to control the prosthetic hand in the subsequent closed-loop session. The real-time decoder estimated the onset of the attempts to move the paralyzed hand using decoders trained by a Gaussian process regression and a support vector machine (SVM). At the detected onset, another SVM decoder inferred the performed movement type, which was grasping or opening. The prosthetic hand was controlled to form the inferred posture.

Offline analysis: The attempted movement type during the open-loop session was decoded by a SVM using SMFs and nested cross-validation. Moreover, to test the onset detection algorithm of the real-time decoder, timing of the onset detection was estimated using SMFs in the open-loop session and cross-validated. Finally, the decoding accuracy and the onset detection accuracy in the closed-loop session were evaluated separately using a one-tailed Fisher's exact test.

Results: During the attempted movements of the paralyzed hand, the spatiotemporal pattern of the SMFs showed characteristic activation similar to that during actual movement of the intact hand. A signal source reconstruction technique revealed that the sensorimotor cortex contralateral to the paralyzed hand was activated. The type of attempted movement was classified with an accuracy of $68.1 \pm 12.7\%$ (mean $\pm$ SD) using the SMFs from the open-loop session. Moreover, the onset detection algorithm successfully inferred the onset timing of the movement intention within ± 500 ms in $63.0 \pm 15.6\%$ trials. In the closed-loop session, the decoding accuracy of the movement type and the detection accuracy of the onset were significant for 2 out of 5 patients.

Discussion: The SMFs measured during attempted movement of the paralyzed hand conveyed enough motor information to control a prosthetic hand in real time. Moreover, the SMFs were thought to originate from the slow components of the cortical current in the contralateral sensorimotor cortex.

Significance: The prosthetic hand used in this study is the first to demonstrate that even *severely paralyzed* patients can control non-invasive BMIs in real-time using information about *both* movement type and intention.

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Online Accuracy of Invasive and Non-invasive MI BCI

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Introduction: A brain-computer interface (BCI) allows a person to intuitively interact with the environment without movement. This functionality can be further enhanced by a BCI that delivers continuous signals. Such BCIs are usually based on event-related desynchronization (ERD) extracted either from electroencephalographic (EEG) or electrocorticographic (ECoG) recordings during a motor imagery (MI) task [1, 2]. Common spatial patterns (CSP) have been widely established in multi-channel BCIs with online feedback since the resulting features are highly discriminative and signal dimensionality can be dramatically reduced [1, 2]. Although BCIs based on ECoG are known to provide more powerful control signals than those operating on signals from EEG, it is difficult yet to directly compare these two methods in terms of performance and accuracy. Such a comparison has been conducted within an offline study, where the subjects did not receive any online feedback [3]. As an extension of that study, in this work, we attempt to compare the online accuracy of invasive and non-invasive BCIs with feedback over several runs.

Material, Methods and Results: Four epilepsy patients with temporarily implanted subdural electrode grids and 20 healthy subjects volunteered to participate in a MI BCI experiment with invasive (i.e. ECoG) and non-invasive (i.e. EEG) recordings, respectively. While the healthy subjects were trained to imagine left and right hand movement during EEG recordings, the patients in the invasive experiment were instructed to either remain idle or imagine hand movement of the contralateral side of the implanted sites. During the experiment, the participants were positioned in front of a feedback monitor showing the cue of the current task as well as the classification result. For evaluation, only data from electrodes covering the motor cortex were taken (ECoG: 20-60 channels, EEG: 27 channels). After visual inspection of recorded signals, the data were band-pass filtered at 8-32 Hz. Signals were further epoched and spatially filtered by CSPs determined from the most discriminative time window. A linear classifier was then trained based on the variance of the four most prominent CSP features, computed by means of a sliding window of 1.0 s. Several runs were executed for each subject, where successive data sets were used for training and test (e.g. classifier determined from data set n was tested with data set n+1). As illustrated in Fig.1, the average accuracy for all EEG and ECoG runs is 76.0 % and 94.6 %, respectively.

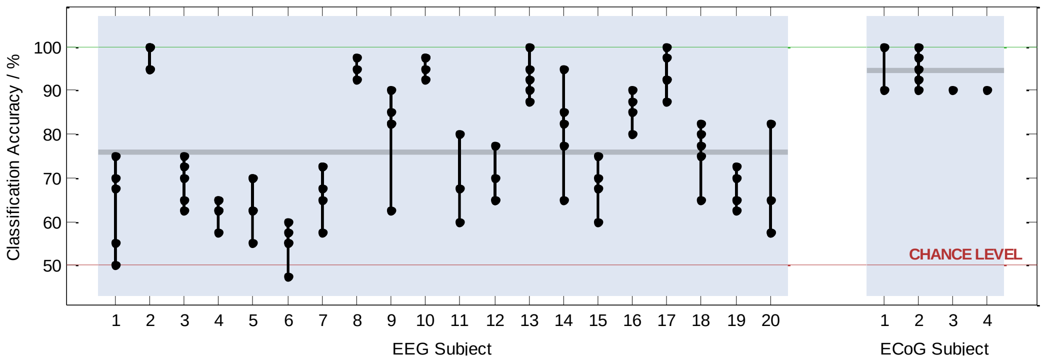

Figure 1. *Online accuarcy of the MI BCI with classification feedback. A filled circle represents the accuracy over 40 trials in total.*

Discussion: Providing a robust idle state is a problem for most BCIs using EEG. The invasive system provides such a state, despite this, the accuracy is higher and seems to be more stable over time. Additionally, for the EEG system, several trials had to be rejected during the calibration, which was not the case for the invasive system.

Significance: MI-based invasive BCIs provide a reliably classifiable idle state, which is crucial for continuous control of a device. Furthermore, compared to EEG, less training is required to achieve a classification accuracy sufficiently high to interact with the environment.

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Reliable BMI control using epidural ECoG by an hemiplegic user

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Introduction: Currently, most of invasive brain-machine interfaces (BMI) rely on signals recorded using electrodes implanted intra-cortically or subdural electrocorticography (ECoG) arrays. Barring a few studies [1,2], epidural electrodes–often used for chronic stimulation to alleviate neuropathic pain—are seldom used for this purpose. Here we report their use to successfully control a brain-machine interface over several days.

Methods: Experiments were performed with a 50 years old male patient who suffered a left brachial plexus avulsion 30 years prior to the surgery and recordings leading to a complete left arm plegia. Two epidural leads (4 channels each) were implanted above central sulcus on the primary motor and sensory cortex contralateral to the plegic hand to apply epidural stimulation to treat deafferentation pain. Contact leads were temporarily externalized for 9 days allowing recording and decoding of cortical activity during attempted movements.

Five experimental sessions were performed (1, 3, 4, 8 and 9 days after the operation). The subject was asked to attempt to move his plegic hand as if controlling the cursor with a mouse towards one target location in a screen. After a cue shows the target the subject should wait until it becomes green before starting the movement, then stopping once the target is reached (Fig 1 *Left*). Each session lasted less than 2 hours and yielded about 80 trials.

ECoG signals were recorded at a sampling rate of 512 Hz (8 channels corresponding to the 2 implanted leads; reference and ground electrodes located at the two mastoids). Data was processed in real time by extracting the spectral power in the range of 2-40 Hz. Data from the first day was used to train an initial classifier to discriminate between resting and movement periods. From the second day onwards, the classifier output was used to control the movement of the cursor. Whenever the classifier identified the neural activity as corresponding to the movement, the cursor was displaced towards the target location. Before each session, the classifier was updated using the data from previous sessions to assess the stability of the decoder.

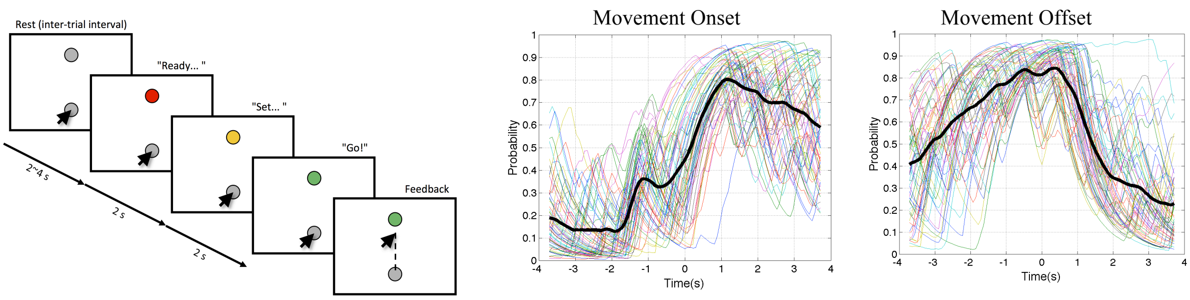

Figure 1. *Left: Experimental protocol. Middle & Right; Online movement decoding (one session: 60 trials). Y-axis shows the decoder output (A value of 1 corresponds to movement detection). Thin lines: Single trials. Thick line: Average across trials. In the Middle and Right plots t=0: corresponds to movement onset and offset, respectively.*

Results: Discriminant movement-related modulations were found in the mu band (8-12 Hz). Activity in this band allowed consistent recognition of attempted movements (onset and offset) in all trials (Fig. 1 *Middle,Right*). Critically false detections (i.e., movements detected after the warning but before the GO cue) were below 6%. Remarkably, the subject exhibited reliable BMI control since the first online session, achieving tasks of increasing complexity over days (data not shown due to space limitations). Importantly, classifiers were trained on the data of previous days without any recalibration on the same day, showing that the selected features are highly reliable and stable across days and that the subject could rapidly acquire a level of control.

Discussion: Neural activity from epidural ECoG can be successfully used to control a BMI device. Accurate and stable detection of movement attempts was achieved across several days by a subject suffering from hemiplegia for three decades. Online feedback enabled the subject to complete tasks of increasing complexity over days.

Significance: Epidural ECoG yielded reliable information to decode attempted movement of the plegic limb in a subject who has been paralyzed for over 30 years. This supports using epidural ECoG as a reliable, less invasive, alternative for BMI.

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Sensorimotor Rhythms During Preparation for Robot-Assisted Movement

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Introduction: Brain-computer interface (BCI) technology can restore communication and control to people who are severely paralyzed. There has been speculation that this technology might also be useful for rehabilitation of motor function [1]. Toward this end, we are exploring the possibility that sensorimotor rhythm (SMR) training could enhance the therapeutic efficacy of robot-assisted training of individuated finger movements for people with stroke. As an initial step, we are characterizing SMR activity in stroke patients preparing for robot-assisted movement.

Materials, methods and initial results: Individuals with paresis of the hand resulting from chronic stroke (n=3 to date, upper limb Fugl-Meyer: 35, 50, 58) and several unimpaired control subjects operated a simple go-nogo task using the FINGER robot-assisted movement system [2]. Visual stimuli cued movement conditions for index, middle, or both fingers. Participants with stroke used their impaired hand; unimpaired participants used their non-dominant hand. In both groups, robust SMR event-related desynchronization (ERD) occurred bilaterally during the preparatory period.

Discussion: Our previous work [3] in normal subjects suggests that operant conditioning of SMR ERD during movement preparation can improve performance. The present results provide a potential basis for conditioning such activity in stroke patients in order to beneficially modify neural circuits important in movement. It would also be possible to determine whether this conditioning should target SMR activity from the perilesional area or contralesional cortex [4].

Significance: By focusing on the movement preparation period, this work is exploring a new way in which BCI technology might contribute to rehabilitation after stroke or in other chronic movement disorders. BCI-based shaping of pre-movement SMR activity together with robot-assisted movement could potentially enhance rehabilitation and augment recovery of useful function.

Acknowledgements: This work was supported by NIH grants HD30146 (NCMRR/NICHD), EB00856 (NIBIB), and 1P41EB018783 (NIBIB).

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Upper Limb Movement Encoding by Intracortical Recordings in Human Sensorimotor Cortex

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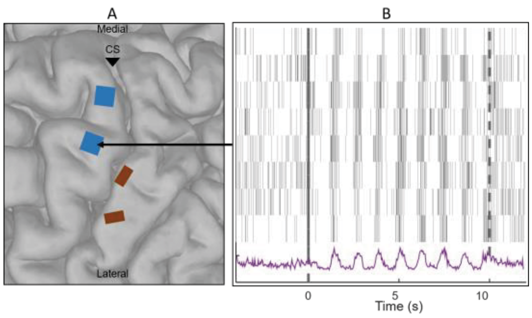
Introduction: In recent years, neuroprosthetics driven by brain-computer interfaces (BCI) have emerged as a potential tool for restoring independence to people paralyzed by disease and injury. Extracting command signals from intracortical recordings in primary motor cortex (M1) allows complex motor commands to be decoded. Here we investigate the distribution of movement-related information in recordings from the motor and somatosensory cortex of a person with chronic tetraplegia.

Materials, Methods, and Results: Two 88-channel arrays were implanted in M1 and two 32-channel arrays were implanted in the somatosensory cortex (S1) of a 27-year old individual with chronic tetraplegia due to C5/C6 SCI (Fig 1A). Implant locations were targeted to arm and hand regions of M1/S1 based on pre-surgical functional neuroimaging. Intracortical recordings were collected once monthly for 7 months while the subject attempted to move in time with videos of arm and hand movements, although most movements could not be performed overtly. Unit tuning was defined by the R^2 coefficient of the linear fit between single-unit firing rates and a 0.5Hz sine wave matching the pacing of stimulus videos (significance $p<0.05$, Bonferroni corrected).

We found robust single-unit tuning to all attempted movements across the entire 7-moth testing period (see Table 1). Single-unit firing rates were tightly correlated with the time-course of attempted movements, including those of fingers paralyzed by the SCI (Fig 1B). Units tuned to finger- and wrist-related movements were fairly evenly distributed between motor arrays, while those tuned to elbow and shoulder movements were highly biased towards the medial array. While there were overall fewer significantly tuned units on the S1 arrays, we identified single sensory neurons tuned to both overt and attempted movements, and both sensory arrays had more units tuned to attempted than overt movements.

Movement	Motor Medial [#units]	Motor Lateral [#units]	Sensory Medial [#units]	Sensory Lateral [#units]
(A)Pinky	11.71	10.00	6.28	4.00
(A)Ring	31.00	25.00	8.50	7.33
(A)Middle	26.33	27.00	10.33	7.83
(A)Index	22.43	20.29	9.43	4.00
(O)Thumb	32.80	35.80	13.4	11.60
(A)Grasp	16.86	14.14	5.43	4.14
(O)Wrist	16.38	18.13	5.00	3.87
(O)Elbow	17.33	12.00	4.33	3.83
(O)Shoulder	35.00	10.33	3.67	2.00



(Left) Table 1: Number of units significantly tuned to each movement, averaged across days. (A) = attempted movement, (O) = overt movement. **(Right) Figure 1 - A**: Placement of microelectrode arrays in M1/S1, plotted on cortical surface render. Blue = motor, red = sensory. **B**: Single-unit activity on the lateral motor array during attempted pinky movement. Purple line represents smoothed across-trial spike count.

Discussion: These results demonstrate the preservation of volitional single-unit sensorimotor activity during both intact and paralyzed movements. The spatial distribution of tuned units shows that while a degree of somatotopy exists, units separated by centimeters of cortex can be similarly tuned to the same movement, suggesting that even simple movements can be encoded by large areas of cortex.

Significance: BCI control is predicated on the ability to decode motor commands from single-unit activity. Understanding how those commands are represented in the sensorimotor cortex of BCI users is an important step towards developing more effective neuroprosthetic control.

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Decoding decision outcomes from single realizations of lateral prefrontal cortex ensemble activity

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Introduction: Neurons in the lateral prefrontal cortex (LPFC) encode sensory and cognitive signals, as well as commands for goal directed actions. This brain region might be a good signal source for a goal-selection brain-computer interface (BCI) that decodes the intended goal of a motor action previous to its execution. In our previous work we demonstrated that we could decode saccade targets from single-realizations of pre-saccadic LPFC neuronal activity [1]. In this work we examine the neuronal representation of the task and task acquisition, and we decode decision outcomes independent of stimulus information.

Material, Methods and Results: We recorded neuronal spiking activity from microelectrode arrays implanted in area 8A of the LPFC of two adult macaques while they made visually guided saccades to one of a pair of presented targets. The rewarded target was indicated by a colour cue and we changed periodically the association between colour and rewarded direction. In total, four different target pairs and three different colours were used.
Behavioural performance was poor at the onset of each new cue-target rule. The monkeys' performance improved rapidly as they learned the new rule.
We first estimated the latent structure of the ensemble at various stages of the experiment. Latent structure was mostly stable but varied slightly during learning of a new rule despite the structure estimation being blind to the behaviour. We then estimated the internal model that mapped neuronal responses during the pre-saccade period to the rewarded location. The ability of the internal model to predict the rewarded target improved as the monkey learned the task, and in some instances the model outperformed the monkey himself.
We also decoded the intended saccade goal among all eight targets independent of whether or not the saccade was to the rewarded target. The classifier predicted intended saccade goals with good accuracy when the peri-saccade neuronal activity was included in the feature set (82.2 ± 7.6%, chance: 35.7 ± 2.1%). Accuracy was only moderately better than chance when using the average firing rate from the pre-saccade period (45.1 ± 3.6%) but improved when multiple time-points from the pre-saccade period were included (58.4 ± 4.7%).

Discussion: The results from the estimation of the latent structure and the internal model suggest that the ensemble participates in the decision-making process and is plastic in response to the changing task but the plasticity is constrained. BCIs that exploit this latent structure may be able to generalize well across tasks and sessions.
It is unknown if the classification accuracy using peri-saccade data is representative of real-world BCI performance because data from this period might not be relevant in individuals without reliable eye movements and concomitant sensory feedback. For this reason, we focus on using the pre-saccade activity. Using only the pre-saccade activity, classification accuracy was greatest when using features from multiple time-points, revealing the importance of incorporating the temporal dynamics into the analysis. However, the temporal dynamics of the neural correlates of decision-making are inconsistent if the decision-making process is delayed or if the decision outcome is reversed. It will be necessary to use more sophisticated feature extraction and classification techniques to incorporate these temporal dynamics.

Significance: These results provide further evidence that LPFC neurons encode decision processes and suggest that LPFC activity can be used as a signal source for a goal-selection cognitive BCI.

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Predicting Forelimb Muscle Activity from Corticospinal Signals in Rats

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Introduction: Brain-computer interfaces have the potential to improve the quality of life in high level spinal cord injury (SCI) patients by restoring their functions lost due to injury. Historically, extracting kinematic parameters from neuronal spiking activity has been the primary method in brain-computer interfaces. Recently, our group has proposed accessing the spinal cord descending tracts to extract the movement related volitional signals as an alternative method. We have reported the ability to reconstruct forelimb kinematics, such as hand velocity and elbow angle, as well as the forelimb isometric forces using the neural signals recorded from the rat corticospinal tract (CST). In this study, we present that the forearm electromyographic (EMG) signals recorded during a reach-and-pull task can be predicted from the CST signals.

Material, Methods and Results: A flexible multi-electrode array (MEA) was custom-designed for this study (NeuroNexus, MI). The array consisted of 27 platinum contacts with 25μm diameter. The contact impedances were lowered by electrochemically depositing PEDOT:TFB [1]. Two Long Evans rats were implanted with MEAs. The arrays were inserted down vertically along the middle of the cord into the dorsal column at C4 level [2]. Teflon coated 25μm diameter stainless steel wires (A-M Systems) were used as EMG electrodes. Four pairs of electrodes (with ~5mm separation between tips) were glued epimysially on distal forelimb flexor and extensor muscles, biceps, and triceps. In order to obtain forelimb specific CST and EMG recordings, the rats were placed inside a plexi-glass box and trained to reach through a 3 by 1 cm vertical window to pull on a metal bar that was attached to a force transducer. Signals were recorded only when the pulling force exceeded a certain threshold. Neural and EMG signals were amplified and transmitted by a 64-channel wireless amplifier (TBSI Systems, NC) at a 16kHz sampling frequency. Multi-unit activity (MUA) was extracted by band-pass filtering the spinal cord signals between 200-2500 Hz in Matlab (Mathworks, MA). Muscle activities were band-pass filtered between 10-1500 Hz. Both MUA and EMG signals were rectified and low-pass filtered at 4 Hz before being fed into the prediction algorithm.

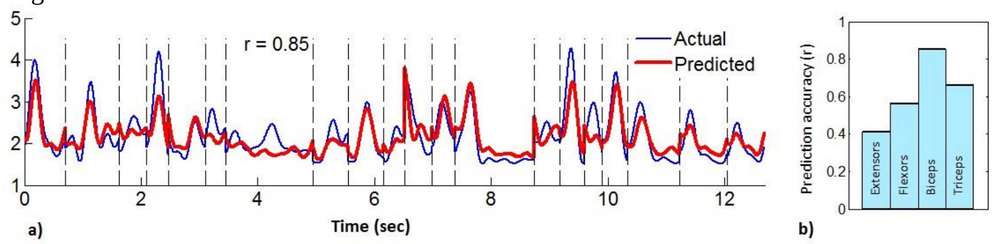

Figure 1. *Actual (blue) and predicted (red) biceps EMG signals recorded during isometric pull task (a). Prediction accuracies of all four EMG signals that belong to the same recording session (b).*

EMGs were predicted using linear regression. The dataset consisted of 80 trials; 75% of them used as the training set while 25% as the test set. As a representative image from one session, figure 1 compares the linear prediction of biceps activity to the actual recorded signal in multiple trials separated by dash lines. Figure 2 depicts the prediction accuracies for all the muscle activities that belong to the same session. The prediction accuracy is measured as the Pearson's correlation coefficient (r) between the predicted and actual signals.

Discussion: The results show that forearm muscle activities can be predicted from descending signals recorded from the spinal cord in rats. We achieved prediction accuracies as high as 0.85 for the biceps EMG. Although the accuracies for other muscles were not as good, this can be justified by the fact that during the isometric pull task biceps are more active than the other three muscles. These initial findings are encouraging, which warrants verification of results in a larger set of animals.

Significance: Since the muscle activity is represented in multiple regions in the brain, tapping into descending signals at the spinal level may provide more volitional information from a relatively smaller implant area. Predicted EMG signals can provide a means to control actuators in a biologically realistic manner.

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Thought-controlled nanoscale robots in a living host

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Introduction: Until recently, no system could provide explicit temporal control of a drug, e.g. generating a sequence of alternating activation/inactivation of the drug for arbitrary periods of time. Recently, drug-loaded nanoscale robots were reported, which reversibly expose and conceal drugs to the environment while maintaining them physically linked to their chassis [1]. In this study we have established, for the first time, an interface between a human brain (mind) and a therapeutic molecule, by allowing electroencephalogram (EEG) patterns associated with cognitive states to remotely trigger, in real time, nanorobot activation in a living animal.

Material, Methods and Results: The nanoscale DNA robots used in this study were a modified version of the nanorobot we described previously [1]. The shell can be reversibly closed or opened by controlling gate strand hybridization, thus concealing or exposing molecular or nanoparticulate payloads from the environment. In order to control DNA remotely from outside the host's system, we re-designed the robots to enable the addition of functionalized metal nanoparticles, which could be heated by applying a radio frequency-induced electromagnetic field (RFMF) on the entire animal. As an animal model for this proof of concept we chose the insect *B. discoidalis* [2].

To induce cognitive load, we trained an algorithm for recognizing cognitive loads, operationalized as solving simple arithmetic problems. EEG was recorded using Ag/Cl active electrodes located at PZ, FZ, AF3 and AF4, As features we used EEG power in the 6 main frequency bands in the 4 electrodes, linear discriminant analysis (LDA) was used for feature reduction and support vector machine (SVM) for classification. DNA origami robots were designed according to a protocol described elsewhere [2].

The algorithm discriminated on-line between low and high cognitive load with average precision of 92.5% and sensitivity of 86.3%, over 6 subjects. The insects loaded with the nanorobots were placed inside an induction coil, and a 14.6 MHz RFMF was applied, only when the test subject's EEG pattern was classified as 'high' cognitive load. RFMF activation induced robot opening and subsequent cellular staining by the exposed fluorescent antibody fragments, which was tracked in real-time.

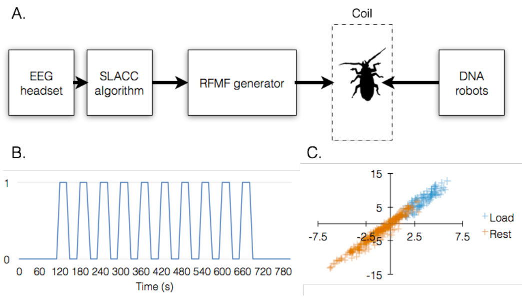

Figure 1. *System outline and performance. A. Basic system outline: signals recorded by the EEG headset on the subject were monitored by the algorithm, which controls the state of an RFMF generator connected to an induction coil. The test animal is placed inside the coil after being injected with DNA robots. B. Experimental protocol structure. 0 and 1 on the Y-axis denote states of cognitive rest and load, respectively, which are induced by displaying alternating screens showing either blank or a list of arithmetic problems. C. Classification of cognitive rest vs. cognitive load signals by LDA.*

The analysis showed that robots bearing metal nanoparticles opened and engaged the cells efficiently, while robots not bearing nanoparticles, or those that bear nanoparticles but were not loaded with fluorescent antibody, did not generate any visible signal.

Discussion: Albeit a very preliminary prototype, this system could inspire improved designs towards thought-mediated control over biochemical and physiological functions assisted by biocompatible molecular machines.

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Neurogoggles for Stroke Rehabilitation

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Introduction: Stroke is a major cause of disability across the globe, leaving survivors with severe motor and cognitive impairments and reducing their participation in the society. It has been widely advocated that early acute rehabilitation exploits the unique neuroplasticity conditions that exist in the first weeks after brain injury, and results in improved motor recovery [1]. However, rehabilitation onset is often delayed and delivered at suboptimal intensities due to the limited motor capabilities in the acute phase. Proven cognitive neuroscience principles such as action observation/execution, mirror therapy, graded/guided motor imagery and kinesthetic motor imagery training are particularly appropriate to promote the early activation of neural structures involved in the recovery process. Additionally, there is emerging clinical evidence on the effectiveness of motor imagery training using a brain-computer interface (BCI) combined with virtual reality (VR) [2]. To this end, we aim to develop a wearable device that equips BCI and virtual/augmented reality (VR/AR) technology, representing a versatile tool to bring these treatment modalities to the neurorehabilitation field.

Material, Methods and Results: We developed a neurogoggles system that integrates motion tracking (arms, hands, fingers and objects in the environment), electrophysiological measurements (32 gel-based active EEG, 8 active EMG, 5-lead passive ECG) and a head-mounted display (HMD) onto one single portable platform (Fig. 1). The system synchronizes multimodal inputs with millisecond precision and processes them in real time to provide appropriate VR/AR feedback. Importantly, the system also provides outputs for biofeedback devices such as functional electrical stimulation (FES), haptics and robotics for facilitating the training of the cortico-spinal pathways.

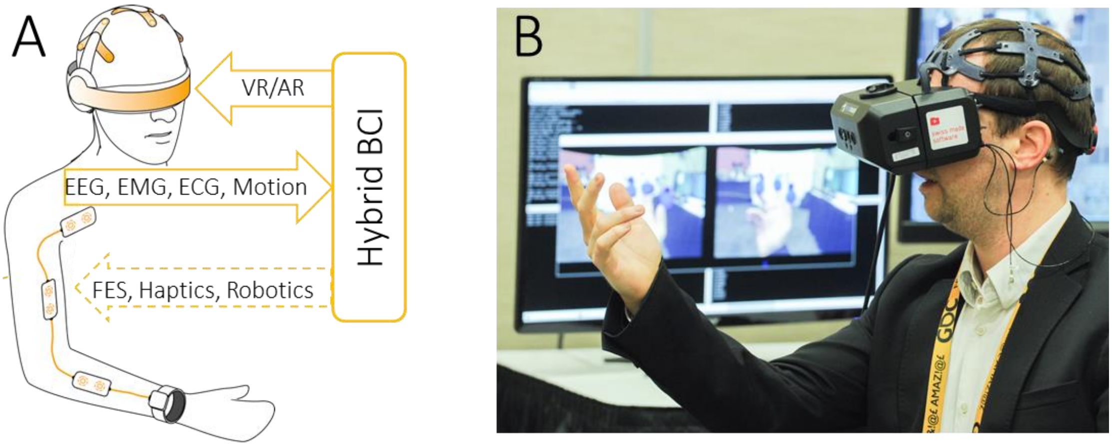

Figure 1. (A) Functional schema of the hybrid BCI system; (B) Neurogoggles prototype (with detachable HMD)

Discussion: The immersive VR feedback provided by the neurogoggles offers exercises that empower the application of action observation/execution training, virtual mirror therapy (movements of the non-paretic arm are translated to the paretic side of an avatar), and motor imagery training. These training strategies enable early intervention, even in case of the severe disability. In addition to VR, the system also offers AR for later stages of the rehabilitation process that enables the interaction with virtual objects in the real world and thus enriches the training quality. Additionally, these feedback modalities can be gamified to maximize motivation and increase training dose.

Significance: The presented neurogoggles opens new avenues for research in multimodal strategies for effective motor rehabilitation in stroke and other neurological conditions (e.g., phantom limb pain, brain trauma, multiple sclerosis, and spinal cord injury).

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Programming for Pediatrics: A literature review of brain-computer interfaces for neurorehabilitation in children

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Introduction: The past decade has seen brain-computer interfaces (BCI) emerge for a myriad of applications, including as assistive technology and for BCI neurorehabilitation (NR) [1]. Despite the breadth of research into BCI applications, the majority of work has been restricted to the mature brain and adults. In this context, this paper investigates current BCI tools and explores the literature for evidence about the need and practicality of translating NR-BCI techniques to children.

Material, Methods: Articles were obtained from databases Pubmed.org and Google Scholar using key search phrases including, but not limited to, 'BCI in children', 'BCI neurorehabilitation', 'BCI developmental disorders', and 'BCI motor disorders'. Articles highlighting BCI in pediatrics, for rehabilitation, and corresponding reviews were then examined in depth. Relevant references were investigated for potential insight and information. In total, 80 articles were examined. Figure 1 illustrates the diverse manuscripts considered, separated and categorized by year of publication.

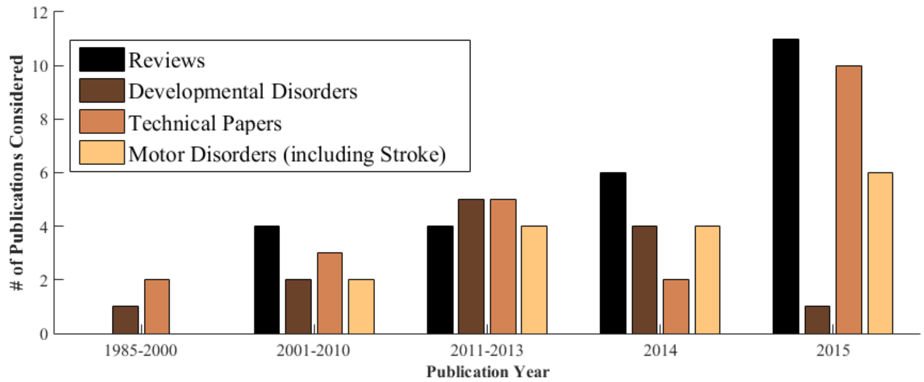

Figure 1. Distribution of supporting manuscripts considered in this review, grouped by publication year and category.

Results: Examining the literature reveals relationships between neuroplasticity, age and NR-BCI which supports possible advantages to earlier BCI intervention and exposure [2,3,4,5]. Further evidence shows BCI can capitalize on neural plasticity, demonstrated by motor-imagery NR for post-stroke patients and neurofeedback applications [3,6]. Given the remarkable neuroplasticity in children [7] and that pediatric motor cortex signals can be decoded [8], it is feasible, and possibly beneficial, to develop BCI applications for early-life NR [4,9].

Discussion: Surveying BCI literature illustrates NR-BCI use in children not been fully developed, and it is feasible to develop NR-BCI for children. However, challenges such as the dynamic signal spectrum in developing brains need to be addressed when designing such BCI applications.

Significance: Examination of current BCI literature highlights a current under served BCI population, children, and uses literature evidence to demonstrate feasibility of designing BCI-NR for children.

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Toward Standards in AAC-BCI Performance Measurement and a Data Repository

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Introduction: An overarching goal of Brain Computer Interface (BCI) research and development is improving outcomes for human communication and accelerating research discoveries into practice. In order to improve the communication outcomes of individuals with complex communication disorders who rely on augmentative and alternative communication (AAC) and benefit from BCI control, more accurate performance data are needed for measuring and monitoring the effectiveness of treatment. Standard calculations of performance or quantitative dependent variables allow AAC-BCI research and clinical services to measure the effectiveness of manipulating independent variables such as language encoding methods, display types and training protocols. Data logging tools to measure performance provide for analysis of the human-computer interface experience using AAC-BCI systems. The purpose of this paper is to review efforts that have been made at the University of Pittsburgh, Carnegie Mellon University and the AAC Institute in creating standards in AAC-BCI performance measurement and building a data repository of language samples contributed by AAC-BCI speakers for data sharing.

Materials, Methods and Results: The term Language Activity Monitoring (LAM) was coined in 1998 during the feasibility testing of an AAC data logging device [1]. With the focus on language sampling, the reliability of the transcription process and the validity of the reported measures to report performance were established. Language samples based on authentic communication tasks such as interviews, conversations, and narratives have formed an initial library and database repository of LAM data. Focus groups and internet-based surveying along with informed alpha and beta testing were used to identify the types of quantitative measures practitioners believed important for monitoring clinical invention and treatment effectiveness.

Survey respondents who were Speech Language Pathologists delivering AAC services (N=26) identified specific performance measures valued from language sampling analysis. The preferred performance measures associated with monitoring AAC utterance generation were: 1) use of language representation methods (LRMs); 2) type of method of utterance generation (spontaneous generation versus pre-stored messages); 3) frequency of core vocabulary versus extended vocabulary. When questioned about monitoring access and key selections, respondents were interested in 1) average and peak communication rates; 2) selection rate; 3) accuracy.

These data were used in the development and usability and user satisfaction testing of the AAC Performance Report Tool (PeRT) [2], a software analysis tool. Calculation methods have been tested and published for such AAC performance measures as 1) selection rate in bits per second; 2) average and peak communication rates in words per minute; 4) frequency use of LRMs and core vocabulary. Built-in LAM, language transcription, and analysis using PeRT have been used in evaluating AAC-BCI device performance and use in the lab [3] by gathering LAM data during copy spelling and picture description tasks and as a clinical trial [4] by gathering LAM data during daily communication at home and for sending email messages.

Discussion and future directions: BCI research is extending from the laboratory into clinical practice. Standards on data logging formats, collection methods and calculation of performance measures are critical for judicious comparison among results achieved on AAC-BCI systems offering different features. Surveyed stakeholders have been consistent in prioritizing summary measures and positive about proposed operationalized standards. As language sampling is expanded as a testing protocol, more data will be available to share, archive or contribute to a repository. Along with an AAC data logging consortium started in January 2015, further discussion and consensus is needed through a collaboration of researchers, clinicians, and manufacturers to include AAC-BCI language samples in the data repository.

Significance: Standards in AAC-BCI performance measurement and data sharing practices support current and planned innovations to AAC-BCI systems. Diffusion of LAM tools and the growth of the consortium network supports multimedia databases, computational power and internet systems for AAC-BCI research, development, commercialization and use by individuals with severe communication and movement disorders.

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A Portable, Low-Cost BCI for Stroke Rehabilitation

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Introduction: Millions of stroke survivors are affected by disability associated with movement impairment. According to preliminary studies [1,2], experimental therapies that couple brain-computer interfaces (BCIs) with movement (e.g., via functional electrical stimulation [FES]) facilitate motor recovery. However, current BCI systems are inappropriate for use outside the lab. These systems typically employ bulky and expensive (~$25,000) commercial amplifiers and desktop computers (Fig. 1A). For BCIs to be a feasible rehabilitative option for those with motor dysfunction, they must be portable and affordable while retaining the performance.

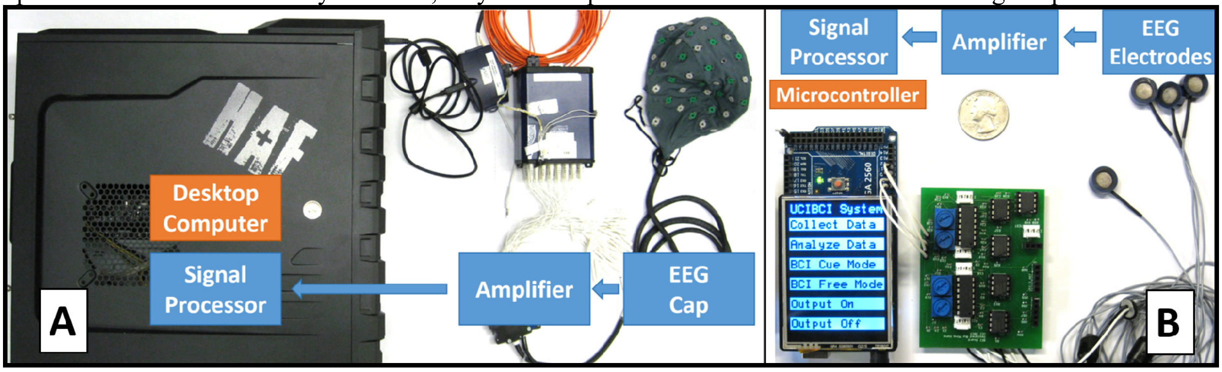

Figure 1. *A: A traditional BCI system (~$30,000). B: The developed, miniaturized BCI system (~$300). In both systems, brain signals are captured by the EEG cap/electrodes, amplified, and then sent to a processor for decoding.*

Methods and Results: The proposed system consists of 5 EEG electrodes, a custom 4-channel EEG amplifier array, a commercial microcontroller (Arduino, Ivrea, Italy), and a touchscreen (Fig. 1B), with overall cost of ~$300. Each EEG channel utilizes 1 instrumentation amplifier and 2 operational amplifiers in active filter configuration (4^{th} order 1.6-33 Hz bandpass filter) to achieve a total voltage gain of 87 dB. A custom C program was implemented in the microcontroller to achieve signal sampling, processing, decoding, and output device control. More specifically, EEG was sampled at 256 Hz, and the average α- and β-band power for each 0.25 s of data were calculated, resulting in 8 dimensional observations (4 channels $\times$ 2 frequency bands). These observations were then used to generate a logistic regression model that distinguished dorsiflexion from idling states. In the online operation, novel EEG data were processed, passed to the logistic regression-based classifier, and a binary state-machine determined the brain state based on the mode of the 3 most recent classifications. Our system was tested on 2 able-bodied subjects (AB1: 20 yo, M; AB2: 27 yo, M), and a chronic stroke subject (ST1, 60 yo, M, left-sided hemiplegia). Subjects were cued to alternatingly dorsiflex and relax their right (AB1-2) or left (ST1) ankle, while the system collected, processed, and stored the EEG signals, as above. Ten-fold cross-validation was then used to estimate the accuracy of the generated classification models. The classification accuracies were as high as 95% for AB1, 97.5% for AB2, and 97.5% for ST1. In addition, ST1 performed two trials of online BCI-FES dorsiflexion using the generated decoding model. The subject was again cued to dorsiflex or relax in 10 epochs over 1 minute, while the BCI system classified his EEG signals in real time and appropriately delivered or withheld FES to the ankle on the hemiplegic side. The online decoding accuracies were 77.6% (80.9%) with 0.829 (0.804) correlation and 1.0 s (0.75 s) lag for the first (second) trial, respectively.

Discussion: We developed a BCI system that is portable and inexpensive compared to conventional counterparts. Despite the reduced channel number and processing power, preliminary testing suggests that it achieves high performance both offline and online. Also, these decoding accuracies were comparable to those achieved previously using a full-size system [3,4]. Future work will focus on testing the system in more subjects.

Significance: This is the first low-cost, fully portable BCI system for post-stroke motor rehabilitation. This system has adequate performance and can be paired with commercial FES devices for in-home therapy.

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Comparing EEG and fNIRS for a covert attention BCI

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Introduction: Visual hemispatial neglect is a common post-stroke neuropsychological deficit, impairing the ability to deploy spatial attention towards one side of the visual field. Neurophysiological studies have unveiled neural correlates of covert attention deployed towards the left versus the right hemifield, using both functional magnetic resonance imaging (fMRI, [1]) and electroencephalography (EEG, [2]). If such covert visual attention states could be reliably discriminated at the single trial level, providing BCI-decoder feedback to patients could be used to promote those desirable neural correlates, thus improving recovery through plastic changes in the brain [3, 4]. In this work we investigated if the single trial decoding performance of functional near-infrared spectroscopy (fNIRS), as an alternative to fMRI, can supplement EEG to improve decoding accuracy.

Material, Methods and Results: Parieto-occipital cortical activity was measured with fNIRS (44 channels) from five subjects during a two-sided covert attention task (left and right, 40 trials each). The same experiment was repeated while recording EEG (60 channels). We derived oxygenated and reduced hemoglobin levels (HbO/HbR) from the fNIRS signal and one-Hertz frequency bands spanning alpha, beta and gamma activity (8-33 Hz) from the EEG. Highest discriminant activity was found across subjects in the time window 1.5-3.5 s after trial onset for the EEG and at 5-12 s for the fNIRS, respectively, reflecting the delay of the hemodynamic response [5]. Mean activity was computed across these windows for each trial and channel and used as input to the classifier. For the grand averages, t-statistics (2-sided t-test) of left-right differences were calculated across trials and then averaged across subjects. The grand averages showed an expected contralateral alpha-power decrease over the occipital cortex, which corresponds to lower HbO levels (Fig. 1,A-B) [2, 5]. Classification of left versus right covert attention was performed using 10 times 10-fold cross-validation with a random forest classifier [6] and assessed using the area under the curve (AUC). Classification results were significantly above chance level (pointwise confidence bounds, FPR = 0.5, $p < 0.05$) for two subjects with EEG and for four subjects with fNIRS. AUC averaged at 59.8% (± 11.0%) for the EEG and at 69.9% (± 7.3%) for the fNIRS (Fig. 1, C).

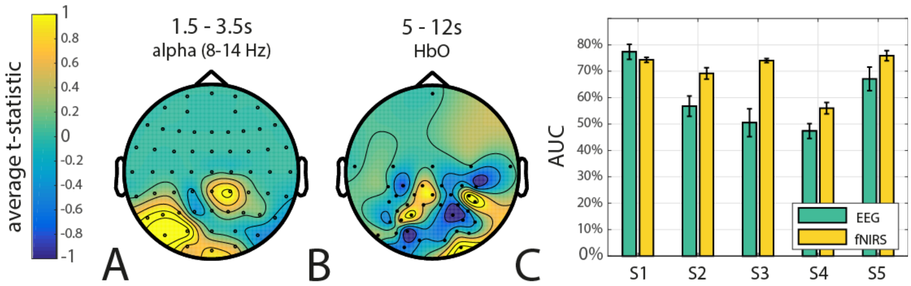

Figure 1: (A),(B) Grand averages of channel-wise t-statistic of left versus right covert visual attention for the alpha band (8-14 Hz) in EEG (A) and the HbO in fNIRS (B). Channels frontal of the coronal midline are muted. (C) Classification performance for EEG and fNIRS for five subjects.

Discussion: In this pilot study we demonstrated that covert attention can be detected and classified using fNIRS signals, and that it compares favorably to the EEG. Since classification performance for both modalities can differ substantially (Fig 1, C S3), a combined EEG-fNIRS BCI offers usability to people who struggle with either one or the other modality alone. For classification performance above chance level in both modalities, a fusion approach could improve the system accuracy. In a next step, these results have to be validated with more subjects in a simultaneous recording setup of EEG and fNIRS to avoid confounds between the recordings like different levels of attention or fatigue. Also, finding optimal fusion methods constitute the target of further work.

Significance: We found evidence supporting the use of fNIRS for decoding covert visual attention at the single trial level. Therefore, supplementing EEG with fNIRS seems promising to improve the decoding accuracy for covert visual attention, which is a key factor for a BCI-based rehabilitation application for hemispatial neglect.

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Detecting walking intention using EEG phase patterns

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Introduction: One use of EEG-based brain computer interfaces (BCIs) in rehabilitation is the detection of walking intention [1]. So far neural correlates of movement intention based on amplitude [2, 3] or power [3] have shown promising results for session-specific evaluation. However, since EEG signals present an inherent variability among sessions, BCIs need to be recalibrated before every usage. Recalibration is a time-consuming and tiring process especially in repetitive therapy sessions. Thus, it would be beneficial to remove the need for session-specific BCI recalibration. In this abstract we propose a novel feature based on the movement related cortical potential (MRCP) phase patterns that contributes to a successful detection of movement intention in transfer cases, without BCI recalibration.

Material, Methods and Results: We demonstrate the utility of MRCP phase patterns in a pre-recorded dataset [2], in which 10 healthy subjects executed a self-initiated gait task in three sessions. MRCP amplitude signals were decomposed using Hilbert transform into phase and power components. The effect sizes of the three features in channel Cz relative to the baseline (shaded interval) are presented in Fig. 1A. Next, BCI detectors of gait intention based on phase, amplitude, and their combination, were evaluated in two conditions: intrasession usage (session specific calibration) and intersession transfer, with results shown in Fig. 1B.

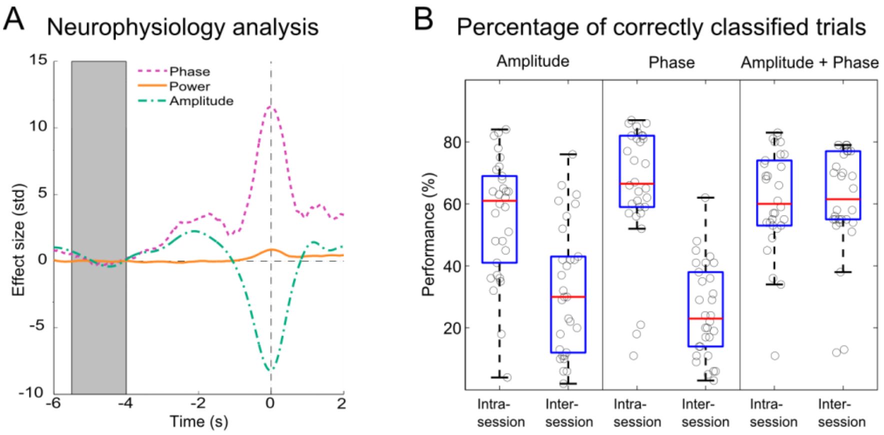

Figure 1. *A. The neurophysiology analysis of the three types of features: phase, power and amplitude. B. The detection performance during intra- and intersession evaluations using three detection models (amplitude based, phase phase and combined amplitude and phase based).*

Discussion: The neurophysiology analysis in Fig. 1A shows that the phase features have higher signal-to-noise ratio than the other features. Results have shown that the phase based detector is the most accurate for session specific calibration. However, in intersession transfer, the detector that combines amplitude and phase features is the most accurate one and the only that retains its accuracy relative to the intrasession condition. Thus, MRCP phase features improve the detection of gait intention and could be used in practice to remove time-consuming BCI recalibration.

Significance: This abstract introduces MRCP phase patterns as novel features for the detection of movement intention. By combining MRCP amplitude and phase information, we attained a detector with a more robust performance between sessions, outperforming the detectors that use only one type of information.

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Enhanced Motor Imagery Classification in EEG-BCI using Multivariate EMD based filtering and CSP Features

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Introduction: The electroencephalogram (EEG) signal tends to have poor time-frequency localization when analysis techniques involve fixed set of basis function such as short-time Fourier transform (STFT) and wavelet transform (WT). It also exhibits highly non-stationary characteristics and suffers from low signal-to-noise ratio (SNR). As a result, there is often poor task detection accuracy and high error rates in brain-computer interfacing (BCI) systems. In this work, we have extended the multivariate empirical mode decomposition (MEMD) [1] by filtering the intrinsic mode functions (IMFs) based on mean frequency measure to obtain an enhanced BCI. Hence, we present a novel filtering technique, namely, MEMD based band-pass filtering (MEMDBF), in order to handle the inherent non-stationarity and utilize the cross channel information present in a multi-channel EEG based BCI.

Methodology: Standard empirical mode decomposition (EMD) suffers from the problem of mode-mixing where the similar frequencies occur in different IMFs. The MEMD handles this problem and allows to achieve high localization of information pertaining to specific frequency-bands. It decomposes the raw EEG signal into a finite set of frequency modulated (FM) and amplitude modulated (AM) components known as IMFs [1]. It provides the same number of IMFs for all the data channels in the time domain. We have considered fifteen channels (i.e., FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2 and CP4) for the analysis. Further, the candidate IMFs are selected based on the mean frequency measure calculation corresponding to mu (8-12 Hz) and beta (16-24 Hz) rhythms. The enhanced IMF is obtained by summation of all the candidate IMFs. This filtering is done ahead of feature extraction and classification steps. Its goal is to provide better feature separability, leading to reduced error rates and high task classification accuracy in a motor imagery (MI) based BCI. Then we have applied spatial filters which maximize the variance in one class and minimize in the other class, and computed CSP features using first and last two pairs of spatial filters from the enhanced EEG signals and a linear discriminant analysis (LDA) classifier is used to classify the feature sets into left and right hand MIs.

Results: Table 1 demonstrates the effectiveness of the proposed method in terms of two class MI task classification accuracy when evaluated on the BCI competition IV dataset 2A[#]. The classification accuracy in the training stage has been computed as 5-fold cross-validation. Notably, eight of the nine subjects have shown improvement and also the average of classification accuracy has improved in the evaluation stage (> 6.9 %). We have obtained a mean kappa value of 0.54 across all of the nine subjects for a two class MI classification. This however, cannot be compared with the competition winner, who reported 0.569 mean kappa value [2] for a different four class classification problem.

Discussion: This initial investigation demonstrates that the non-stationary phenomenon present in EEG signals has been reduced to some extent as evidenced by significantly higher classification accuracy in the evaluation session obtained on the BCI competition IV dataset 2A. Also, it has been verified that the shift in the input data distribution across sessions has been reduced because of the MEMDBF, as the training and evaluation input data distributions have zero mean. The scope of future work will include proposing new non-linear features based on IMFs of EEG signals for multiclass classification of MI based BCI.

TABLE 1. Classification accuracies (%) obtained with the proposed MEMD based filtering and raw EEG data.

Subjects		A01	A02	A03	A04	A05	A06	A07	A08	A09	Average	*p* value*
MEMDBF	Training	88.14	65.39	92.38	79.82	63.23	78.54	80.58	95.12	87.44	81.18	0.2683
	Evaluation	**90.28**	**59.72**	**93.06**	**70.14**	**52.78**	**61.81**	**75**	95.83	**92.36**	76.77	0.0166
Raw EEG	Training	72.27	63.21	91.65	71.58	67.92	67.99	86.18	95.19	88.86	78.32	-
	Evaluation	69.44	50	90.28	59.03	50	54.86	65.28	97.92	91.67	69.83	-

[*]Two-way analysis of variance (ANOVA2) test has been used to compute p-value.

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Evaluation of Motion Artifacts on EEG Signals during Exoskeleton Gait.

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Introduction: Brain-Machine Interfaces (BMIs) are currently being applied to enhance rehabilitation strategies by increasing patient's involvement level [1-2]. Most common BMIs work with electroencephalographic (EEG) signals registered from the scalp. Even EEG signals have very good temporal resolution, they have low spatial resolution and signal/noise ratio. When an exoskeleton is used in combination with a BMI for lower limb rehabilitation, the study of how motion artifacts affects EEG signal is a critical point for the correct performance of the final system. The goal of this work is to study these artifacts and how they contaminate the EEG signals.

Material, Methods and Results:
To perform the current study, a recent approach to obtain motion artifacts during walking on EEG signals is used [3]. To do this, users wear a plastic cap to isolate the electrical signals from the scalp. On the cap, a wig coated with conductive gel is located to simulate the conductive surface of the scalp. Finally, the EEG electrodes are located on the wig. The acquisition system use 32 channels over the motor and visual cortex located in the scalp with an elastic cap, AFZ electrode was used as ground with a reference in the right earlobe. Signals are amplified and digitalized using an ActiCHamp commercial amplifier with a sample frequency of 1200 Hz. During the experiments, the users are asked to walk on 4 different conditions: Normal walking registering EEG signals, Normal walking isolating EEG signals, Exoskeleton walking registering EEG signals and Exoskeleton walking isolating EEG signals. Two healthy subjects performed the experiment. On Fig. 1, the spectrum of 30 seconds of data of each condition is shown for electrode CPZ using the welch method. All electrodes present a similar behavior. The exoskeleton used was form by a couple of ankle actuators developed for BioMot Project.

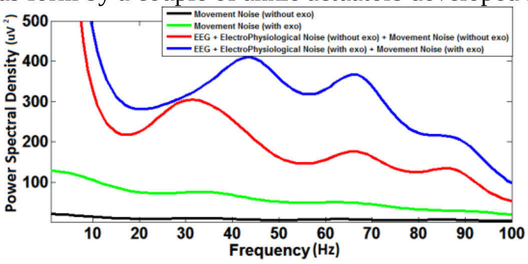

Figure 1. *Spectrum of each experimental condition from electrode CPZ. From the top: Exosqueleton gait registering EEG signals, Normal walking registering EEG signals, Exoskeleton walking isolating EEG signals and Normal walking isolating EEG signals.*

Discussion: Results show the appearance of motion noise affecting all frequencies (being higher the influence on low frequencies). The motion noise during normal walking (black line) is considerably lower than the power of the EEG signals (red line). On the other hand, using the exoskeleton (green line) increase significantly the power of the motion noises, corresponding approximately to the 25% of the EEG signals registered under the same conditions (blue line). The use of the exoskeleton induces extra electromyographic signals that contaminate frequencies from ~40 to ~100Hz (blue line). Power peaks on high frequencies present an unsteady behavior for different users and electrodes.

Significance: This work shows high artifact contribution on EEG signals during exoskeleton gait. This is a critical point on EEG measurements during lower limb rehabilitation based on an exoskeleton. Studies focused on this topic should paid special attention on this reported issue.

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Home-Based Rehabilitation System Using Portable Brain-Computer Interface and Functional Electrical Stimulation

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Introduction: Brain Computer Interface (BCI) controlled Functional Electrical Stimulation (FES) has been proposed in literature for rehabilitation of spinal cord injury (SCI) and stroke patients [1, 2]. It is believed that faster rehabilitation can be achieved by combining the activation of the motor pathways through motor imagery (MI) and sensory pathways using FES [3]. Currently, suggested solutions typically rely on costly equipment, limiting their application to a hospital environment. The period of potential rehabilitation for patients is longer than the average time spent at the hospital post-injury; therefore patients would benefit from extended home-based therapy with an inexpensive, user-friendly device. Here we propose a portable BCI system consisting of a wireless multi-channel headset (EPOC, Emotiv, USA) and a tablet (ASUS Win 8.1), combined with multi-channel FES (Rehastim, Hasomed, Germany).

Material, Methods and Results: Eight able bodied participants took part in this study (age=31.7±5.05) (5M, 3F). Custom-made software was developed in Visual C++ to synchronize the EPOC with FES using a tablet computer. The FES was applied to the participants' right hand flexor muscles. Electroencephalography (EEG) was recorded bipolarly from FC3-CP3 location (sampling frequency 128 Hz). The relative power of the sensory motor rhythm (SMR, 8-12 Hz), calculated online by band pass filtering the signal, squaring, smoothing and averaging over 0.5 s window, was used as a parameter to provide a visual feedback to the users. A time-controlled switch algorithm [1] was used for BCI-FES system with the time set to 1s and SMR threshold set individually. To control the FES using BCI, subjects were instructed to imagine moving their right hand, following a visual feedback in the form of a scale (Fig. 1). If the threshold was achieved within 10s and sustained for 1s, the FES was activated and caused muscle contraction resulting in wrist flexion, otherwise the trial was considered unsuccessful. Each participant attempted 2 sessions of 30 trials each. All the participants were able to use the system with an average success rate of 77.1% in session 1 and 87.5% in session 2 (Table 1), which shows fast improvement of BCI performances in participants due to the training. Fig. 2 shows the power spectral density (PSD) as the alpha band at rest and during imagined movement (MI) for a representative subject.

Table 1 . Success rate

Subjects	1	2	3	4	5	6	7	8	**Avg.**
Session 1 Success rate (%)	77	67	93	80	80	67	70	83	**77.1**
Session 2 Success rate (%)	93	87	100	83	80	77	87	93	**87.5**

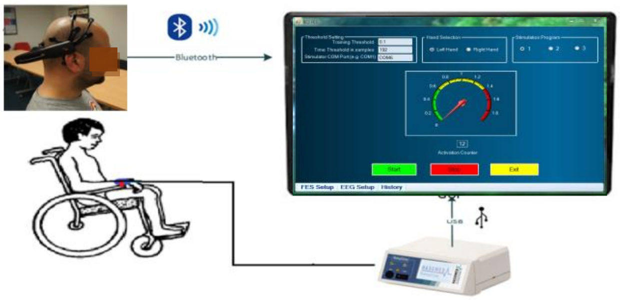

Fig. 1 BCI-FES System

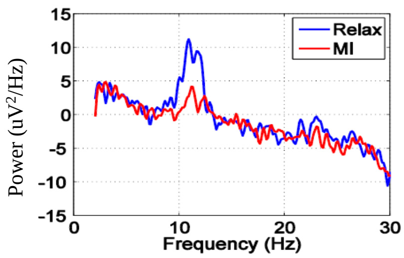

Fig. 2 PSD for alpha band at rest and during MI State

Discussion and Conclusion: This study demonstrates the technical feasibility of a portable, inexpensive and user friendly BCI-FES system. Experiments with patients in their home environment are planned in the near future to establish long-term reliability and user friendliness of the system.

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Lateralization patterns for movement execution and imagination investigated with concurrent EEG-fMRI and EEG-fNIRS

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Introduction: According to the neural simulation of action theory, movement execution (ME) and imagination (MI) of the same movement are different stages on a continuum and are therefore based on similar neuronal networks [1]. MI may facilitate experience-driven cortical reorganization and functional restoration, even in the absence of residual voluntary limb movement. Moreover, it has been shown that neurofeedback enhances task-specific activity and MI learning. Despite the clinical importance, it remains not known which neuroimaging technique adequately captures cortical lateralization induced by ME and MI, the latter being the basis for most MI neurofeedback applications. The present investigation therefore compared ME and MI induced lateralization using concurrent EEG-fMRI and concurrent EEG-fNIRS recordings.

Methods: Two datasets were analyzed. In both experiments MI naïve young healthy adults performed one block of ME and three blocks of MI. The first experiment (N = 22, mean age: 23.9 years) comprised two sessions, one simultaneous EEG-fMRI and one EEG session. As ME execution corrupted the EEG signal obtained inside the fMRI scanner beyond recovery, only the ME EEG data obtained outside the scanner were considered. This was justified because, as reported previously, the MI induced ERD of offline corrected EEG data and EEG data obtained outside the MRI scanner were significantly correlated [2]. The second experiment (N = 19, mean age: 24.4 years) comprised one session of simultaneous EEG-fNIRS. For each experiment and imaging modality separate repeated measures 2 x 2 ANOVAs with the factors condition (execution, MI) and lateralization (contralateral, ipsilateral) were performed, and in case of significant interaction followed up with t-test.

Results: fMRI BOLD activity was more lateralized during ME than during MI (Fig. 1A, $F_{1,21} = 166.35$, $p < .001$, $\eta^2 = .89$). Descriptively, this pattern is confirmed by both fNIRS measures, oxygenated (HbO) and deoxygenated (HbR) hemoglobin concentration changes, but only for HbO was the effect of lateralization significant (HbO: Fig. 1B, $F_{1,18} = 9.77$, $p = .006$, $\eta^2 = .35$; HbR: Fig. 1C, $F_{1,18} = 2.92$, $p = .1$, $\eta^2 = .14$). In contrast, electrophysiological activity, specifically 8 to 30 Hz band power, was found to be more lateralized during MI than during ME in both datasets (Exp 1: Fig. 1D, $F_{1,21} = 9.46$, $p = .006$, $\eta^2 = .31$; Exp 2: Fig. 1E, $F_{1,18} = 7.82$, $p = .012$, $\eta^2 = .30$).

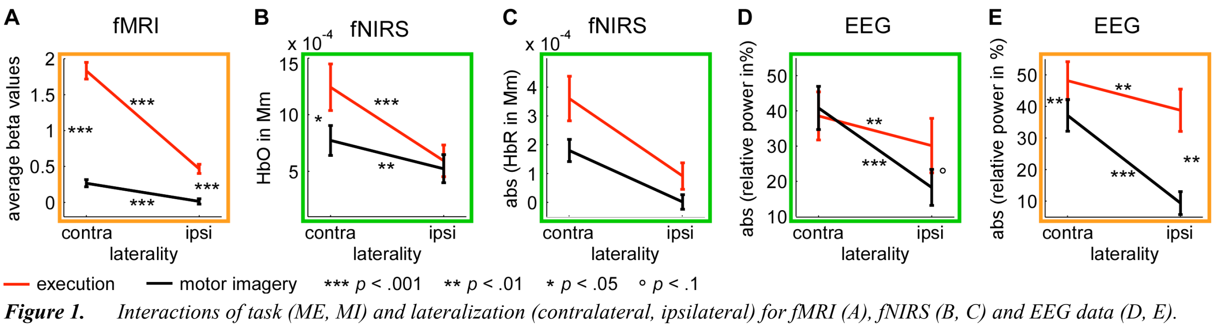

Figure 1. *Interactions of task (ME, MI) and lateralization (contralateral, ipsilateral) for fMRI (A), fNIRS (B, C) and EEG data (D, E). Data from experiment 1 and 2 are respectively highlighted in orange and green.*

Discussion: Both studies revealed a clear consistent dissociation between hemodynamic and electrophysiological signatures regarding ME and MI induced cortical lateralization. Future work investigating this dissociation on EEG source level seems important to better understand the patterns of cortical activation induced by MI supported by neurofeedback. This would help to advance MI neurofeedback applications towards use in motor recovery after stroke.

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Prediction of Subject Ratings of Emotional Pictures from EEG Features

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Introduction: Emotion dysregulation is a major component of many brain disorders. Brain-computer interface (BCI) technology might enable a valuable new approach to enhancing therapeutic self-regulation of emotions. One possible BCI method would be to provide stimulus-specific feedback based on subject-specific electroencephalographic (EEG) responses to the stimulus. Up to the present, the correlations of three EEG features with emotional salience/arousal have been evaluated in group-averaged data. These features are: asymmetry in alpha activity over frontal cortex; amplitude of theta activity over frontal midline cortex; and the late positive potential over central and posterior mid-line regions. We examined the subject-specific correlations with emotional salience/arousal for these three features.

Materials, methods and results: Twenty healthy participants (14 women, 6 men; ages 23-59) rated each of 192 pictures from the IAPS collection in terms of valence and arousal twice (96 pictures on each of 4 days over 2 weeks). EEG was collected simultaneously and used to develop models based on sparse canonical correlation to predict subject-specific single-trial ratings. Separate models were evaluated for the three EEG features: frontal alpha asymmetry; frontal midline theta; and the late positive potential. In each case, these features were used to simultaneously predict both the normed ratings and the subject-specific ratings. The correlations varied greatly across subjects. Most models successfully predicted subjective ratings on training data; however, generalization to test data was less successful. Sparse models performed better than models without regularization.

Discussion: The results indicate that, if BCI-based feedback is to enhance emotional self-regulation, feature selection should be subject-specific. At the same time, the results to date suggest that the frontal midline theta is most often the best candidate for BCI-based modification of emotional reactions. Whether BCI-based feature modification will actually translate to better emotional self-regulation remains to be determined.

Significance: The present results suggest that appropriate use of BCI technology might facilitate emotional self-regulation. BCI-based EEG feature assessment could provide the timely feedback after each trial that is needed for effective self-regulation.

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Theta phase coupling with rhythmic motor output during visuomotor tracking

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Introduction: The entrainment of low frequency cortical brain oscillations to rhythmic stimuli was proposed to serve as a mechanism of selective attention, periodically tuning neuronal ensembles to reach maximal excitability at the optimal time [1]. In this work, we show that during visuomotor tracking, frontal theta oscillations phase-couple with rhythmic corrective sub-movements spontaneously emerging during the tracking task. An event-related potential (ERP) analysis, time-locked to these motor events revealed waveforms of theta-band spectral content, whose amplitudes were modulated by both hand kinematics and errors committed by the subjects.

Material, Methods and Results: Subjects (n=26) used a computer mouse to track a moving target along displayed trajectories while electroencephalographic (EEG) data and mouse/target positions were recorded. In a control condition, subjects performed a similar task in terms of motor output but not requiring tracking. Hand kinematics were composed of rhythmic (5 Hz) corrective sub-movements, best revealed by the hand acceleration profiles (Fig. 1A, blue). The phase-locking value (PLV) [2] was computed between those hand acceleration profiles and every electrode's theta [4-7 Hz] filtered EEG. Mean PLVs were then z-scored using the mean and standard deviation of 200 PLVs computed from surrogate signals, in order to remove the effect of non-genuine coupling.

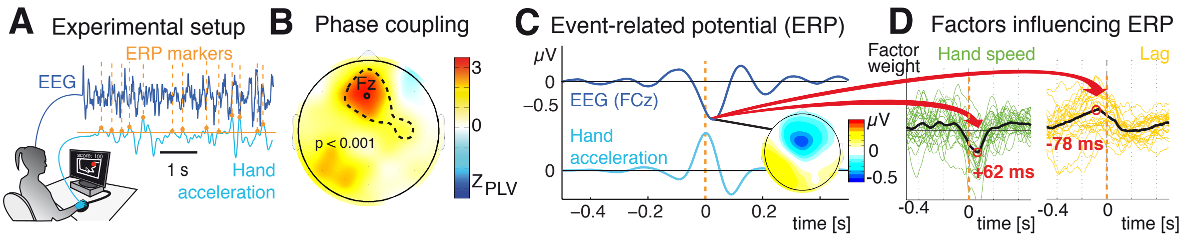

Figure 1. *A) The experimental setup with a representative example of five seconds of EEG (FCz) and rhythmic hand acceleration. The ERP markers (hand acceleration peaks) are shown in orange. B) the scalp distribution of the (z-scored) phase-locking values C) The ERP obtained by time-locking to hand acceleration peaks (blue) and the corresponding acceleration peak (cyan). D) The regression weights of the two influencial factors, for differrent time-lags and for each subject. Mean represented in black.*

Significant ($p<0.001$, corrected) couplings were found (Fig. 1B) at anterior midline scalp regions (peak: Fz), spreading over the hand representation of the motor cortex ipsilateral to the tracking hand. We then time-locked an ERP analysis to these sub-movements (by finding prominent hand acceleration peaks) and found a negative wave with a similar anterior scalp distribution (peak: FCz, EOG-contaminated epochs discarded), reaching a minimum ($p < 0.01$, corrected) around 40 ms after hand acceleration peaks (Fig. 1C). Finally, to find out what factors influence this negative deflection, we applied multivariate linear regression models to explain single-trial EEG amplitudes (FCz) using three behavioral factors: the speed of the hand (Fig. 1D, green), a measure of instantaneous error: how much the hand was lagging behind the target (Fig. 1D, yellow) and the speed of the target (not shown). The ERP amplitude was best explained by the speed of the hand ($p<0.01$, corrected) ~60 ms after the hand acceleration peak (corresponding to the sub-movement's peak speed) and by the instantaneous error ($p < 0.01$, corrected), ~80 ms before. No effect of target speed was found ($p > 0.05$). In the control condition, significantly lower theta coupling was found.

Discussion: We found a significant coupling between hand kinematics and a frontal network of theta frequency cortical oscillations during visuomotor tracking. Growing evidence supports the idea that theta cycles subserve some rhythmic selective attention process by entraining to periodic sensory input [1]. In this study, we show that even when this sensory input flows in continuously, similar couplings can exist between motor output and theta. We hypothesise that during continuous tasks requiring high attention (such as ours), the theta rhythm could be generated by the brain's performance monitoring system rhythmically sampling the instantaneous errors and producing higher amplitudes when salient errors, i.e. large and/or expeditiously corrected, are generated.

Significance: This study paves the way to a possible usage of midline frontal EEG as a proxy to probe patients' cognitive engagement in rehabilitative motor tasks, which could be used to inform assistive rehabilitation therapies.

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A novel BCI based rehabilitation approach for aphasia rehabilitation

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Introduction: Current scientific opinion considers language as an interaction of ventral and dorsal systems mainly on the left hemisphere and stroke-induced language disorders (aphasia) as the results of a lesion of one of these systems or of disturbed interaction [1] between them. Word production, in particular, depends onto a rapid online interaction between top-down processing (i.e. the formulation of a conceptual representation into a linguistic and phonological form) and bottom-up processing (i.e. the adaptation of speech production based on sensory input) within the dual system [2]. Conventional speech therapy is based on an open loop process, where the interaction between top down and bottom up processing is mediated by an external person, the therapist. There is a moderate evidence of the efficacy of this therapeutic approach [3]. We propose a simple brain-computer interface (BCI)-supported auditory paradigm for the rehabilitation of speech production deficits in aphasia patients. A BCI system may be utilized for monitoring and exploiting relevant cognitive states in real-time, e.g. auditory attention [4]. This shall be achieved by closing the loop between top-down execution and bottom-up perception by positive reinforcement of the patient. The reinforcement, however, will be constraint to the detection of neuronal markers of auditory attention and acoustic processing. Both aspects are prerequisites for the use of such an auditory BCI, and we are aware, that these may be affected in aphasia patients. Therefore, the primary goal of this pilot study is to clarify, whether or not stroke patients produce reliable neuronal markers of auditory attention to word stimuli, and whether such EEG responses can be decoded by a BCI in single trial.

Material and Methods: In an offline study, word ERP responses were explored in twenty elderly healthy subjects (mean age 60.20±8.04 years, normal hearing, no history of neurological deficits) and in one aphasic stroke patient (60 years). He showed a chronic severe Broca's aphasia caused by a left fronto-temporal-parietal infarct. Subjects were seated in a ring of 6 loudspeakers (AMUSE paradigm, [3]). Explicit familiarization with the word paradigm was carried out prior to the EEG recoding. Stimuli consisted of 6 bisyllabic words. Within a trial, this set was repeated 15 times in pseudo-randomized order. Stimulus onset asynchrony (SOA) was switched between experimental blocks and lasted 250 ms or 350 ms. A total of 12 trials were recorded in each of the two offline EEG sessions (64 channel passive Ag/AgCl electrodes with nose reference) for each condition.
A*Results:* Offline analysis of data from the patient and both sessions revealed that the classification of target versus non-target words, using chronological 5-fold cross-validation with a shrinkage-regularized LDA, was 71.45% (SOA = 350 ms) and 63.67% (SOA = 250 ms). The average target and non-target ERP responses of the patient were clearly separable in both conditions (Figure 1A depicts results for SOA = 250 ms). Figure 1B shows the grand average (GA) ERPs of the age-matched controls at the same SOA. The GA classification accuracy for this group was 72.85% (SOA = 250 ms).

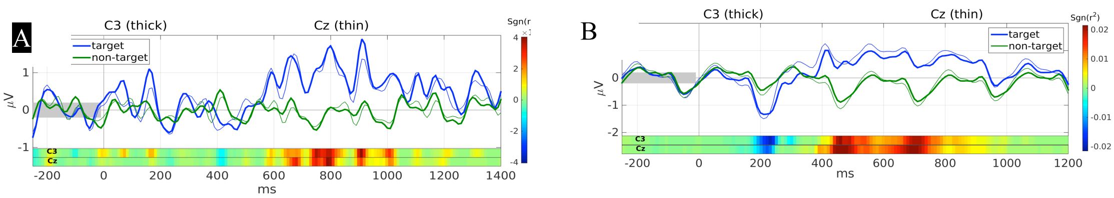

Figure 1: Comparison of average target (blue) and non-target (green) ERP responses at channels C3 and Cz upon bisyllabic word stimuli played at t=0 s and with an SOA of 250 ms. A grand average response of the aphasic patient: B: grand average responses of 20 controls. Colorbars visualize class-discriminant information as signed r² values over time.

Discussion & Significance: Although the stroke patient had severe language production deficits, he was able to perform the BCI paradigm. His target and non-target ERP responses were clearly separable, indicating that an online BCI training could be realizable for him. Based on these promising results, we are going to test other aphasia patients to further evaluate the feasibility of BCI-supported aphasia rehabilitation.
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A Prognostic Measure on EEG-based Motor Imagery Brain-Computer Interface for Stroke

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Introduction: Several clinical trials using Electroencephalograpy-based (EEG) Motor Imagery Brain-Computer Interface (MI-BCI) had yielded clinically significant motor improvements in stroke rehabilitation [1]. Recent results had revealed that the revised Brain Symmetry Index (rBSI) computed using EEG from 11 stroke patients who received MI-BCI intervention were negatively correlated with their motor improvements measured by Fugl Meyer Motor Assessment (FMMA) scores [2].

Material, Methods and Results: This paper investigates the correlation of rBSI with FMMA improvements on a larger population of 26 stroke patients that underwent BCI for stroke rehabilitation, which includes 9 patients of the 2nd trial [3] we conducted from 1 January 2011 to 1 January 2014, and 6 from the 3rd trial we conducted from 1 January 2011to 31 June2013 [4], in addition to the 11 patients from the 1st trial [2] we conducted from 1 April 2007 to 30 October 2009.

The result of using the temporal parameter of 8-25 Hz on the time segment 0.5 to 2.5 relative to the instruction cue to perform motor imagery using all the channels of the EEG data collected from the therapy sessions yielded a significant negative correlation of r=-0.412 (p=0.036) between the revised Brain Symmetry Index (rBSI) computed from the EEG and the motor improvements measured by FMMA scores as shown in Figure 1.

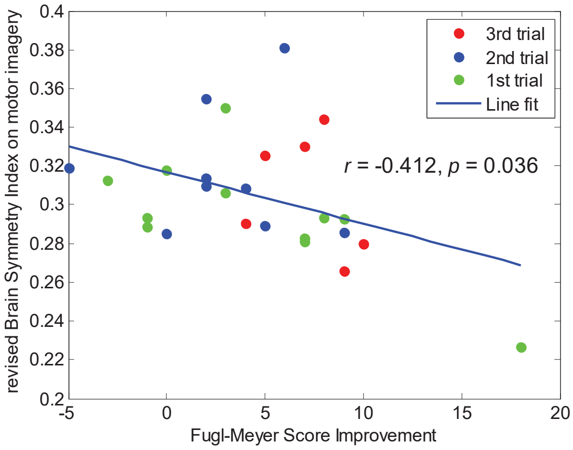

Figure 1. *Plot of rBSI using the temporal parameter of 8-25 Hz on all the channels of the EEG data collected from the therapy sessions of the 26 stroke patients (11 from the 1st trial, 9 from the 2nd trial, and 6 from the 3rd trial) against the FMMA score improvement*

Discussion: The rBSI captures the asymmetry in spectral power between the two cerebral hemispheres, and the result indicates that the asymmetry in spectral power from 8-25 is related to the motor improvements of the 26 patients who underwent MI-BCI stroke rehabilitation.

Significance: The result suggests a promising direction to investigate further on the use of rBSI as a prognostic measure to predict the motor recovery of using MI-BCI in stroke rehabilitation.

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An Automated Method for Determining Awareness and Predicting Recovery after Brain Injury, Using Event-Related Potentials

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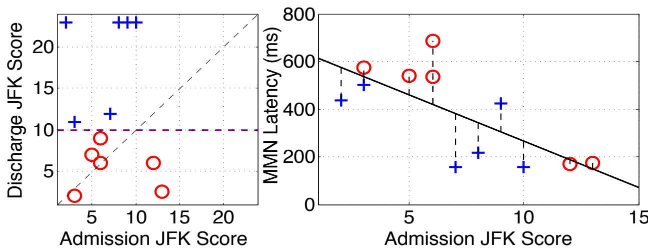
Introduction: There is mounting evidence that event-related potentials (ERPs) are useful predictors of recovery from disorders of consciousness following brain injury. So far, these approaches have typically used the amplitude of certain ERP components, such as the mismatch negativity (MMN) that typically appears fronto-centrally at 150–250 ms following an oddball stimulus. However, the latency of ERP components can also be expected to change as a function of awareness level. This leads to a problem in identifying ERP components of interest, since in damaged, atypical brains they no longer correspond to known textbook patterns. This problem is compounded by the reduced signal-to-noise ratio of EEG following brain injury. One approach to this problem is to identify ERP components by expert examination—however, the results are then affected by the subjectivity of this process. Alternatively, amplitude can be computed at fixed textbook latencies—but this leads to noisy estimation, and/or applicability only to the subset of subjects that exhibit standard latencies (leading to a high rate of rejection of subjects from the analysis). In the current study, we address these problems by: (a) using a subspace decomposition method to enhance signal-to-noise ratio in estimating the source of interest; (b) developing this into a fully-automated processing pipeline for identifying ERP components despite latency differences; and (c) using the latency itself as a diagnostic and predictive feature.

Method and Materials: **Subjects:** 13 participants ≥16 years old, with traumatic brain injury admitted to the Neurorecovery Program at Helen Hayes Hospital (West Haverstraw, NY, USA), 30-60 days post-injury. JFK Coma Recovery Scale score was measured at admission and discharge. **Protocol:** 32-channel referential EEG was recorded (0-3 days of admission), while the subject passively listened to an oddball tone sequence (80% standards, 16% duration deviants, and 4% rare deviants). Standard stimuli were 1000-Hz tones of 100-msec duration delivered at 80 dB SPL. Duration-deviant stimuli were similar except that their duration could be 50 or 150 msec. Rare deviant stimuli were English spoken words at 80 dB SPL. The paradigm was 15 min long, with a total of 2025 stimuli, partitioned into 15 one-min runs. **Analysis:** EEG data were pre-processed by applying a notch filter, a common average spatial filter, and a bandpass filter of 0.5-8 Hz. Trials containing artifacts were eliminated automatically by statistical detection of outliers. Spatially constrained ICA (ScICA) was then applied to the epochs following standard and deviant stimuli, using a soft fronto-central spatial constraint to estimate a single source that had the classic MMN topography. This single source was projected back into the signal space to retrieve the correct signal polarity, and a signed coefficient of determination (signed r^2) was computed between standard and deviant trials. The final measure was the latency of the first negative peak of the difference wave in the interval 100-700 msec whose r^2 exceeded the 5%-significance threshold (one of the 13 subjects was removed as no significant peak was found).

Results: The left figure shows JFK score at admission and discharge. We define "recovery" as a discharge JFK score >10 with a 5-point or more improvement on the JFK score (blue crosses). Admission JFK score alone did not predict recovery ($r = -0.03$, $p = 0.9$, $r^2 = 0.002$). We found that the ERP latency was significantly correlated with the admission JFK score ($r = -0.71$, $p = 0.009$), showing the diagnostic value of the ERP (right figure).



For prognosis, we aimed to obtain a predictor that was independent of admission JFK score: therefore, we were interested in whether an individual had a long or short ERP latency *relative to the latency that the clinical score would lead us to expect*. In the future, we envisage that expected latencies would be obtained from a large normative database; for now, we interpolate them from the current data set itself. Hence, we use the *residuals* of ERP latency in the regression against admission JFK score (vertical dashed lines in right figure). We found that the residuals were significantly correlated with recovery ($r = -0.65$, $r^2 = 0.41$, $p = 0.02$). ***Significance:*** These initial results support the feasibility of using ERP latencies as a biomarker for assessing awareness and predicting recovery after brain injury. They also demonstrate an advanced signal-processing pipeline based on ScICA to objectively reduce data dimension, enhance the signal-to-noise ratio, and extract informative ERPs in a fully automated way from atypical, noisy EEG. With further development, this approach might provide a useful new diagnostic and prognostic tool for evaluating patients in a minimally conscious or apparently unresponsive state. This new tool might aid in formulating individual treatment and disposition plans, including selection of patients who could use brain-computer interface (BCI) communication systems to aid in their functional recovery.

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Analysis of Subcortical Beta Activities in Stroke Patients for Motor Rehabilitation

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Introduction: Motor disabilities are one of the main symptoms in stroke patients. For the stroke patients, it is important to understand differences in motor function-related subcortical activities compared to healthy subjects. However, subcortical activities in chronic stroke patients are still unknown during motor execution. In this study, we investigated the different subcortical activities between the stroke patients and the healthy controls using a source localization from electroencephalogram (EEG) signals.

Material, Methods and Results: Eleven chronic stroke patients with subcortical lesion (54.3 ± 8.2 years) and twelve healthy controls (54.8 ± 2.2 years) participated in the finger tapping experiment using affected hand or dominant hand, respectively. Eight patients suffered from infarction and three patients suffered from hemorrhage. Mean Fugl-Mayer Assessment (FMA) score of their upper extremities was 52.6 ± 13.4 in the stroke patients. The task consisted of 20 runs, and each run is composed of motor execution (800 ms) and rest (500 ms) randomly given by visual cues (see Fig. 1-(A)). The EEG signals were acquired using the NeuroPrax® EEG system (NeuroConn GmbH) with 32 channels. To overcome the limitation of the use of low density EEG, the standardized low resolution brain electromagnetic tomography (sLORETA) was carried out in the source localization analysis. The current source density distribution in brain electrical activity was estimated at 5 nm spatial resolution using sLORETA. To reduce the large variabilities among subjects, a global normalization of the sLORETA images was performed. The EEG data were divided into two frequency bands (alpha: 7.5~12.5 Hz, beta: 18~26 Hz). For the patients with lesions on the right side, the data were flipped from right to left side. We applied two sample *t*-test to find the differences of the subcortical/cortical area between two groups. In the stroke patients, significant subcortical activities (p<0.05) were only observed over the posterior cingulate, the posterior subcortical areas, and limbic lobe in the beta band (see Fig. 1-(B)). In the healthy controls, however, there were no significant activities and areas in the alpha and beta bands.

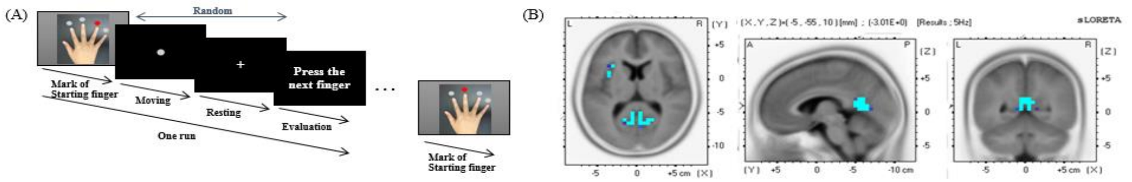

Figure 1. *(A) Experimental paradigm, (B) The difference between stroke patients and healthy controls in sLORETA brain activation maps. Cyan color indicates the significant activation areas in the stroke patients compared to the healthy controls (p<0.05).*

Discussion: We found the significant differences that have a close relation to motor control circuits using a source localization in the two groups. The posterior cingulate and the posterior subcortical areas are connected with intrinsic control networks including executive motor control [1]. And the limbic lobe is involved in basal ganglia-thalamocortical circuits associated with motor control [2]. The beta band prominently affects disinhibition of neuronal population concerned with motor function compared to the alpha band [3].

Significance: The results showed that the motor control is a meaningful role in the stroke patients with motor disabilities. The differences of subcortical activities between stroke patients and healthy controls can be a new metric for diagnosing and evaluating a degree of motor rehabilitation based on brain-computer interfaces.

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BCI controlled neuromuscular electrical stimulation enables sustained motor recovery in chronic stroke victims

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Introduction: Recently, it has been shown that brain-computer interfaces (BCI) can be used in stroke rehabilitation to decode motor attempts from brain signals and to trigger movements of the paralyzed limb [1]. Among other available practices in rehabilitation, neuromuscular electrical stimulation (NMES) is often used to directly engage muscles on the affected parts of the body during physical therapy. Nevertheless, the benefits of a combined approach, to directly link the brain intention with a muscular response, are not yet fully validated. In this abstract, we report first results of a BCI-NMES system for stroke rehabilitation.

Material and Methods: Up to now, we enrolled 18 chronic stroke victims (minimum 10 months past the incident) suffering from an impairment of the upper limb in a randomized controlled clinical trial. Half of the subjects were assigned to the BCI group and half to a “sham” group, whereby the criteria such as motor impairment –measured via the Fugl-Meyer scale for upper extremity (FM) score–, age, time since incident and lesion location were balanced. Generally, the experimental protocol consisted of three different phases: (i) patients underwent a pre-evaluation to check the motor capabilities, to characterize the initial state of the brain and to calibrate the BCI classifier (see BCI details in [2]). (ii) In the following weeks, they were trained with an online BCI twice a week for 10 sessions (45 to 90 minutes including setup). (iii) Finally, they performed a post-experimental screening to determine changes in EEG patterns and in motor functions following the treatment, and a 6-month follow-up to evaluate the sustainment. Patients in the BCI group received NMES of the extensor digitorum muscles triggered by the BCI detecting the intention of movement at the cortical level (modulation of the sensorimotor rhythm in the contralateral motor cortex). For patients in the sham group the NMES was not correlated with the brain activity. All subjects were asked to attempt to open their paretic hand (full sustained finger extension) with the aim of activating the NMES upon detection of a suitable sensorimotor rhythms (Fig. 1-a). Subjects in the two groups (BCI and sham) received comparable amount of NMES.

Results: Remarkably, subjects in the BCI group improved their motor function (post minus pre) by 8.6±5.0 FM points (which is more than the minimal clinical change of 5.25 FM points), while those in the sham group improved only by 2.4±3.4 FM points (Fig. 1-b). As expected, the features used by the BCI classifier were mostly located over the affected hemisphere and the motor cortex (see topographic presentation in Fig. 1-c).

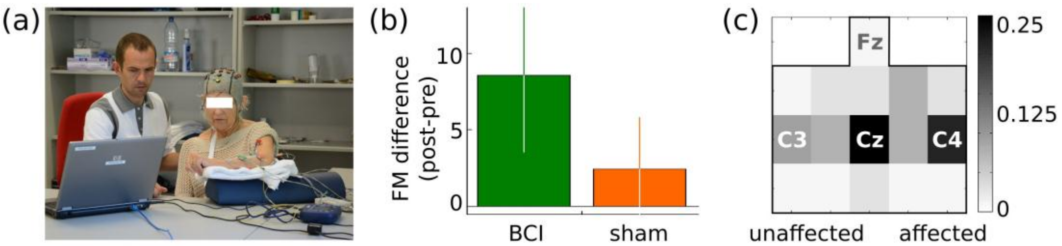

Figure 1. *(a) Experimental BCI-NMES setup with the patient and the physical therapist. (b) Improvement in the Fugl-Meyer scales for the upper extremity for the BCI and the sham group (mean ± standard deviation). (c) Topographic presentation of the ratio of used BCI features (EEG channels might have been flipped so that the lesioned hemisphere appears always on the right side).*

Discussion: We hypothesize that the motor improvement in the BCI group (in contrast to the sham group) is triggered by the tight timed and functional link between the intended action in the brain, and the executed and perceived motor action, through the activation of the body’s natural efferent and afferent pathways.

Significance: In our randomized controlled trial, we demonstrate that the modulation of sensorimotor rhythms driving contingent neuromuscular stimulation is more effective than sham stimulation with active motor attempt, and that the proposed therapy dosage produces a clinically important recovery in chronic stroke survivors having a moderate-to-severe motor impairment.

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BCI-NMES therapy enhances effective connectivity in the damaged hemisphere in stroke patients

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Introduction: In stroke rehabilitation, one of the key components for motor improvement is brain plasticity and, in particular, the reestablishment of cortical and subcortical networks [1] that can be studied with connectivity analysis. Despite recent advances in brain-computer interface (BCI)-driven stroke therapy [2], it is still unclear what are the underlying changes that lead to a clinical improvement.

Methods: During a controlled randomized clinical trial 18 chronic stroke patients received 10 sessions of neuromuscular electrical stimulation (NMES) triggered by the BCI (N=9) detecting EEG correlates of movement intention (modulation of the sensorimotor rhythm in the contralateral motor cortex), or a sham (N=9) therapy during which the NMES activation was not correlated with the brain activity. Subjects were asked to attempt to open their paretic hand with the aim of activating the NMES upon detection of suitable brain patterns. We studied neuroplastic reorganization within the lesioned hemisphere by computing the effective connectivity (estimated via the short-time direct directed transfer function, SdDTF, in the mu frequency band) from the resting state activity of the brain before and after the whole treatment.

Results: Inside the damaged motor cortex, in the mu frequency band, the connectivity significantly increased for patients who were using the BCI-NMES therapy compared to the sham group (mixed ANOVA, group x time interaction, $p<0.01$, see Figure 1). Moreover, the connectivity increase inside the damaged motor cortex is significantly correlated ($r = 0.57$, $p<0.01$) to the improvement of motor function of the upper limb for the chronic stroke patients. Similar results were found in the beta frequency range ($r = 0.53$, $p < 0.05$).

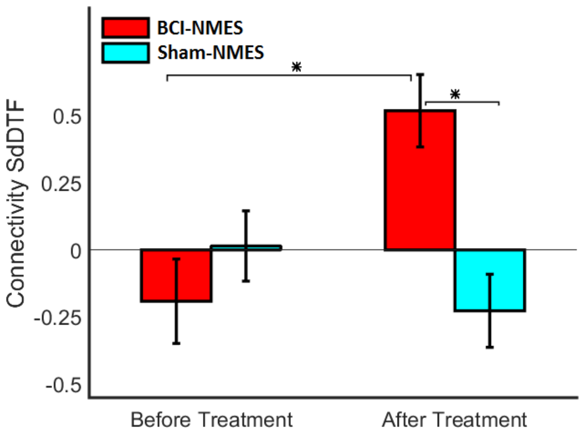

Figure 1. *Connectivity before and after treatment in the damaged motor cortex in th mu rhythm.*p<0.05, Bonferroni corrected post-hoc t-tests*

Discussion: Based on our results, we hypothesize that functional improvement of the upper limb has been achieved as a result of the congruence between the BCI detection and the NMES stimulation. Rewarding of expected brain activity patterns can be thought to be responsible for the plastic enhancement of connectivity within the damaged motor cortex. Future connectivity analyses will allow us to further understand which areas and neural networks are involved in the motor improvement for stroke patients using BCI therapy.

Significance: Our study showcases that BCI effectively enhances brain plasticity, as shown recently also with connectivity analysis [3], and could be used to counteract the natural decrease of brain connectivity in the affected hemisphere that is known to occur after stroke [1] thanks to a closed loop between the efferent intention of movement and the congruent rich afferent feedback of movement.

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Brain-Computer Interface based communication in patients diagnosed with post-stroke aphasia

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Introduction: Brain-Computer Interfaces (BCI) which are based on the P300 evoked potential were successfully used for communication in patients who were paralyzed as a result of progressive neurodegenerative disease [1]. This substitution of language motor output via BCI might also be useful in patients diagnosed with post-stroke Broca aphasia as those patients cannot produce language while their language comprehension ability stays intact. One major problem reported by speech therapists is the high level of frustration in people with Broca aphasia. During the sub-acute rehabilitation phase in which cortical plasticity can be expected, these patients experience feelings of helplessness because they are not able to express themselves. By using a BCI system for language expression during rehabilitation, language areas may be activated and neuronal plasticity may be supported. However, first the feasibility of using BCIs with this target population needs to be demonstrated which we addressed with this study.

Methods: For data acquisition we used the P300 speller paradigm within the BCI2000 software environment [2]. Participants had to spell the words “BRAIN” and “POWER” for calibration, additional three five letter words in the copy-spelling mode (“FUCHS”, “RADIO”, “BLUME”) and were also trained for free-spelling. We used 10 sequences of target letter flashing in every task. Participants were trained for at least three sessions.

Participants: Preliminary data of *N*=2 participants were collected (more being assessed currently). Both patients were diagnosed with post-stroke aphasia, showed a lesion in the left hemisphere were treated at the rehabilitation hospital Bavaria at Bad Kissingen, Germany. Participant A is male (36 years, 5 months after stroke) and was diagnosed with anomic aphasia and attention deficits. Participant B is female (46 years, 12 months after stroke), could express herself using spoken language and was diagnosed with neglect and inability to read. This study was approved by the Psychology Department Ethics Review Board of the University of Würzburg and participants gave informed consent before participation.

Results: Participant A could not use the speller matrix independently in the beginning and was unable to select any target letter correctly in session 1. We thus, used a paper based masking procedure such that only the letter to spell was visible for the patient. Beginning with session 2, the participant was able to select every letter correctly. In session 4, the participant performed free-spelling with an accuracy of 70% and in session six he could free-spell his wife´s name with an accuracy of 100%. Participant B could copy-spell with an accuracy of 100% in the first session and performed free-spelling with 100% accuracy in the third session. After copy-spelling an eight letter word which the participant was unable to read before, she could read the word aloud. The participant improved such that she could read 14 letter words without assistance.

Discussion: Both participants who were reported here were described as being severely affected by aphasia. In the case of participant A, the interdisciplinary therapists’ team questioned his abilities for command following and comprehension in general. Even though we could not increase his expressive language abilities, we proved that this patient did understand language as he could use the BCI system after training also in the free-spelling mode. Participant B’s reading deficits were described as being severe by her language therapist as well as by herself. In the third session of our BCI training she could read 14 letter words without assistance, a result her language therapist described as being stunning. Of course, in both reported cases we cannot disentangle other therapies’ effects from BCI training effects. However, we showed that BCI use is possible in patients with post-stroke aphasia and clearly need more data to judge the potential benefit of using BCI systems to support rehabilitation in this target population.

Significance: If successful, the here described BCI based rehabilitation procedure might contribute to post-stroke aphasia recovery. So far, we can only report single cases and therefore cannot yet judge the full potential of the approach.

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Comparison of Three Modalities of SMR-BCI within Stroke Patients

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Introduction: Sensorimotor rhythm based brain-computer interface (SMR-BCI) has been widely used for stroke rehabilitation. Stroke patients with motor dysfunction could consciously move the paralyzed hand with BCI, which is demonstrated to be beneficial to the rehabilitation of lost motor function[1]. However, discrimination performance of BCI has large effects on the rehabilitation efficacy. To solve the problem, investigators have already proposed many different modalities of mental tasks for BCI control, in which movement intention[2], motor imagery[3] and selective sensation[4] are most widely studied. Here, we aim to compare the BCI performance of these three mental tasks in stroke patients, and find out which is the best for rehabilitation.

Material, Methods and Results: Six stroke patients were recruited in this research, and all of them had motor disability with right side of body due to lesions on left hemisphere. Each of the patients were assigned to perform three blocks of different mental tasks, including movement intention, motor imagery and selective sensation. Each block contains 30 trials for both left and right hand tasks. Timeline of one single trial was shown in Fig.1(1). In this abstract, we only analysis the performance of paralyzed hand (right hand), and EEG signal features from right hand tasks would be discriminated from idle mode. The decoding results were shown in Fig.1(2). T-test indicates movement intention has better performance than other two modalities with $p<0.05$.

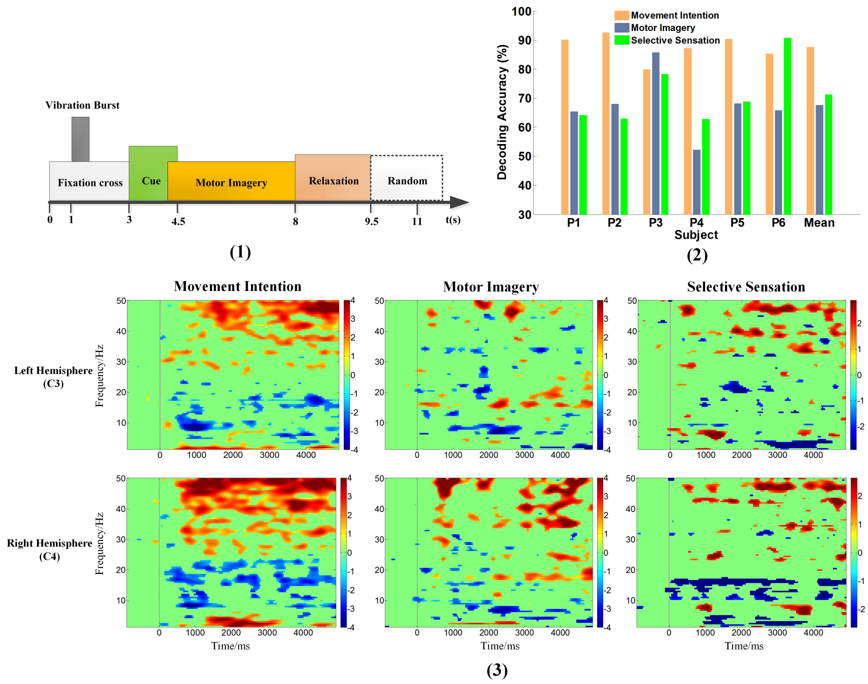

Figure 1. *(1)Timeline of single trial in this experiment. (2)Decoding accuracy of 3 different mental tasks. (3)Motor cortical activations on both left (C3) and right (C4) hemispheres druing different tasks.*

Discussion: For stroke patients, movement intention maybe more similar with real movement, and has more activations in alpha and beta bands than motor imagery and selective sensation, which makes it has the highest decoding accuracy. As indicated in Fig.1(3), gamma band was also significantly activated during mental task of paralyzed hand, which was not found in healthy subject's studies.

Significance: This work has compared three different modalities of SMR-BCI, and demonstrated movement intention to be the best choice as mental task for stroke patients.

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Extended BCI controlled alpha band neurofeedback training in schizophrenia patients

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Introduction: Cognitive deficits constitute a core feature of schizophrenia disorders [1], they are observed in more than 70% of patients, are relatively stable over time, independent of the symptomatic manifestations of the illness, and considered as prominent endophenotype [2]. Spontaneous and event-related electrocortical activity have been a prime target in this attempt. In particular, activity in the theta (4-7 Hz) and alpha (8-16 Hz) frequency range have been associated with cognitive processes like attention deployment, stimulus encoding and retention, and found to be abnormal in patients with schizophrenia. Yet, such correlative evidence seems insufficient to hypothesize neural correlates or underpinnings of cortical (dys)functions. The link between neural and functional level might be strengthened by complementing the measurement of spontaneous or task-related oscillatory activity during cognitive tests with manipulation of brain activity through neurofeedback. Alpha band neurofeedback (NF) training has been found to affect attention and memory performance in healthy subjects [3]. As learning ability is impaired in schizophrenia, the present pilot study examined the effects of online neurofeedback embedded in learning conditions favouring cortical reorganization (i.e., massed practice, motivation by feedback and success) on alpha power modulation. The aim of the study was to investigate whether patients with schizophrenia would tolerate extended training and would be able to modulate alpha power when receiving online neurofeedback.

Material, Methods and Results: Six inpatients (4 male, age range 24-43 meeting ICD-10 diagnosis of paranoid-hallucinatory schizophrenia (F20.0) were recruited at the Center of Psychiatry Reichenau, Germany. Patients' learning ability was compared to that of four healthy subjects (2 male; age range 23-25). Twenty neurofeedback training sessions were scheduled on consecutive days within 3-4 weeks. EEG was recorded with 6 Ag/AgCl electrodes. A large Laplacian spatial filter was applied, with the values on electrode location Cz used for online feedback. EEG power was calculated by means of a sliding FFT algorithm, updated every 0.5 s during each training run (BCI2000 software). Every 12 s the past data were used to update the gain and offset of online feedback. This alpha frequency-specific EEG-power (9-11 Hz) constituted the variable of online-feedback, reflecting increase or decrease in alpha power by an extending grey bar that turned green if power was modulated in the requested direction. Subjects had to increase and decrease the grey bar/feedback stimulus, i.e., their alpha amplitude. Successful trials (>50% of the feedback phase in the requested direction) were positively reinforced with a smiling face; no negative feedback was provided. All healthy subjects and 4 of 5 patients learned to increase the alpha power amplitude (significant linear trends of alpha amplitude and number of session). Start performance was at the same level in both groups (around 65% correct responses). Healthy subjects achieved 80% in the 20th session as compared to 68% in patients. Variance of performance was large in the patient group.

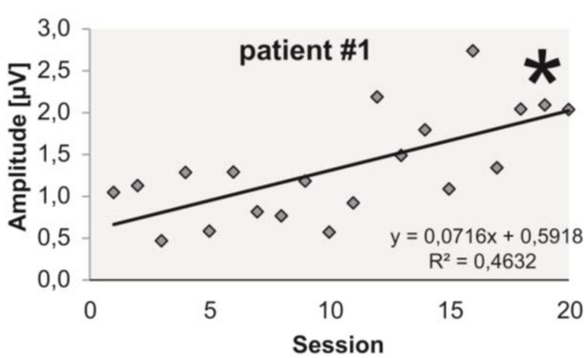

Figure 1. *Amplitude of alpha band power at Cz as a function of sessions in patient 1. The linear trend is significant and implies an increased amplitude with training. Learning trends of 3 other patients were also significant but with a smaller slope.*

Discussion: This feasibility study demonstrated (1) that alpha band neurofeedback training can be applied to in-patients with schizophrenia; this importantly implies that the training could be integrated in the clinical routine of the patients. (2) Four of 5 patients learned to modulate their alpha band amplitude. In a larger sample it has to be investigated whether the training leads to increased attentional abilities such that the attentional deficits can be remedied.

Significance: Alpha-band neurofeedback training, lasting 3 to 5 weeks can be applied in an in-patient setting and leads to increased alpha-band amplitude. Patients with schizophrenia tolerated well the training.

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Hemicraniectomy-based EEG as a platform for low-risk investigations of BCIs in subjects with brain injuries

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Introduction: Brain-computer interface (BCI) devices sample brain signals to discern intent, often the intent to move the limbs. Much BCI research is performed in motor-intact subjects, limiting the conclusions we can draw about BCI efficacy in a motor-impaired population. An alternative use for BCI is to rehabilitate function, rather than replace it, following a stroke or other brain injury[1]. This would greatly expand the potential end-user population. Here, we explore the feasibility of decoding motor intent from human patients recovering from traumatic brain injury who have undergone a decompressive hemicraniectomy as part of the treatment of their condition. Working with this subject pool provides the opportunity to noninvasively record brain signals in the absence of attenuation by the skull. Previous studies have shown that EEG signals recorded over a skull defect left by a hemicraniectomy (hEEG) have higher spectral bandwidth than signals recorded over intact skull, and are more informative about movement than homologous skull sites[2]. Here, we used hEEG signals to decode continuous, isometric force produced by the thumb and index finger, as subjects performed a random-target pursuit, force-based behavioral task.

Materials, Methods and Results:

All experimental procedures were approved by Institutional Review Board at Northwestern University. All subjects gave written informed consent prior to study participation. The subjects used their hand contralateral to the hemicraniectomy to perform the random-target pursuit task. We recorded hEEG from frontal, central, and parietal regions (10-20 electrode locations). We decomposed the neural data into the local motor potential (LMP)[3], and five spectral features (0-4 Hz, 7-20 Hz, 70-115 Hz, 130-200 Hz, 200-300 Hz). We trained decoders on the hEEG features using a Wiener cascade filter, and implemented a real-time BCI using techniques developed in our lab for BCI control with continuous neural data[4]. We postulated that the absence of skull between the recording sites and underlying cortex would enable us to capture more of the spectral content of the signals. We then hypothesized that the increased ability to extract high frequency content, such as high-gamma band activity, would lead to more accurate decoding of force than with standard EEG, perhaps close to that achieved with epidural or subdural signals[5]. Further, the subjects should be able to exert continuous BCI control over a computer cursor, using these high frequency signals.

We performed this experiment with five human subjects. We used Fraction of Variance Accounted For (FVAF) as a measure of performance in the offline decoding of force. Substantial information was present in the high gamma band for all subjects. The mean cross-validated FVAF values for the subjects were as high as 0.5, with smaller segments of the data accounting for as much as 72% of the variance in force. The overall mean (±SE) across subjects was 0.32 ± 0.05. Two of the subjects achieved real-time BCI control, successfully acquiring 50% and 75% of targets, respectively.

Discussion: This proof-of-concept study demonstrates that 1) hEEG signals can provide nearly as much information about force as those directly on the dura, and 2) this information can enable patients with brain injuries to control a BCI. This paradigm provides an important way to study high-gamma based BCIs in brain-injured patients without incurring additional risk. We have begun to use this paradigm to study BCI-based rehabilitation in brain-injured patients.

Significance: Hemicraniectomy-based BCIs offer a noninvasive way to study high-frequency brain signals in end-user populations.

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Improving Motor Recovery after Stroke by Combined rTMS and BCI Training

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Introduction: Treatment strategies to address motor impairment after stroke should optimally address both contributors towards hemiparesis, namely by encouraging activity within the lesioned hemisphere and down regulating inhibition from the healthy hemisphere. In this study, we assessed the hypothesis that combined repetitive Transcranial Magnetic Stimulation (rTMS) with motor imagery Brain Computer Interface (BCI) training would enhance hand motor function after stroke.

Methods: One stroke patient with upper extremity impairment following ischemic stroke (11.5 months post stroke) received combined rTMS and BCI treatments. Nine combined rTMS/BCI sessions were completed (three times per week for three weeks), followed by an additional nine sessions of BCI training only. Low frequency (1Hz) rTMS was applied to the motor hotspot of the non-stroke hemisphere (target muscle: nonparetic first dorsal interosseous) at 90% motor threshold for 10 minutes, immediately followed by 8-10 runs of BCI training using a virtual reality hand grasping task, with 20 trials per run. Clinical tests of motor performance, and paired-pulse TMS inter-hemispheric inhibition (IHI) tests were evaluated at three time points: baseline, post-rTMS/BCI, and post-BCI. Anatomical and functional MRI scans, both during rest and during a finger tracking test, were acquired using a Siemens Magnetom 3T scanner at all testing time points.

Results: The subject was able to achieve adequate control of the virtual reality BCI paradigm, with a daily average of nearly 70 % correct responses in the final BCI sessions, as shown in Figure 1. Performance on the finger tracking test improved significantly over time, while scores on the Motricity or Box and Block Test were stable over time. IHI testing revealed reduced inhibition from the contralesional to ipsilesional hemisphere between baseline and post-TMS/BCI time points. fMRI activation maps showed increased activation of ipsilesional motor cortex from baseline to both post-intervention time points.

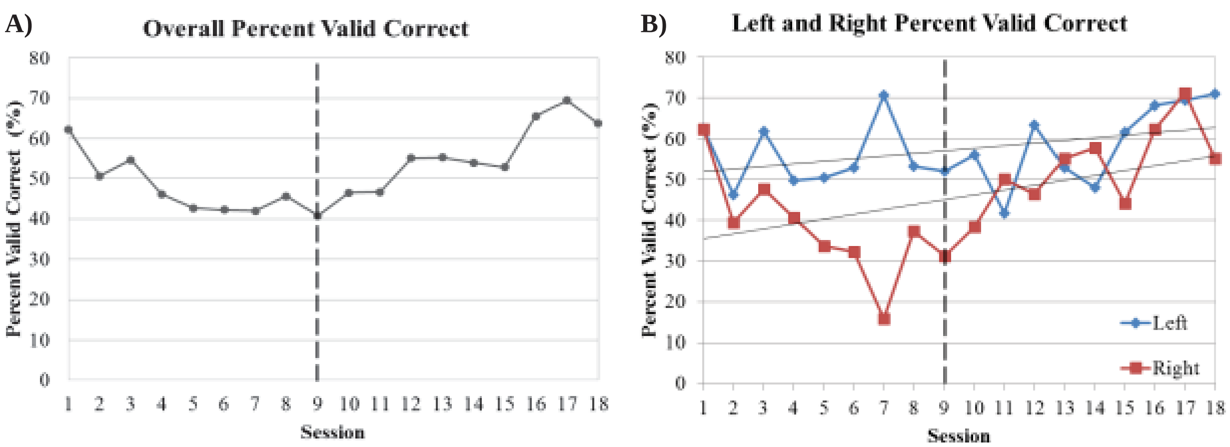

Figure 1. *A) Overall daily percent valid correct in the BCI task. B) Overall daily percent valid correct in BCI task separated for left and right trials (corresponding to the stroke affected side). Dashed lines indicate separation rTMS+BCI and BCI only sessions.*

Discussion: The results demonstrate that the subject was able to control the BCI task, and performance differed significantly between left and right trials when preceded by rTMS. The subject also experienced gains in hand motor function as evaluated by the finger tracking test, along with changes in fMRI activation maps suggesting increased recruitment of ipsilesional motor cortical networks.

Significance: The results demonstrate the feasibility of combining rTMS with BCI training in stroke patients, and lay a foundation for continued work with additional subjects to evaluate the potential of this combined therapy.

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When and how to address ethical issues in BCI: A qualitative study of BCI researcher and end user perspectives

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Introduction: It is widely accepted that successful translation of BCI applications depends on identifying and integrating the needs of potential end users into device design, and studies have reported BCI researchers' perspectives on ethical issues [8] and real or potential end users' priorities in device development [1-7]. Yet few have investigated these groups together to determine end users' feelings about how ethical issues ought to be addressed and researchers' perceptions of barriers to incorporating end users' perspectives outside "user-centered design." To fill this gap, we interviewed 15 BCI investigators within an NSF-funded Engineering Research Center (ERC) and conducted three (3) focus groups with potential end users of BCI technology to compare different BCI stakeholders' understanding of how ethical issues in research ought to be addressed.

Methods: Semi-structured interviews with investigators (n=15) were conducted in person or by phone. Verbal consent was obtained and all interviews were audio recorded. The investigator interview guide focused on interviewees' experience with and attitudes towards end user involvement and perception of ethical issues in research. Three moderated focus groups were conducted (n=17) with potential end users of BCI devices who self-identified as having motor disabilities due to spinal cord injury or stroke. The end user interview guide concentrated on end users' feelings about how ethical issues such as privacy and responsibility should be addressed. Pairs of researchers coded the transcribed data using grounded theory to identify themes [9].

Results: BCI researchers and potential BCI end users with motor disabilities agreed on risks and benefits of BCI devices for mobility, including concerns about surgical risks, privacy and security, and responsibility. Of most interest were areas on which they diverged: BCI researchers often assumed that ethical issues would be addressed further along the translational pathway; some said they were "not my job." By contrast, potential end users expected researchers to be responsible for addressing ethical issues throughout the design process. There was also divergence on particular ethical issues, such as methods for addressing privacy and security concerns.

Discussion: Our findings suggest that BCI researchers and potential end users share many of the same ethical concerns regarding BCI research, but that potential end users – perhaps because they consider the technologies from their situations as people living with motor disabilities – expect ethical issues to be addressed differently from BCI researchers. That is, people with motor disabilities thought that ethical issues should be addressed early and often with the public, while researchers tended to place conversations about ethical issues further along the translational pathway and expect that ethicists or other intermediaries would guide these discussions.

Significance: Beyond issues of usability, potential end users have deep concerns about individual privacy and equality of access that ought to be addressed in research along with technical design issues. Incorporating end users' perspectives on these broader issues is an ethical requirement of responsible neural engineering research.

Acknowledgements: This work was supported by a grant from the National Science Foundation (NSF Award #EEC-1028725).

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The Effect of Deep Brain Stimulation on the Pallido-Cortical Coherency Pattern of Parkinson's Disease

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Introduction: The mechanism of deep brain stimulation (DBS) through Globus pallidus (GPi), used for the neurotherapy of Parkinson's disease (PD), is still not well understood [1-2]. In this study we investigated the pallido-cortical neuronal coupling during DBS while PD patients were at rest. The preliminary analysis shows reduction in the beta band activity during DBS-ON relative to DBS-OFF state. Better understanding of brain neural function during stimulation, can not only point the way towards better medications for PD but can also act as a biomarker to facilitate the development of a closed loop neuromodulation BCI system.

Material, Methods and Results: Three PD patients underwent DBS surgery targeting the GPi with simultaneous insertion of an eight contact ECoG strip covering the frontal and parietal cortices. Simultaneous local field potential (LFP) recordings were also obtained from four leads implanted in the right GPi. The data have been recorded and amplified (g.tec Medical g.USBamp) with the sampling rate of 2400 Hz and high pass filter of 0.1 Hz [3]. Concomitant kinematic data were also recorded using a glove (5DT DataGlove, Mumbai, India) that was worn on the hand contralateral to the DBS lead and oversampled at 2400 Hz using BCI2000 software. Rest periods were detected using automated electromyography (EMG) envelope detection and analysis was conducted over this period with the therapeutic stimulation parameters set at 1V and 185 Hz. Using a zero phase FIR filter [2-200 Hz] data were bandpass filtered and the line noise was removed with a notch filter. For a better spatial resolution and in order to reduce the stimulation artifact, bipolar configuration of two leads located on the motor and pre-motor cortex was used for further analysis. To investigate the pallido-cortical connectivity pattern for each patient at each condition, eight non-overlapping blocks of two seconds were used to calculate the coherency between sensorimotor and pallidal signals at each frequency using one second sliding window with 50% overlap. The average coherence was computed over four frequency bands of alpha (8-12 Hz), beta (13-35 Hz), low gamma (36-80 Hz) and high gamma (81-150 Hz). Non-parametric Wilcoxon signed rank statistical test was applied to show how significant the DBS-ON state can affect the pallido-cortical coherency pattern during rest at different frequency bands. The results showed that there is a significant ($p<0.05$) pallido-cortical coherence reduction during DBS in the beta band while there were no considerable coherency changes in the gamma bands (Fig. 1).

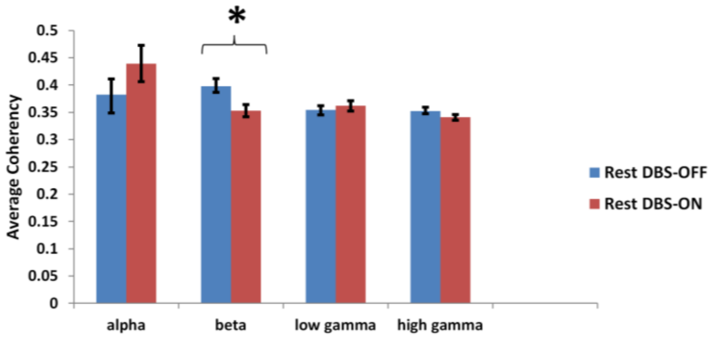

Figure 1. *Mean and standard errors for two different states of DBS-ON and DBS-OFF over four different frequency bands. Significant differences (p<0.05) have been shown with a star (*).*

Discussion: Our preliminary analysis suggests a significant pallido-cortical coherency reduction in the beta frequency band during DBS-ON. This finding can be attributed to the inhibitory nature of DBS on cortico-subcortical synchronous activity associated in beta oscillations. Further investigation is required with more PD patients using the same protocol to increase the power of analysis.

Significance: The outcomes of this study will contribute to better understanding of DBS mechanism on pallido-cortical synchrony changes and may suggest strategies for the development of more sophisticated therapeutic procedures in PD.

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Volitional control of basal ganglia activity for the treatment of Parkinson's disease

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Introduction: Parkinson's disease (PD) is characterized by motor deficits due to disrupted transmission in the basal ganglia (BG)-thalamus-cortex circuit [1]. This circuit exhibits enhanced neuronal synchronization in the beta frequency band (13-30 Hz) proportional to motor deficit severity and beta synchronization is decreased during treatment by levodopa or deep brain stimulation (DBS) [2, 3]. Disruption to the pathological synchronization through long-term intrinsic circuit modification may lead to symptom improvement. Brain computer interfaces (BCIs) can be used to induce and guide adaptive plasticity through operant conditioning of disease-related brain signals; it may be possible to use BCI technology to reduce PD symptom-severity through operant conditioning of PD-related brain signals.

Material, Methods and Results: The participants are individuals diagnosed with Parkinson's disease who have been selected to undergo surgical implantation of deep brain stimulation (DBS) electrodes as part of their standard-of-care treatment. The signals from the clinical microelectrode recording system are passed into a separate computer running the experimental software that processes the brain signals and presents the tasks through a virtual reality program. This program coordinates the inputs from the clinical neurophysiology equipment and the optical trackers then displays the results through a consumer-grade head-mounted display that allows the participants to perceive his/her true hand location in the virtual workspace.
The experimental protocol comprises three tasks: one to identify subject-specific brain signals, one to train the participant on the identified signals, and another to test the interaction of volitional brain signal control and motor performance. As of this writing, six participants have each completed at least one of the tasks.
The first task requires the participant to perform cued movements to virtual targets. We quickly calculate the brain signal features that best predict behavioural performance (i.e., reaction time, movement time, initial error). The most relevant features have been the beta power and the phase amplitude coupling (PAC) between the phase of the beta-band signal and the amplitude of the high-frequency signal.
In the second task, the magnitude of the brain signal features identified in task 1 are fed back to the participant as the colour of the effector in the virtual environment. The participant is instructed to change the colour to match the colour of the visual cue by imagining smooth movements for blue colour or parkinsonian movements for orange colour. To date, we have used beta power as the control signal and most participants are able to acquire significant control over BG beta power after 30-40 trials.
Finally, in the third task, the effector colour control task is embedded in the cued movement task. This experiment is underway.

Discussion: This work is still underway. Preliminary results indicate that patients with Parkinson's disease are able to acquire volitional control of disease-relevant brain signals. We are now working toward demonstrating that volitional modulation of these signals affect motor symptoms. The short amount of intraoperative training is unlikely to induce lasting changes in the BG-thalamus-cortex circuit but this work is a precursor to the development of closed-loop DBS devices that make available the ongoing basal ganglia activity for prolonged neurofeedback training.

Significance: This work will motivate the development of technology for a novel BCI-based therapeutic device for the treatment of Parkinson's disease.

Acknowledgment: This work is supported by grants from the Parkinson Research Consortium (PRC) of the University of Ottawa Brain and Mind Research Institute.

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Neural activity in a simultaneous BCI & manual task

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Introduction: The cortical signals most directly associated with movement are observed in the primary motor cortex contra-lateral to the limb. In patients with lateralized cortical stroke, however, these signals are often lost. Brain-computer interfaces (BCI) may still provide a route to regaining lost motor function after stroke if neural control signals can be extracted from spared cortex. The presence of cortical neurons encoding ipsilateral wrist motion suggests this is possible [1]. Such an interface, however, demands that neural activity responsible for control of the unaffected limb is dissociated from activity responsible for BCI control. To determine the ability of neurons in motor cortex to successfully dissociate their output, we designed a dual control task in which a monkey simultaneously controlled a BCI while performing a motor task with their contra-lateral hand. By simultaneously observing neurons not directly used as a brain-control signal, we investigate to what extent the dissociation between hand movement and neural activity occurs at the individual neuron level.

Material, Methods and Results: One macaque nemestrina monkey was trained to perform a random target-pursuit motor task [2]. He began each day by controlling the cursor with isometric wrist torque (manual control, MC), then progressed to using the aggregate neural activity of two single units to control a cursor moving orthogonal to the units' preferred direction (brain-control, BC). Subsequently, he used the same neural activity to control the BCI in one dimension, while simultaneously using isometric wrist torque of the contralateral forelimb to control the cursor in a second dimension (Fig 1A). Within the sequence of tasks (MC->BC->DC->MC), we tracked a population of single, isolated units. To identify preferred torque output, tuning angle and strength, a linear encoding model was fit to each neuron as a function of torque.

Compared to the manual control task, units change both tuning strength ($p < 0.001$, two sided t-test) and preferred direction ($p < 0.001$; Fig 1B) when performing the brain control task rotated by 90 degrees. During this brain control task, tuning direction of the units directly controlling the BCI changed more than units not involved in BCI control ($p = 0.008$). During dual control, however, preferred direction changed similarly for both types of neurons ($p = 0.699$; Fig 1C).

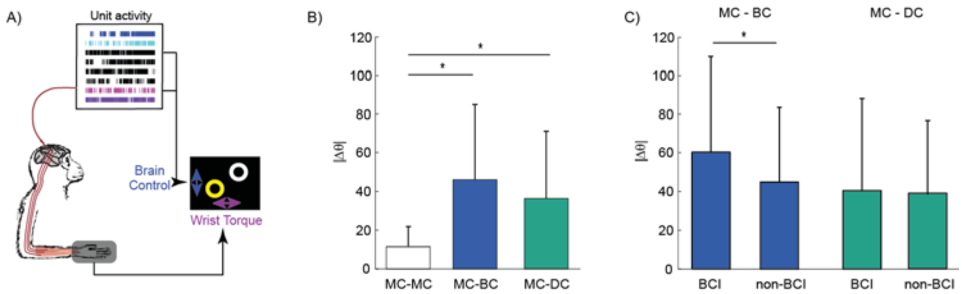

Figure 1 ***(A)*** *Dual control experimental setup.* ***(B)*** *Compared to the manual control task, the population of units changed their direction of tuning significantly during brain control (p << 0.001, t-test) and dual control (p << 0.001).* ***(C)*** *Units controlling the BCI change their preferred direction significantly more than non-BCI units during BC (p = 0.008). In the dual control task, however, BCI units did not change their preferred direction significantly more than non-BCI units (p = 0.699). All values are mean + standard deviation.*

Discussion: In both the brain control and dual control tasks we observe population-wide changes in tuning strength and angle. These population-wide changes may underlie the ability to select pairs of brain control neurons independent of their natural tuning properties [2]. Similar population-wide changes have been observed in brain control center out tasks [3]. The difference in BCI unit decoupling between brain and dual control (Fig 1C) may occur because the manual component of the dual control task constrains neural activity in such a way that the dissociation required of the dual control task can only be achieved at a population-level.

Significance: Our results describe how primary motor cortex accommodates a BCI task requiring explicit decoupling of neural activity from ongoing movement, as might be required for BCI use following stroke.

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Importance of the Window Size for Neurofeedback based on fMRI Functional Connectivity

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Introduction: Current researches suggest that fMRI-Neurofeedback can play an important role for therapeutic purposes, and first successful applications have been demonstrated (for a review see [1]). fMRI-based functional connectivity measures are neurofeedback candidates to treat pathological brain processes in psychiatric and neurological disorders. However, measuring dynamic changes in functional coupling using sliding-window correlation involves a trade-off between the window size, the neurofeedback time, and the reliability of the estimate. In order to investigate how the window size relates to (1) the estimation of correlation and (2) the differentiation between coupling strengths, we run several simulations with known coupling strengths and SNR.

Methods: We simulated neural activity using a simple vector autoregressive (VAR) model adapted from [2] with 7 nodes. To generate BOLD signal the VAR model output was convolved with hemodynamic response function generated using a difference-of-gamma approach. Data were simulated with a TR of 1s. First node drove activity in nodes 2 to 7 with a decreasing coupling strength. We simulated 1000 trials with 600 time points each. Five different levels of white noise were added to the data to obtain a SNR of 1, 2, 4, 6 and 10. Sliding-window correlation was measured with non-overlapping windows of 2 to 200s. We computed correlations between node 1 and each other node resulting in correlation of different strengths on average. (1) We studied the minimum window length for a correct estimation of the correlation strength by comparing the distribution of correlation obtained with the 200s window with the distribution of correlation obtained with all other window sizes. (2) We tested the ability to differentiate between correlation strengths for a given window size by classifying correlation values from two different coupling strengths with linear discriminant analysis and a 10-fold cross-validation. A classification accuracy of 70% was set as the minimum threshold to distinguish between two strengths.

Results: Distributions of correlation significantly differed (Kolmogorov-Smirnov test, $p<.05$) from the distribution of the 200s window correlation up to window of 150s (Fig. 1). The 70% threshold was passed with windows of 10, 8 or 6s, and a difference in mean correlation of 0.50 for SNR of 2, 4 and 6 respectively (Table 1).

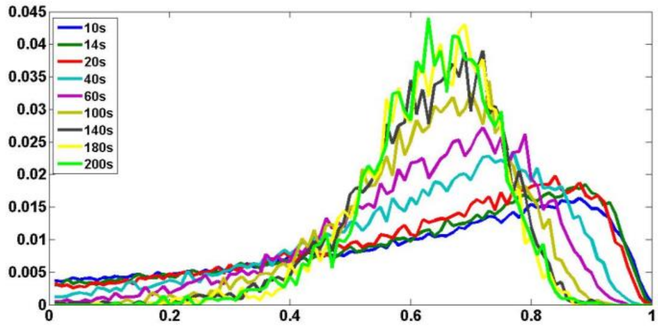

Figure 1. Probability density functions of the windowed correlation for a middle coupling strength (correlation between nodes 1 and 4).

1-2 vs.	1-3	1-5	1-7
8s	54	65	**74**
14s	55	**70**	**80**
20s	56	**73**	**83**
40s	59	**80**	**91**
100s	66	**91**	**97**
180s	**70**	**95**	**99**

Table 1. Classification accuracies (%) for classification of correlation values of nodes 1-2 vs. other correlations for different window sizes and SNR equals to 4.

Discussion: Our results show that small window can be used to distinguish between different correlation strengths and therefore can be used for neurofeedback. Accurate estimation of the correlation, however, requests much longer window. Several limitations should be noted, including the model used to simulate the data, and the 70% threshold to distinguish between coupling strengths. In the future, we will look at the influence of the TR and the effect of block design paradigms on correlation values.

Significance: Small window sizes can be used to compute correlation and to provide neurofeedback.

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A Quest for the Cortical Representation of Subjective Surprise With a Virtual Reality Neurofeedback Platform

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Introduction: It is well known that responses to external stimuli are context dependent [e.g. 1,2]. Specifically, when a rare event occurs, it elicits the P300 event-related potential (ERP), while when a stimulus repeats itself responses are attenuated. Context dependency can be modelled by conditional probabilities of future events. Arguably, these are the measures that give rise to the experience of expectation and surprise. These expectations, or conditional probabilities, should depend on both the memory capacity of subjects and on their goals. Using the Information Bottleneck method developed by Tishby et al. [3], a trial-by-trial subjective surprise signal can be calculated, taking into account the subject's memory resources and goals. This calculated surprise signal can then be tested against physiological data.

Methods and Results: We examine the above hypotheses in the framework of an auditory oddball experiment. Our preliminary results indicate a correlation between the trial-by-trial measure of subjective surprise and an EEG metric based on the P300 component. Moreover, a platform we developed (see Fig. 1) containing a virtual reality game combined with EEG measurements, allows us to have an ERP-based neurofeedback (NF) in which the subject is getting feedback within the game on his current surprise-related EEG feature.

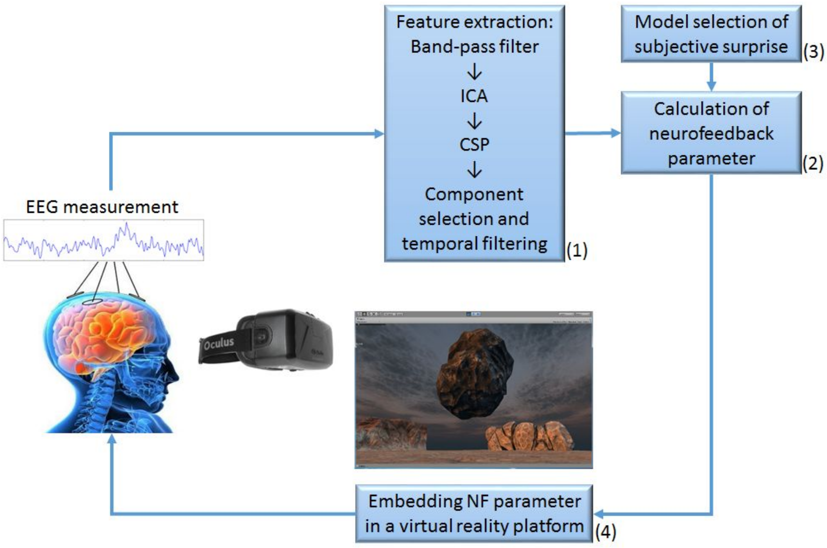

Figure 1. *An ERP-based neurofeedback platform, composed of (1) a feature extraction step of spatial and temporal filtering, (2,3) calculating the NF parameter using the extracted feature and a pre-selected subjective surprise model parameters, and closing the NF loop with (4) a virtual-reality game, which the subject controls by manipulating the chosen EEG feature.*

Significance: Our feature extraction method combined with our NF platform has several theoretical and practical advantages, compared to conventional procedures. This unique combination enables better assessment of the feature extraction process on one hand, and on the other hand it opens the path for better targeted and more engaging neurofeedback procedures.

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Why and How to Use Intelligent Tutoring Systems to Adapt MI-BCI Training to Each User.

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Introduction: While Mental Imagery based BCIs (MI-BCIs) are promising for many applications, their usability "out-of-the-lab" has been questioned due to their lack of reliability: literature reports that 15% to 30% of users cannot control such a technology, while most of the remaining users obtain only modest performances [1]. Standard MI-BCI training protocols have been suggested to be partly responsible for these modest performances as they do not comply with general human learning principles [2]. The modest performances as well as the flaws in the protocols led to the investigation of solutions to improve MI-BCI training by adapting it to each user. Such an approach is possible using Intelligent Tutoring Systems (ITS), i.e., computerised systems aiming at supporting learning [3]. Hence, we show **why** ITS are relevant for MI-BCI training and **how** this technology could be used.

Why? – MI-BCI training resembles *distance learning* (DL) as it is performed autonomously, with neither teacher nor classmates. Consistently with DL literature, highly anxious and poorly autonomous learners have been shown to struggle with MI-BCI training [5]. Since ITS have been proven efficient for improving DL [3], MI-BCI training may also benefit from ITS. The strength of ITS lies in (1) a personalised support provided by a learning companion [3] and (2) an adaptation of the training process according to the learner's profile and skill evolution.

How? - We are proposing the conceptual framework for an ITS which would support MI-BCI user-training. ITS comprise 4 modules. First, the *Student Model* is the core component containing information about the user's personality and cognitive profile and state. Second, the *Expert module* contains the concepts, rules and strategies of the field to be learned. Third, the *Tutoring module* uses input from the two previous modules to select a tutoring strategy, and finally the *Interface* provides the user with access to the learning environment. Each module will be described in an MI-BCI training context (see Fig.1). The *Student Model* contains 2 kinds of information: 1) the user-profile, as assessed by questionnaires, and more specifically spatial abilities and personality traits (e.g., abstractness, tension or autonomy), which have been shown to be related to MI-BCI performance [4]; and 2), the user's cognitive state, e.g., fatigue and workload levels and MI-BCI skill development, provided by the BCI system through classification-accuracy measures. The *Expert module* contains a cognitive model of the skills to be learned, e.g., the ability to generate stable and distinct brain-activity patterns while performing the MI-tasks. It also includes a bank of exercises with different levels of difficulty [6], which would help the user to acquire these skills. Based on the *Student Model* and on the *Expert module*, and using specialised algorithms [3], the *Tutor* selects the appropriate exercises and provides the users with a suitable support, i.e., adapted to their performance and profile. This support will be provided using a physical learning companion [3], which has been proven to increase motivation and learning [3]. In particular, this companion will provide any users who have high tension and low autonomy levels [4] with a social presence and an emotional support (e.g., empathy). We are currently designing and evaluating the content of these different modules.

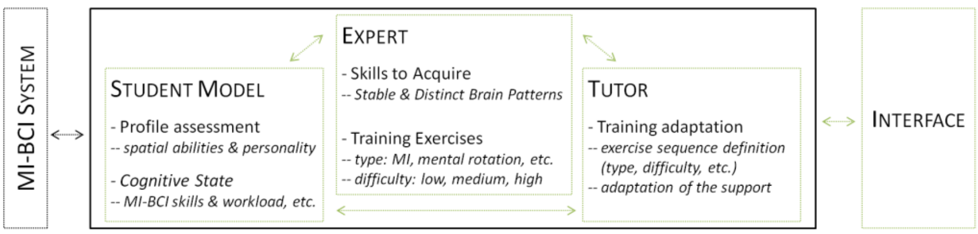

Figure 1. *Diagram representing the conceptual architecture of an ITS supporting MI-BCI training.*

Discussion: ITS may be very useful for MI-BCI user training, especially if the *Student Model* and *Expert module* are reinforced. The former could include more detail on the user's profile and cognitive state, while the latter could be improved by a better fundamental understanding of MI-BCI related skills and how they are acquired.

Significance: Such an ITS represents a promising pluridisciplinary approach for improving MI-BCI performance as it would enable to gather different levers and articulate them in order to optimise the user-training process.

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Controlling Gestures of a Social Robot in a Brain Machine Interface Platform

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Introduction: Neural-based robotic platforms have become increasingly attractive option as a mean of direct communication between the brain and environment without any further physical contact. The information extracted from the brain signals will determine the degree and level of control in robot control tasks. Brain-robot interaction capability has shown great promise in development of forward control compatible with a patient's intentions and in cognitive training or rehabilitation using neurofeedback approach. Here, we propose a novel Brain Machine Interface (BMI) robotic platform using a personalized social robot in order to assist human participants during mind training. Brainwaves of a human participant were collected in a noninvasive-based BCI system during tasks of imaginary movements. The imagined body kinematics parameters were decoded to control a cursor on a computer screen during a fast training protocol (~ 10 minutes) and then the trained subject was allowed to interact with a social robot in our real-time BMI robotic platform. This wireless interaction not only can be useful for mind control of social robot's movements, but also could set foundations for the next stage application in rehabilitation of the cognitive abilities such as enhancing attention and memory of individuals with brain injury by providing real-time neurofeedback from social robot.

Material, Methods and Results: During a fast training protocol, EEG signals were acquired by using an Emotiv EPOC device with 14 channels and through BCI2000 software (with high pass filter at 0.1Hz and low pass filter at 30Hz). By engaging the subject in our three-phase protocol including training, calibration, and test, the subject could achieve satisfactory control of a computer cursor after a short-time of training and based on imagined body kinematics paradigm. Then, the trained subject was allowed to make interaction with our BMI robotic platform to control the various gestures of a social robot in real-time course. As robotic interface, an affordable social robot called "Rapiro" was employed to provide neurofeedback to the subject. Simulink program was applied as interface software and was responsible to map the control signals (from BCI2000) to the correct pre-defined gesture in Rapiro. Figure 1 shows one example of real-time reactions of robot during mind-control of cursor in 2D space by a human subject.

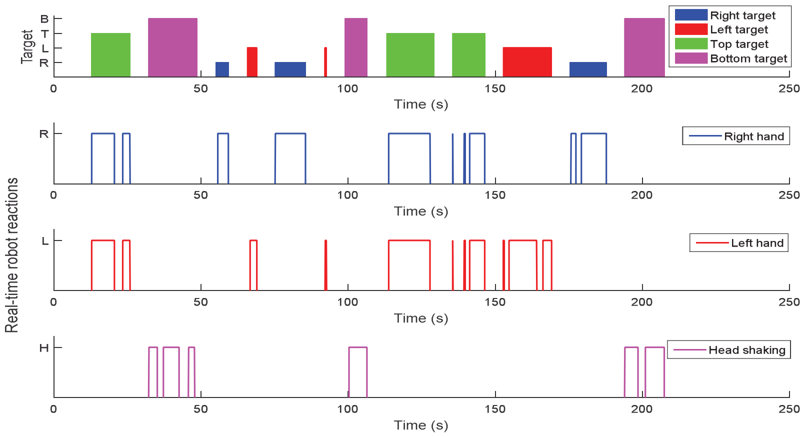

Figure 1. *Mind controlled robot gestures (Right hand movement/left hand movement/both hands movement/head shaking) in real time. The figure illustrates cursor control task performance in 2D space during 12 trialsof a trained human subject. The mirrored robot movements served as simultaneous neurofeedback to the subject. It was programmed as such that the right target control activated the right hand movement; the left target control activated the left hand movement; the top target control lead to both hands movements and the bottom target control caused head shaking neurofeedback from the robot.*

Discussion: As it is shown in Figure 1, a human subject was able to activate the correct gesture in social robot and achieved satisfactory performance. As the result of guiding cursor in wrong direction by the subject in some moments of inter-trial times, some discontinuities were observed in activating of robot neurofeedback.

Significance: Several BMI platforms have been developed for patients with motor disorders during recover of the cortical plasticity underlying movements. However, limited research has applied robot as neurofeedback back to the human. Hence we offered a novel BCI robotic platform with possible future application for neurorehabilitation in patients with cognitive or mental disorders such as attention deficits. The presented BMI system using human-robot interaction can be further developed as a portable, wireless, and affordable platform to be used by patients.

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Adaptive Interactive Learning for Training BCI Systems

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Introduction: A usual set of instructions for a test subject participating in an imagery-based BCI experiment would ask to think *left* when the arrow on the screen points to the left and to think *right* when the arrow is pointing to the right. A very common question a BCI experimenter could hear from a test subject at this point is "How should I think?" Indeed the request to think *left* is quite ambiguous. Should the test subject imagine an arrow in his mind, concentrate on the abstract notion of "left", engage in imagery motor activity or just think about an unrelated concept? The answer to this question is user-specific and thus it is required to run a separate experiment to find a mental action the user should evoke when cued with the "left" stimulus. In this work, we improve the training process of an imagery-based BCI system by introducing an interactive component, which facilitates a "dialog" between the underlying learning algorithm and the test subject. The method described in this work employs self-organizing map (SOM) [1] to project brain signal representation from the high-dimensional feature space into 2D space, allowing the test subject to visually explore the space of his mental states and observe the relative effect of the mental actions he evokes. Via the interaction with the system user can search for the mental actions he can evoke consistently and which are distinguishable by the classification algorithm. Once a set of such mental actions is found, it can be used in a real-time BCI system.

Materials, Methods and Results: In our approach we rely on an extension to SOM, which we refer to as *Predictive SOM*. Predictive SOM is built in the same way as the usual SOM, but each unit u of the map has an additional vector $\mathbf{p}(u) \in \mathrm{R}^a$ where a is the number of stimuli. This vector holds stimlus probability distribution for the unit u: it shows what is the probability that a signal $\mathbf{x}$, which was classified into unit u, has been produced in response to the stimulus a. This mechanism allows SOM to act as an online classifier, which outputs predictions for each new data sample and then updates the model (thus *adaptive*). An important property of SOM is that it attempts to preserve topology of the data: samples (EEG signals in our case) which where close in the original high-dimensional Fourier space will also be close in the 2D space after the projection to the map. The projected signal is shown to the user on the screen (this *interactive*) and reflects in real time how user's mental actions affect the internal signal representations the system has.

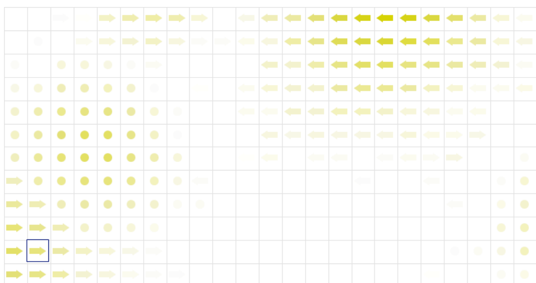

Figure 1. *2D visualization of the signal space insead of the usual stimulus screen. The map changes in real time as new brain signals arrive. Icons represent mental actions associated with the units on the grid. Highlighed cell shows to the user where the signal he is currently producing ends up on the map of internal representations.*

The prototype system was tested using Emotiv EPOC. We are currently in the stage of conducting experiments with a proper EEG device (BioSemi ActiveTwo) and larger number of test subjects. The proposed method is compared to the baseline with the classical way of presenting the stimulus with real-time feedback. The results on the prototype system with 5 test subjects show an increase of accuracy by 0.07 on a mental activity task with 3 classes (left, neutral, right).

Discussion: Although the current work focuses on a particular type of BCI systems, the concept can be applied to a wider range of human-computer interaction tasks. In this work we show how the method is used to find the set of mental actions that would be suitable for a BCI system, however one can imagine employing the same investigative paradigm to explore the mental state space of a test subject in less restricted regime, where there is no fixed goal. This might turn out to be useful in psychological studies and also could be intersting to the general audience as it provides a peak into relative organization of their mental state space.

Significance: The article proposes a novel way of interaction between the learning system and BCI user and demonstrates the advantages of the proposed approach.

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Controlling UAVs with a SSVEP-Based BCI

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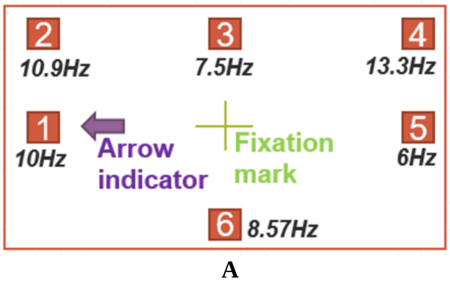
Introduction: The rapid advancement of technology and innovative multi-disciplinary approaches allows the freedom to use BCIs for a wide range of medical, commercial, military and even entertainment applications. Our focus is to design and implement a non-invasive BCI based on Steady State Visual Evoked Potentials (SSVEP) for controlling Quad-copters based on Electroencephalography (EEG) signals. Unlike motor imagery-based BCIs, SSVEP does not require training. This SSVEP approach has demonstrated to be robust and efficient for BCI control.

Material, Methods and Results: An SSVEP presentation program was developed to present participants with 6 3x3cm flickering visual stimulus changing color from white to black. Flickering frequencies and position arrangements are presented on Figure 1A. EEG recordings are acquired at a 256Hz sampling rate using the BioSemi Active Two system and 12 electrodes located at Pz, POz, PO3, PO4, Oz, O1, O2, P3, P4, PO7, and PO8 on the 10/20 international system. A quick pre-processing is then applied consisting of a 1 – 40Hz band-pass filter, a digital re-referencing to averaged mastoids, and a single-epoch baseline removal where multiple epoch lengths from 2.0 to 5.0 seconds were investigated. Canonical Correlation Analysis (CCA) is used for SSVEP frequency detection. An experiment was conducted to measure the robustness of detection performance of the SSVEP frequencies. 36 individuals (25 male) ranging from 18 to 45 years old participated in the experiment that requires them to look at each flickers clockwise for periods of 7 seconds. An approximate 90% accuracy was obtained across all frequencies. Frequencies encode commands which are send to a ROS system on the same network using the lab streaming library as presented on Figure 1B. Available commands are move up, move down, move forward, move back, move left, and move right. When using multiple quad-copters up/down movement is replaced by the scatter and gather commands.



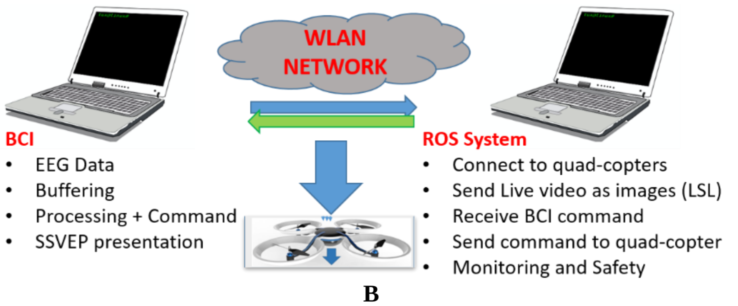


Figure 1. ***A)*** *Frequency and position of 6 flickering visual stimulus on the SSVEP presentation program.* ***B.)*** *Diagram of BCI implementation to control a quad-copter. All 3 devices share a WLAN network. Lab streaming layer is used for messaging and data transfer.*

Discussion: We proposed a novel SSVEP-based UAV control system. SSVEP flickering detection is based on the CCA approaches. The test results demonstrated fair accuracy and high robustness across multiple participants. It is required to correctly calibrate monitor position and distance if the participant is visually impaired. Flickering observations should be a natural gaze, rather than an intense focus to prevent visual fatigue during prolonged use.

Significance: This BCI offers great flexibility to add more commands easily. Patrolling, surveillance and complex tasks distributed across multiple quad-copters are being adapted to be integrated on this BCI. The system has a high-speed deployment: after connection and quick checking the BCI can be used immediately without training. The implementation of a quad-copter and web-cam video feedback system is an innovative feature that enhances the practical application of this BCI.

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Emotion Imagery BCI

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Introduction: A non-negligible portion subjects has been shown to be unable to learn how to control a motor imagery (MI) based brain-computer interface (BCI), within a limited duration of training. There is a need for alternative imagery strategies for such users. In this study, imagery of self-induced emotion states were explored as an alternative to MI, using a standard motor imagery BCI paradigm and setup. Electroencephalogram (EEG) correlates of self-induced emotions have been previously used to recognize emotions, as in [1], and here, we hypothesize that emotion imagery (EI) can be used to modulate brain activity and used as a BCI control strategy. Preliminary results comparing the performance of three subjects (N=3, age range = 27-35) performing MI and EI are presented.

Material and Methods: EEG was sampled at 125 Hz from 16 channels across the cortex using the g®.Nautilus setup. Each subject underwent training with no feedback and feedback in a single session for both EI and MI in a typical MI timing paradigm, and feedback was provided using a game in which the character moved along the horizontal axis to complete the game challenge. One training run and one feedback run were performed for each imagery. In EI runs, participants recalled a real or imagined fictitious happy event and sad event for each class (left or right cue). For MI runs, participants were instructed to imagine left or right hand movement. Each run had 60 trials, 30 for each class.

After the first run of both EI and MI, leave-one-out cross validation (LOOCV) was conducted with a multistage signal processing framework which includes neural-time-series-prediction-preprocessing (NTSPP), spectral filtering (SF) in subject specific frequency bands and common spatial patterns (CSP) [2]. Features were extracted as log-variance of preprocessed EEG signals within a 2 second sliding window [3]. A linear discriminant analysis (LDA) classifier was then trained and applied in the feedback run.

Results: Offline LOOCV classifications accuracies (CA) for each run along with online single-trial CA results for run 2 and sample results from event-related (de)synchronization (ERD/S) analysis are reported (Table and Figure 1). The differences between EI and MI are not statistically significant (p>0.05) although the EI training results appear higher for all subjects. ERD/S analysis showed EI tasks separability in the temporal and frontal channels; visual separability happen after the cue (3 s). Most of the ERD or ERS appeared in the occipital and parietal electrodes; this can be seen on some of the topographic maps for subject 3 shown in Figure 1.

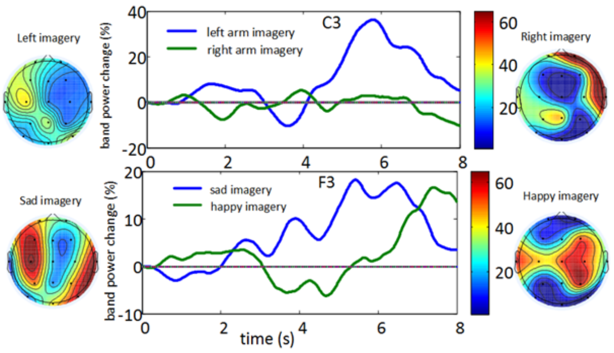

Table 1. *The frequency band [Hz] and classification accuracy for feedback (FB) and without feedback (noFB) runs. The feedback runs for subject 1 did not follow the study setup (used a 3-channel setup)*

Sub	EI noFB	EI-FB	MI noFB	MI-FB	Online EI	Online MI
1	[8-15] 80%	---	[8-15] 76.6%	---	--	--
2	[8-19] 78%	[10-16] 71.6%	[8-15] 76.6%	[12-17] 70%	57%	81%
3	[9-17] 81.6%	[8-12] 80%	[8-15] 76%	[9-14] 86.6%	67%	61%

Figure 1. *Band power change (%) respective to the baseline in feedback MI and EI runs for subject 3 in the bands [9-14] and [8-12] Hz is shown for two channels (C3 for MI and F3 for EI). Activity in other channels can be seen in the shown topographic maps for [4-6] s interval.*

Discussion: These preliminary results show that EI can be used in the same way as MI; Wilcoxon signed rank tests showed no significant difference in MI and EI. However, more analysis needs to be carried out with a larger sample of participants and multiple training sessions. The subject “2” is an experienced/expert MI participant and performed well in online CA of MI but had poor performance in EI. Subject “3” on the other hand, the online EI performance is slightly higher than MI.

Significance: The results show for the first time that emotional imagery may be used as a replacement to motor imagery. Further validation is required to determine if emotion imagery could be used by BCI users who do not perform well with motor imagery.

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Enhanced modulation of working memory activity through fMRI neurofeedback

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Introduction: BCI paradigms often rely on the ability to modulate brain activity between active and resting states. Improving the ability to shift between these states will provide better BCI control. We tested the hypothesis that it is possible to improve the shift between rest and performance in working memory (WM) through neurofeedback. Neurofeedback was given on the left dorsolateral prefrontal cortex (DLPFC), an important brain region for WM that has been shown to be a reliable brain region for BCI control [1, 2, 3].

Material, Methods and Results: 24 healthy volunteers participated in a 7 tesla real-time fMRI experiment (2D EPI, TR/TE: 2.0 s/25 ms; 2.2 mm isotropic). Participants performed a neurofeedback task, where they were required to move an animated figure up and down a ladder to pick apples. The position of the figure was controlled by performing a 'count back' paradigm that activated the left DLPFC. The goal of the task was to pick as many apples as possible in five periods of 2.5 minutes. An experimental group (N=13) was allowed to practice the neurofeedback task during five practice periods of 2.5 minutes. A control group (N=11) participated in an identical experiment, except that they received sham feedback during the five practice periods. In both groups the performance on the neurofeedback task (with actual feedback) was measured before and after the five practice periods, as well as the effect of neurofeedback on the overshoot, undershoot and slopes of the BOLD signal in a number of subjects.

The improvement in task performance after practice was significantly higher in the experimental group than in the control group ($p = .040$; see figure 1). The improvement in task performance in the experimental group could predominantly be attributed to the improved ability to decrease the BOLD after practice ($p = .016$). The control group did not show this improvement.

Discussion: Our results indicate the possibility to improve control over DLPFC activity using neurofeedback after a short amount of training. Analysis of the BOLD signal indicates that in particular the ability to switch form high to low activity in the DLPFC can benefit from neurofeedback. This enhanced ability can improve control of a BCI that uses activation and deactivation of DLPFC for triggers.

Significance: Our research shows that it is possible to improve the ability to modulate brain activity in the left DLPFC practice through neurofeedback, mainly due to improved ability to reduce activation. This improvement can increase performance of a WM-BCI which uses a resting state - active state paradigm for BCI control.

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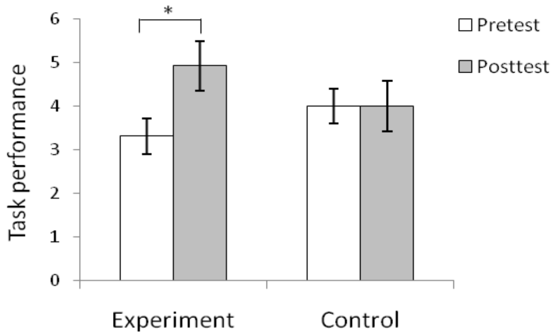

Figure 1. Behavioral results on the neurofeedback task before and after practice.

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fMRI informed EEG Neurofeedback from the IFG

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Introduction: The Right Inferior Frontal gyrus (rIFG); has a pivotal role in attention deficit disorders [1], hence gaining control over its activity could facilitate better treatment and recovery. Learning to volitionally regulate IFG activity was thus far possible only via real-time fMRI. In the present study a novel fMRI enriched EEG model (herby, "EEG-Finger-Print") of the rIFG, was developed to enable the prediction of its fMRI-BOLD activity using only EEG. Simultaneous EEG/fMRI neurofeedback (NF) was conducted in the current study to test whether the rIFG-EFG reliably predicts IFG fMRI-BOLD activity and can be used by subjects to regulate IFG activity.

Methods: A model of the rIFG activity was constructed using simultaneous EEG/fMRI data from 10 subjects from a different study [2, 3] based on a previously described method [4] using EEG data extracted from electrode F8. The resulting estimated model correlates well with the rIFG BOLD activity ($r=0.6$, $p<0.5$). 14 healthy subjects performed rIFG EEG-NF training simultaneously with fMRI acquisition in the scanner. The training included two test runs and one sham run. The EFP-NF training was implemented as a game where a skateboard rider and speedometer above the riders head were displayed on the screen. The game included 5 blocks of three conditions: 1.'Rest' condition (60 seconds), subjects instructed to passively view the skateboard rider which was moving at a constant speed; 2. 'Play' condition (60 seconds), the speed represented the corresponding level of EEG-EFP activity. Subjects were instructed to increase the speed of the skateboard as much as possible by practicing mental strategies of their choosing; 3. At the end of each NF block a bar indicating the average speed during the current block was presented. In the EFP-Sham runs subjects had the same instructions but received visual feedback driven by their rIFG-EFP signal from a previous EFP-NF run that was randomly assigned.

Results: Success rate index, which represents the percentage of the time in which the mean EFP value was significantly higher than mean baseline value, during all runs was defined. As expected this index was significantly positive (one sample T-test, $t(26)=18.92$, $p<0.001$; Mean=66.59 ± 18.29). The whole-brain random-effects (RFX-GLM) analysis using rIFP-EEG signal as a regressor, revealed correlation with the right IFG-BOLD activity with full respect to the region originally used to develop the model ($p<0.017$, FDR $p<0.1$, $n=11$). Block design whole brain (RFX-GLM) group analysis overall NF runs vs baseline ($n=14$ subject; 27 NF runs) revealed significant BOLD activations in the rIFG that was originally used to develop the model within a network of functionally relevant areas. Analysis of weighted beta values extracted from rIFG-EFP during NF relative to baseline indicated that, as hypothesized, the EFP-NF runs responded differently from the EFP-Sham runs. Paired samples T-test revealed a significant difference between EFP-NF (NF=0.73 ± 0.45, $n=10$) and EFP-Sham (Sham=0.43 ± 0.37, $n=10$); ($t(9)=2.46$, $p<0.03$). In order to evaluate the neural impact of successful rIFG-EFP modulation, different patterns of brain activations between successful and unsuccessful runs will be explored.

Discussion: The results obtained by the simultaneous recording of EEG and fMRI show that the rIFG-EFP model reliably predicts fMRI-BOLD activity in the rIFG ROI, for which it was originally developed. Remarkably the rIFG-EFP NF training elicited distributed activation in the rIFG ROI that was used to develop the model. Additionally, as evidenced by the results, subjects managed to up-regulate the activation in the rIFG during neurofeedback relative to baseline significantly higher during rIFG-EFP-NF runs compared to rIFG-EFP-Sham runs.

Significance: The current work demonstrated the potential of the EFP imaging approach to enhance the spatial resolution of EEG alone and to be used as a monitor for specific regional activation. Furthermore, our results suggest that implementing the EFP approach in NF training could be used by subjects to facilitate up-regulation of rIFG activity without the use of fMRI.

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Improving Memory Performance Using a Wearable BCI

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Introduction: Human ability to encode and memorize information fluctuates from moment to moment. Several studies have reported differences in electroencephalography (EEG) signals recorded during memorization of items that were forgotten at a later point of time compared to those that were remembered [1,2,3]. Given these observations the question then arises whether or not a wearable BCI system can be designed to identify poorly encoded items. Such a device could be used to provide feedback to the user so as to improve the memory encoding process. This paper reports on an experimental study designed to assess this possibility.

Material, Methods and Results: 14 healthy individuals participated in this study. The experiment paradigm consisted of an encoding phase followed by a recognition phase. In the encoding phase, 120 words were presented to the participants for memorizing in two blocks. The presentation of each word lasted for 2 s followed by a 0.5 s inter-trial stimulus. In the recognition phase, 240 words including the 120 words previously learned in the encoding phase were randomly displayed to the participants. The participants were asked to identify whether or not they had seen each word during the encoding phase, and how confident they were in their given answer.
EEG was recorded during the encoding phase using a wireless Emotiv EPOC headset with 14 electrodes (i.e. F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1, O2) and 2 mastoid reference electrodes. The EEG signals were band-pass filtered (i.e 0.01-35 Hz), segmented and baseline corrected. Automatic artifact rejection was applied.
Our experimental results revealed that our participants successfully remembered on average 72% of the presented words in the recognition phase. Corroborating previous studies [1,2,3], averaging over multiple EEG trials of the encoding phase suggest that the power of the pre-stimulus theta and beta and the power of alpha after the onset of the words over the parietal/occipital electrodes could be potentially useful as features for identifying poorly versus well encoded words. Moreover, signal amplitudes from 1.5 to 2s after the onset of the words in the parietal/occipital electrodes were significantly different between the two conditions (see Fig. 1).

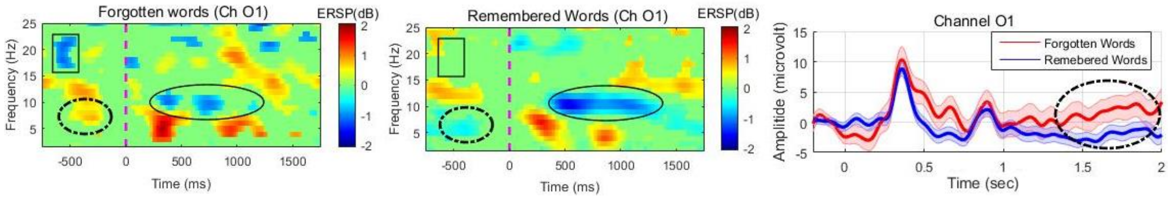

Figure 1. *Time-frquency and ERP plots of the encoding phase from 14 subjects at O1. The elipses and squares denote the significantly different regions across the forgotten and remebered words (p<0.05). The dashed purple lines denote the onset of the words.*

To evaluate the discriminability of these features on a single-trial basis, the trials of each subject were sorted based on the magnitude of each feature. Thereafter, the number of forgotten and remembered words were counted in the 6 and 12 trials (i.e. 5% and 10% of the set size) with the highest and lowest magnitudes. Among the different features evaluated, the power of pre-stimulus theta (i.e. -0.5 s to 0) over the occipital electrodes was the most successful in discriminating between the forgotten and remembered words. As an example, in the 6 and 12 words with the highest (lowest) pre-stimulus theta at O1, on average 44% and 36% (14% and 22%) were forgotten respectively. In contrast, if the same number of words were randomly selected, on average 28% of them were forgotten. Interestingly, paired t-tests showed that in the 6 words with either the highest or the lowest pre-stimulus theta power and the 12 words with the highest pre-stimulus theta power, the number of forgotten words was significantly different from chance level (P<0.05).

Discussion: Our preliminary results suggest that it is possible to design a wearable BCI system for improving memory. Currently, reliable prediction relies upon a number of trials (i.e. those with the highest or lowest pre-stimulus theta power). We aim to improve upon this through more sophisticated feature selection procedures and spatial filters. Moreover we will explore features discriminative of subject confidence in recalling items.

Significance: Our study can potentially lead to practical, wearable BCIs which can help users learn more effectively and efficiently through presenting items to be encoded during times of optimal cognitive capacity and by repeating stimuli that have been predicted most likely to be forgotten.

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Improving Motor Imagination with Support of Real-Time LORETA Neurofeedback

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Introduction: Recording cortical activity during imagined leg movement is a challenging task due to cortical representation of legs deeper within the central sulcus. Therefore Brain Computer Interface (BCI) studies typically rely on imagined movement of both legs [1]. Activity of deeper cortical structures can be estimated off-line from multichannel Electroencephalography (EEG) by using LORETA numerical method [2]. LORETA can also be calculated in real time to provide an instantaneous estimate of brain activity, but currently available solution supports only up to 19 channels (BrainAvatar, BrainMaster, Inc). In this study we propose a custom designed real time LORETA neurofeedback based on multichannel EEG to increase cortical activity at the central sulcus during continuous imagining tapping with one leg only. This strategy could be useful in neurorehabilitation of hemiplegia (i.e. stroke).

Material, Methods and Results: EEG data was recorded using usbamp device (Guger technologies, Austria), from 44 channels covering the whole cortex (sample rate 128Hz, linked ear reference, impedance under 5 KΩ). EEG was collected in Simulink/Matlab (Mathworks, USA) in 1s non overlapping windows and data were saved in *.txt file. Data was then sent to LORETA via custom designed software application written in C#. In LORETA data were extracted from a pre-defined Brodmann area and visualised through a custom made GUI (designed in C#) in a form of a bar chart, shown to a participant with a total delay of 1.25s. Two naive healthy participants took part in this pilot study (age =35±5). EEG was recorded during a baseline session, imagined right leg tapping without feedback, real tapping and 8 neurofeedback runs, lasting 2 min each. During neurofeedback participants received a visual feedback from left BA4 and 6 in 8-15Hz band. To remove noise off-line, EEG was exported to EEGLAB where it was epoched into 4 seconds, cleaned from artefacts using Independent component analysis and re-referenced to an average reference. EEG was then analysed off-line using sLORETA.

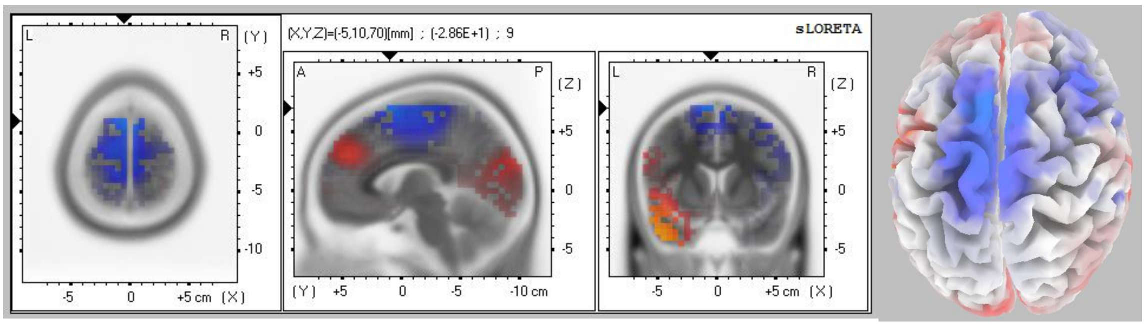

Figure 1. *Regions of most significantly increased activity (blue) between the first and last session of neurofeedback in 8-15Hz band.*

Both participants significantly increased cortical activity from 1st to 8th run. Figure 1 shows statistically significant difference between first and last run at the left cortex. Figure to the right is a top view showing cortical activity lateralized to the left (sensory-motor cortex of the right leg).

Discussion: We have demonstrated novel software application for providing multichannel neurofeedback that can be used to selectively activate deeper cortical structures, while participants imagined tapping with right leg only.

Significance: Selective unilateral enhancement of cortical activity can be useful for neurological recovery after stroke. This can be used as an inexpensive alternative to real-time fMRI neurofeedback training.

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My Virtual Dream: Brain Computer Interface in an Immersive Art Environment

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Introduction: Most of the Brain Computer Interface (BCI) experiments are performed in the controlled laboratory environment with the high number of repetitions, known as training. However, living in the world full of chaos will never allow us to achieve same classification accuracy when performed outside the lab environment with no to minimal amount of training. This motivates a question '**How to implement BCI technologies in open-environment but at the same time retaining the similar amount of accuracy as in controlled environment?**'. My Virtual Dream (MVD) [1], a step to answer this question and making BCIs publicly available. Powered by The Virtual Brain [2], MVD is science and art installation that allows general public to learn about their brains by providing them audio-visual neurofeedback.

Materials, Methods and Results: Total 64 subjects participated in a public event that took place in the Irvine University in October 2015. The complete experiment consisted of 16 sessions. In each session, 4 volunteers interacted simultaneously with a passive-BCI that measures two cognitive states: relaxation and focus. The electrophysiological activity was recorded by placing an Emotiv EEG headset (14 sensors, 128 Hz of sampling rate) on each participant. Only 5 channels were used in this experiment: AF3, P7, P8, O1 and O2.

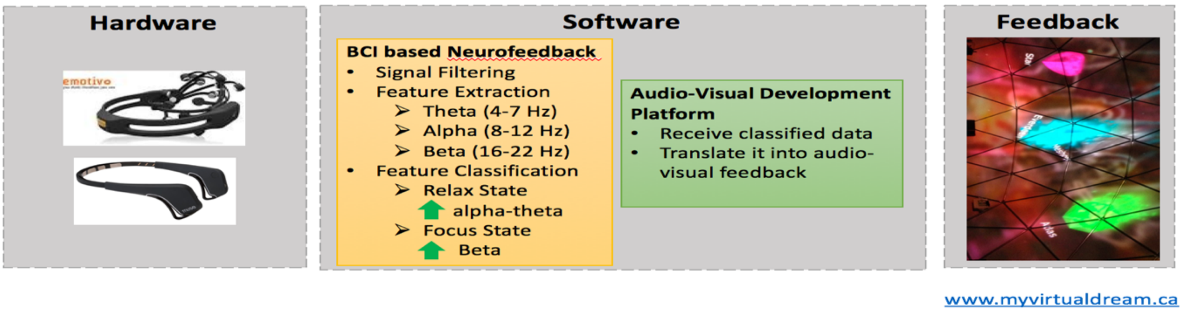

Figure 1 *Flow of data in MVD: EEG signals acquired from headsets (hardware) are further pre-processed to extract important features (software) and changes in these features are represented as a audio-visual symbols (feedback)*

The cognitive features were calculated according to the relative increments in power in three bands: theta (4-7Hz), alpha (8-12 Hz) and beta (16-22 Hz). Channels with ocular or motion artifacts were detected and excluded from the analysis. The audio-visual feedback consisted of a projected scene with four avatars, each one controlled by one participant. The size, glow, colors and positions of these avatars represent the states that the BCI calculates for each subject. At the same time, the users' scores control the music layers and several visual elements projected into the scene, creating in this way a unique artistic representation with several auditory and visual stimuli.

Discussion: Our survey results show that majority of our participants (73%) reported good control over their avatar. This, as a first step, suggests that BCI technologies can be implemented and tested in the real world environment with minimal amount of training. Further analysis will be performed on the participants' EEG data and neurofeedback scores to reveal other interesting effects.

Significance: MVD is a step towards encouraging BCI researchers to implement and test BCI paradigms in real world scenarios. Thus, allowing us to conclude the performance of core BCI components, such as artefact rejection, signal processing and classification algorithms that might have high accuracies even under the effects of surrounding stimuli. At the same time, providing neurofeedback with artistic visuals and musical tones makes MVD a perfect platform to study the effects of artistic beauty on the human brain [3]. Thus, we expect that MVD will not only be able to increase the performance of real time BCI but also enhance our knowledge about the field of neuroaesthetics.

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Neurophysiological correlates of mind-wandering, towards a predictive BCI-based Neurofeedback

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Introduction: A brain computer interface (BCI) able to predict the disengagement of attention, e.g. mind-wandering episodes, regardless of the task being performed bears useful applications. Converging neuroscientific evidence has determined that our ability to remain attentive to a task, over a prolonged period of time, is subject to strong fluctuations. Recent electroencephalography (EEG) studies have identified neurophysiological signals reflecting inadequate task engagement preceding attentional lapses, in particular modulation of P300 amplitude and α-activity [1, 2, 3]. The present study investigated the evolution of neurophysiological signals preceding the report of 5 different levels of attention, from on-task to mind-wandering without awareness, during a breath-counting task and a sustained attention to response task (SART, [4]).

Material and Methods: Twenty-six healthy subjects (12 female; 23.4 ± 3.2 years) performed two tasks, a breath-counting task and a fixed version of the SART. The former asked participant to fixate a cross, count each breath from 1 to 9 and press the left mouse button for the first eight counts and the right mouse button for the final count before starting anew. The SART presented subjects with numbers from 1 to 9 subsequently and participants were required to respond with a button press to each number except the target (here number 6). Subjects were instructed to monitor their attention and interrupt the task if they noticed their thoughts stray from the task. Thought probes also interrupted the task at pseudo-random times. The probes presented subjects with a 5-step scale to categorize their level of attention/mind-wandering just prior to the interruption, (1) on-task (no mind-wandering), (2) on thoughts pertaining to the task, (3) distracted by internal sensations or external distractions, (4) on reminiscing or planning thoughts, (5) daydreaming (mind-wandering without awareness).

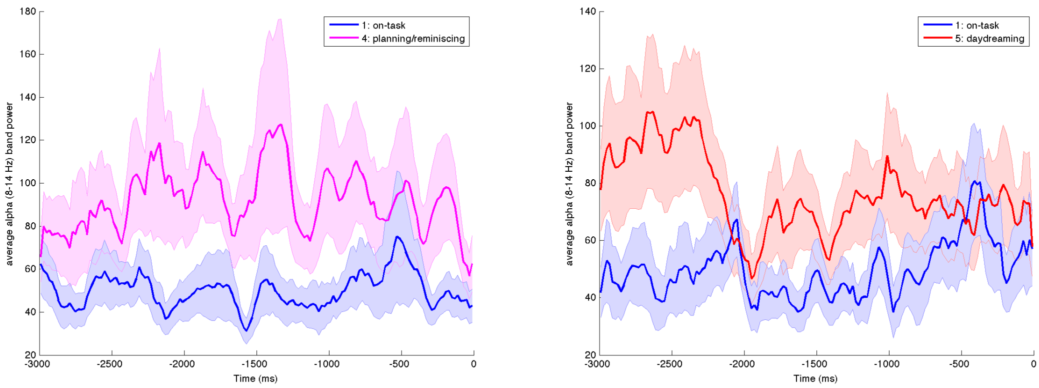

Figure 1. *Smoothed average **α** band power measured over channel POz for all participants with standard errors of the mean. Left; the average **α** band power for the 3000ms period prior to the on-task (blue) and planning/reminiscing (magenta) reports during the breath counting task. Right; the average **α** band power for the 3500ms period prior to the on-task (blue) and daydreaming (red) reports during the SART (the sudden desynchronisation at around -1900ms is the result of the appearance of the SART stimulus).*

Preliminary results: Analysis of the 64-channel EEG recorded data revealed that average α activity prior to thought probes differentiates between the on-task and planning/reminiscing condition during the breath counting task and between the on-task and daydreaming with awareness reports during the SART (Fig. 1). These preliminary results are encouraging for further analysis to determine whether mind-wandering could be detected online for the development of a Neurofeedback training (NFT).

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Real-time self-regulation across multiple visual neurofeedback presentations

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Introduction: The interest in using real-time functional magnetic resonance imaging (rtfMRI) for neurofeedback (NF) has been constantly growing [1]. One crucial, and largely unexplored, aspect is whether the choice of feedback representation can affect neurofeedback efficiency. In the current study, six healthy participants were asked to self-regulate the activation of a pre-defined brain region in the posterior parietal cortex by means of a mental calculation task, with the help of three different visual feedback representations: (1) a vertical thermometer display, (2) a circle display which de-/increased in physical size and (3) a number display showing Arabic digits.

Methods: Six healthy volunteers were engaged in three real-time fMRI neurofeedback sessions at three different days. In each session participants saw one of three visual feedback displays (Thermometer, Circle, Numbers; see Figure 1) while alternately resting or performing mental addition and subtraction with one of three intensities (30%, 70%, 100%). A session consisted of five functional runs. The first (localiser) run was used to select a target region. In run 2 to 4 continuously updated gradual feedback on the activation level of the target region with respect to the previous rest condition was given (feedback runs). After the feedback runs, participants were engaged in one last (no-feedback) run in which no feedback was given. 3T MR images were preprocessed in real-time using *Turbo-BrainVoyager* (version 3.2; Brain Innovation, Maastricht, The Netherlands). Neurofeedback displays were presented with *Expyriment* [3].

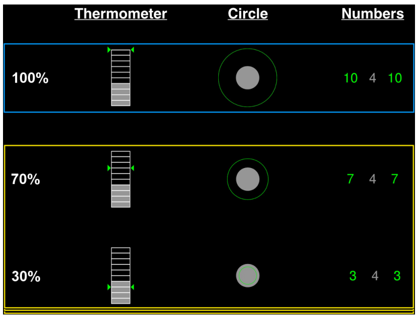

Figure 1. Feedback displays for up- (blue) and fine-grained (yellow) regulation.

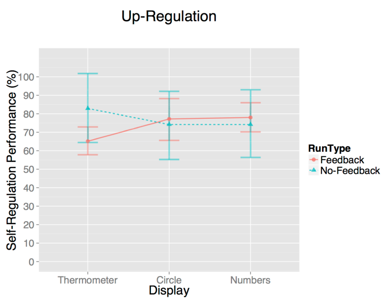

Figure 2. Up-regulation performance as function of NF-display. Err. bars: 95% CI.

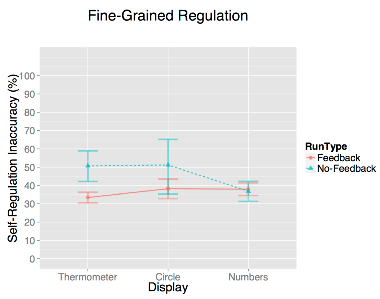

Figure 3. Fine-grained regulation inaccuracy as function of NF-display. Err. bars: 95% CI.

Results: Self-regulation performance data (i.e. reached state) from up-regulation (100%) and self-regulation inaccuracy data (i.e. absolute distance between reached state and targeted state) from fine-grained regulation (30% and 70%) each individually entered non-parametric fixed-effects analysis. Data from all participants was concatenated and 95% bootstrapping confidence intervals (CI) were obtained. While successful self-regulation was generally possible with all three displays, a small but significant difference between displays was observed during feedback runs, for both up-regulation (Figure 2) and fine-grained regulation (Figure 3). In addition, for fine-grained regulation a significant difference between feedback and no-feedback runs was present.

Discussion: We observed differences in self-regulation performance and inaccuracy between different visual neurofeedback presentations in a group of six healthy participants. Interestingly, the directionality of these differences varies between up-regulation and fine-grained regulation, suggesting that different aspects of the visual feedback presentation are relevant for each type of regulation.

Significance: Preliminary evidence that feedback presentation choice can affect neurofeedback efficiency.

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Reducing BCI calibration time with transfer learning: a shrinkage approach

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Introduction: A brain-computer interface system (BCI) allows subjects to make use of neural control signals to drive a computer application. Therefor a BCI is generally equipped with a decoder to differentiate between types of responses recorded in the brain. For example, an application giving feedback to the user can benefit from recognizing the presence or absence of a so-called error potential (Errp), elicited in the brain of the user when this feedback is perceived as being 'wrong', a mistake of the system. Due to the high inter- and intra- subject variability in these response signals, calibration data needs to be recorded to train the decoder. This calibration session is exhausting and demotivating for the subject. Transfer Learning is a general name for techniques in which data from previous subjects is used as additional information to train a decoder for a new subject, thereby reducing the amount of subject specific data that needs to be recorded during calibration. In this work we apply transfer learning to an Errp detection task by applying single-target shrinkage to Linear Discriminant Analysis (LDA), a method originally proposed by Höhne et. al. to improve accuracy by compensating for inter-stimuli differences in an ERP-speller [1].

Material, Methods and Results: For our study we used the error potential dataset recorded by Perrin et al. in [2]. For 26 subjects each, 340 Errp/nonErrp responses were recorded with a #Errp to #nonErrp ratio of 0.41 to 0.94. 272 responses were available for training the decoder and the remaining 68 responses were left out for testing. For every subject separately we built three different decoders. First, a subject specific LDA decoder was built solely making use of the subject's own train data. Second, we added the train data of the other 25 subjects to train a global LDA decoder, naively ignoring the difference between subjects. Finally, the single-target-shrinkage method (STS) [1] is used to regularize the parameters of the subject specific decoder towards those of the global decoder. Making use of cross validation this method assigns an optimal weight to the subject specific data and data from previous subjects to be used for training. Figure 1 shows the performance of the three decoders on the test data in terms of AUC as a function of the amount of subject specific calibration data used.

Discussion. The subject specific decoder in Figure 1 shows how sensitive the decoding performance is to the amount of calibration data provided. Using data from previously recorded subjects the amount of calibration data, and as such the calibration time, can be reduced as shown by the global decoder. A certain amount of quality is however sacrificed. Making an optimal compromise between the subject specific and global decoder, the single-target-shrinkage decoder allows the calibration time to be reduced by 20% without any change in decoder quality (confirmed by a paired sample t-test giving p=0.72).

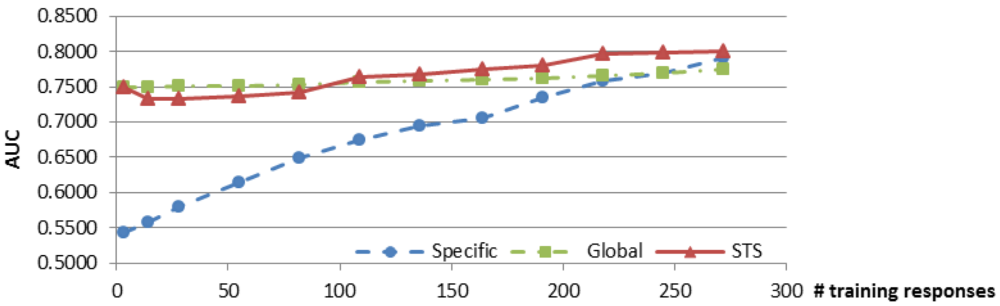

Figure 1. *Decoding performance in terms of AUC (averaged over 26 subjects) as a function of the amount of subject specific calibration data. Decoders are trained with three different methods: solely using subject specific data (specific), adding data from previously recorded subjects (global) and a compromise between these two methods using shrinkage LDA (STS).*

Significance This work serves as a first proof of concept in the use of shrinkage LDA as a transfer learning method. More specific, the error potential decoder built with reduced calibration time boosts the opportunity for error correcting methods in BCI.

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Sensorimotor Rhythm BCI with Simultaneous High Definition-Transcranial Direct Current Stimulation Alters Task Performance

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Introduction: A challenge for broad applications of sensorimotor rhythm based brain-computer interface (BCI) is its need for extensive training in order to acquire useful control of a cursor or physical object [1-2]. Transcranial direct current stimulation (tDCS) has been used to alter the excitability of neurons within the cerebral cortex in order to improve motor learning and performance when tDCS was applied prior to and simultaneous with performance [3]. We aim to test the hypothesis that utilizing high definition tDCS (HD-tDCS) will alter the performance of sensorimotor rhythm based BCI within a single session and across sessions over multiple training days.

Material, Methods and Results: 29 healthy subjects (14 female; 26 right handed) naïve to BCI control were randomized into anodal, cathodal, and sham groups and participated in three experimental sessions of 1D left/right motor imagination performance. A 64-channel EEG system was used to record and a 4x1 HD-tDCS was used to stimulate all subjects, with the center electrode located between C3 and CP3 and return electrodes located between adjacent 10/20 EEG electrodes. Subjects performed motor-imagery BCI tasks before, during, immediately after (I-Post), and 30 minutes after (D-Post) 20 minutes of tDCS stimulation.

We report a decreased time-to-hit for right hand trials after anodal stimulation both within and across sessions (Fig 1). Additionally, we found differing after-effects of stimulation on the electrophysiology of the stimulated sensorimotor cortex during online BCI task performance for right hand trials based on the stimulation type. Sham and anodal stimulation groups both had increased online alpha power in C3 and CP3 for right hand trials immediately after stimulation, however the cathodal stimulation group did not show this increase. These differences were not seen in left hand imagination trials nor were they seen in sensorimotor electrodes in the contralateral hemisphere for either left or right hand trials.

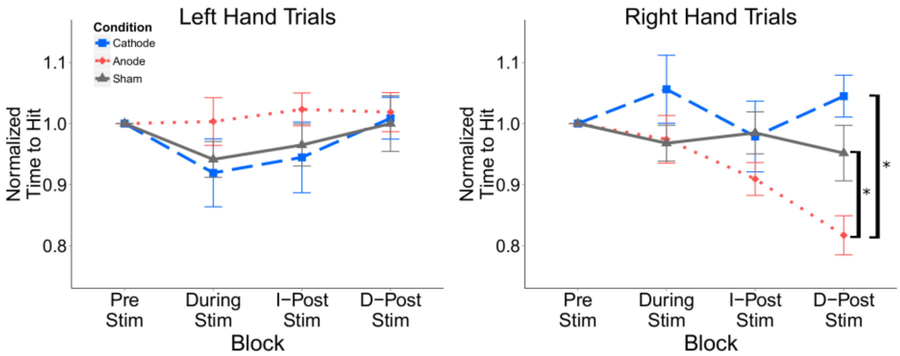

Figure 1. *Time to hit for right and left trials within a session normalized to the pre-stimulation baseline for each session. The anodal group had a reduced time-to-hit for right hand trials following stimulation at the delayed time point. Values: Mean +/- S.E. *p<0.05 for Wilcoxon rank sum test.*

Discussion: Unilateral HD-tDCS alters electrophysiology and behavior during BCI performance based on task specific neural activation within and across experimental sessions. The decreased time to hit right hand targets after anodal stimulation suggests that this stimulation may allow subjects to modulate their sensorimotor rhythm power faster than sham and cathodal stimulation. The decreased C3/CP3 alpha power after cathodal stimulation suggests this stimulation may impair a subject's ability to modulate their sensorimotor rhythm power during task performance.

Significance: We find differential effects of anodal and cathodal stimulation on behavioral and electrophysiological measures. These effects should be considered when applying noninvasive brain stimulation to improve BCI performance by altering the underlying physiology.

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BCI-approach for cognitive rehabilitation in stroke: pilot data from patient with spatial neglect

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Introduction: Stroke remains a primary cause of morbidity throughout the world mainly because of its effect on cognition [1]. Nowadays rehabilitation of post-stroke cognitive deficits is underdeveloped. Spatial neglect is a post-stroke cognitive deficit occurring in about 70% of patients after right hemisphere stroke; it persists in one third of patients and worsens stroke outcome [2]. Current therapeutic approaches in neglect do not include any learning strategies [2], which would be more effective for long-term training effect. BCI-methods might be an alternative for neglect rehabilitation also by presenting neurofeedback (closed-loop) to patients with accompanying anosognosia. In the present study we aimed to explore evoked-response potentials (ERP) and oscillatory features preceding and accompanying distinct performance features (attention orientation to left/right, hit/miss trials) during visuospatial task in neglect patients to evaluate the potential of BCI-methods for neglect rehabilitation.

Material, Methods: We recruited one patient with right fronto-parietal infarct, 53 years, 10 days post-stroke showing neglect deficit, admission NIHSS=2. The 32-channel EEG was recorded in resting state and during conducting of spatial task. The latter was a Posner-like paradigm [3] with central cue (duration 2000 to 3000 msec) pointing equally to the left or right followed by target (duration 1000 msec) presented in the valid hemifield in 90% of trials. The ERP-responses and oscillatory features upon cue and target presentation were analyzed in dependence to the cue lateralization and hit/miss trials. The frequency band of [7-9] Hz was analyzed using the Common Spatial Patterns (CSP) algorithm for the oscillatory features, whereas for the ERP responses, the intervals corresponding to early negativity and late positivity were used as features for the classification stage. Three aged-matched healthy subjects represented a control group.

Results: A total of 170 trials were recorded for the stroke patient with classification of ERP- and CSP-patterns upon left/right cue was not better than chance level, whereas in healthy subjects it was above 66%. ERP-based classification of hit/miss trials for the patient was only 60%. Channels of the undamaged left hemisphere were the most informative for classification hit/miss trials (Fig. 1), while no such lateralization effect was observed in healthy subjects. We were not able to detect features preceding hit/miss trial in the patient's data. Interestingly, the early ERP-response even in miss trials could be observed confirming that neglect is a disorder of high-level attention function [4].

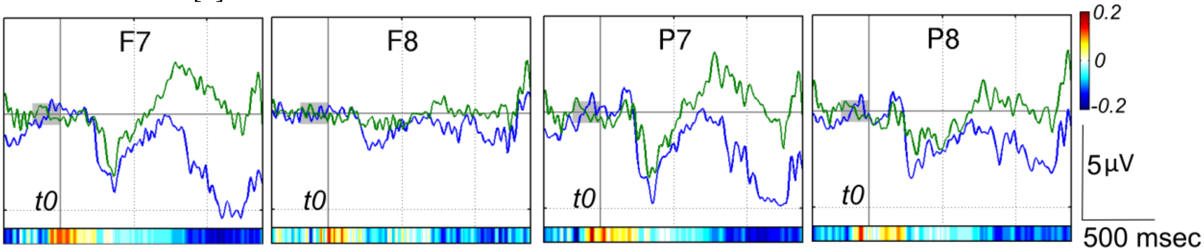

Figure 1. *ERP-responses to hit (blue) and miss (green) trials in acute stroke patient with neglect. T0 points to the target presentation.*

Discussion, Significance: This is the first pilot application of BCI-method in acute stroke patient with neglect. The failed classification upon left/right cue in patient's data demonstrates that application of BCI-methods in patients with territorial stroke is challenging and distinct compared to healthy subjects, but feasible. Though hit/miss trials classification exceeded the chance level, the detection of their preceding features would be more valuable to establish the method for rehabilitation. Further data acquisition is required, as well as optimization of classification algorithms due to the distinct ERP/CSP-patterns in stroke.

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Cortico-Muscular-Coupling and Covariate Shift Adaptation based BCI for Personalized Neuro-Rehabilitation of Stroke Patients

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Introduction: Every year an estimated 17 million people get affected by stoke among which 30% to 60% of stroke survivors may suffer from permanent upper limb paralysis [1], which may significantly impact their quality of life and employability. Often the upper limb paralysis becomes chronic due to lack of active and engaging rehabilitation exercises over a prolonged period. This research investigates advanced approaches to devising EMG and EEG based brain-computer interface (BCI) systems, which provide neuro-feedback to the patients and/or operate powered exoskeleton to facilitate active and engaging upper limb rehabilitation exercises. The feasibility of the BCI assisted motor imagery (MI) training has successfully been established for post-stroke patients, in reorganizing the neuronal connections around the affected areas of the brain, which is also termed as neuro-plasticity [2]. In this paper, we devised a novel feature extraction approach using a correlation between the variations of signal power of EEG and EMG signals in time domain, which is termed here as Power-Level-Correlation (PLC). As a part of BCI-based neuro-rehabilitation system, this PLC acts as a measure of cortico-muscular-coupling. The PLC index is used to decide the movement intension of a user (e.g., whether a user is making an effort to move the fingers), and accordingly the hand exoskeleton is triggered to help perform motor exercises and provide a neuro-feedback to the user. However during post-stroke acute phase, the EMG activity may be very little or none, and hence PLC index is not suitable for determining user intension. Therefore, we have also analyzed the EEG signals alone, using covariate shift-detection (CSD) based adaptive classification, as it detects the non-stationary brainwave changes (often occurring due to neuronal re-organization and other known/unknown causes), and accordingly a new classification decision boundary is obtained by re-training a pattern classifier on the newly acquired features. We have tested our single-trial based online BCI paradigm on 17 healthy subjects to classify the hand at rest state (class 1) and grasp attempt (class 2) of the user and the results are found to be promising over the conventional EEG-based non-adaptive BCI.

Material, Methods and Results: EEG signals have been acquired using C3, Cz, and C4 channels and EMG signals have been extracted from the forearm muscles (i.e., Flexor-Digitorum-Superficialis (FDS), and Flexor-Policus-Longus (FPL)). Consenting healthy participants were asked to undergo two training sessions and one feedback session. Each session consisted of 40 trials and subjects were asked to perform either a grasp attempt or stay at rest according to the appearance of the cue in each trial. Using training dataset, a classifier has been trained on three different approaches. The first method is an EEG-based non-adaptive classifier (EEG-NAC); the second method is an EEG-based adaptive learning classifier (EEG-ALC); and third method is a PLC based NAC. Unlike EEG-NAC, EEG-ALC uses CSD test [3] to detect the covariate shift in the EEG features, and update the classifier parameters to adapt to the data distributional changes. In, PLC-NAC, we correlate the power distribution in EEG and EMG in a particular trial over a suitable time-window to get an index, which can be used to discriminate the two classes. Here, a support vector machine based pattern classifier has been used for the single-trial binary classification. During the evaluation phase, the following classification accuracies have been achieved; EEG-NAC (78.53%), EEG-ALC (80.44%), and PLC-NAC (94.85). Moreover, by comparing the results of the EEG-NAC method with the other proposed methods using a Wilcoxon signed rank test, the EEG-ALC gives a p-value=0.0078 and PLC-NAC gives a p-value=0.0028, which are statistically significant.

Discussion and Conclusion: From the results, it is evident that the PLC-NAC and EEG-ALC methods have a clear advantage over the EEG-NAC method. These two modes (PLC-NAC and EEG-ALC) also help in monitoring the improvement in brain-muscle coordination throughout the neuro-rehabilitation process. It is expected that by regularly using this system for a specific period of time, patients could increase their finger mobility to perform grasping action of their hand for activities of daily life.

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First steps towards adaptive deep brain stimulation in Parkinson's disease

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Introduction: Deep brain stimulation (DBS) is used to treat Parkinson's disease (PD), when medical therapies are not efficient enough [1]. DBS requires the implantation of stimulation electrodes reaching into deep brain areas, commonly into the subthalamic nucleus (STN) that is one of the relay of the extrapyramidal circuit. Electrical pulses are sent on a fixed regular pace. Despite the proven efficacy of DBS on rigidity, bradykinesia and tremor, the principle clinical features of PD, its underlying principles and mechanisms are still not completely clear. Moreover, stimulation side effects such as speech problems, heat or numbness sensations, and dyskinesia can be caused by the stimulation. Current DBS systems are still in their early stages and can be compared to the early generation of heart pacemaker systems. Stimulation parameters (amplitude, frequencies or pulse-width) are typically fixed shortly after the implantation and remain unchanged. Altogether, the current practice –providing continuous stimulation with fixed parameters– may be suboptimal since it does not take into account any symptoms fluctuations. Adaptive DBS, where stimulation is triggered by certain neurophysiological markers, has emerged as an improvement over conventional systems. Such systems would reduce the amount of stimulation provided, thus extending battery life and potentially reducing side effects [2]. An adaptive DBS should be able to record the local field activity via the same electrodes as used for stimulation, recognize pathological brain activity, and finally drive the stimulation based on the specific needs of the patient [3]. Here we present our initial results on the development of a closed-loop adaptive DBS system.

Methods and Results: We recorded brain activity from the subthalamic nucleus via the deep electrodes while stimulating simultaneously. This was made possible because of the design of a custom-made system that allowed filtering out stimulation artifacts from the underlying brain signals. Tests of the closed-loop adaptive DBS have been performed in 3 PD patients. The protocol consisted of three stimulation conditions over 3 days: continuous (normal), adaptive, and no stimulation, whereby each condition was 20 min long. A neurologist evaluated the clinical assessments of the motor effect via the Unified Parkinson's disease rating scale (UPDRS) before, during, and after each condition. In the no-stimulation condition, we found a pathological synchronization of the beta band in both hemispheres and a strong coherence between both hemispheres in the high-beta and low-gamma band (Fig. 1a). Therefore, detection of increased (over the 50 percentile) beta band activity (22-28 Hz) was used to trigger the stimulation in the adaptive condition. During the adaptive condition, the stimulation time was reduced along the recording time (Fig. 1b), while the UPDRS improved over the recording days (Fig. 1c).

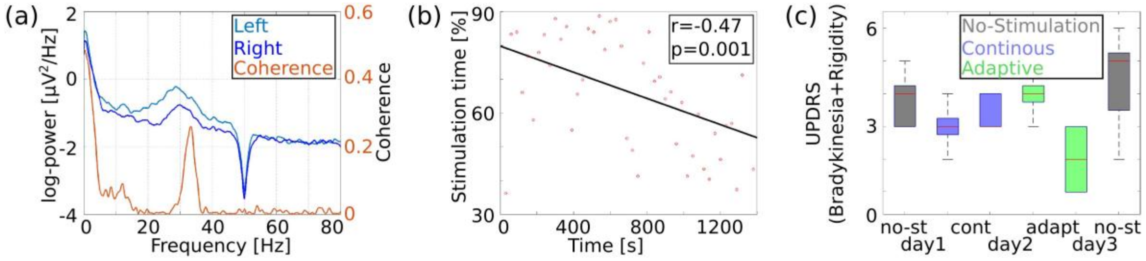

Figure 1. *Exemplarily results of one subject: (a) Log power of left and right hemisphere during no-stimulation condition and their coherence. (b) Stimulation amount in % over the recording time. (c) UPDRS results for all conditions over the experiment.*

Discussion: Our initial results demonstrate that we can successfully record local field potentials, detect the physiological biomarkers of motor symptoms in PD patients and adaptively trigger the DBS. The subject-specific closed loop stimulation yielded similar efficiency to conventional continuous DBS. Nevertheless, more subjects and tests over longer periods of time are necessary to confirm these preliminary findings.

Significance: Closed-loop adaptive DBS is possible which opens up strategies to better tune the stimulation leading to increased battery life and better control over symptom variations.

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Intracortical Microstimulation as a Feedback Source for Brain-Computer Interface Users

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Introduction: Somatosensory feedback is necessary for skilled movement. While brain-computer interfaces (BCI) have enabled users to achieve high degree-of-freedom control using a prosthetic limb, feedback has been limited to vision. In tasks such as object manipulation however, providing somatosensory feedback could be an important step to improving BCI limb control. One possible mode of delivering this feedback is by using intracortical microstimulation (ICMS) of the primary somatosensory cortex (S1).

Material, Methods and Results: A twenty-seven year old participant with a chronic C5 motor and C6 sensory AIS B spinal cord injury was implanted with two intracortical microelectrode arrays (MEAs) in S1. The MEAs were targeted to the hand region of area 1 in the left hemisphere based on presurgical imaging. The goal was to elicit cutaneous percepts that project to the fingers of the right hand (see Fig 1c).

Electrodes were stimulated at supraliminal intensities so that the participant could describe the locations and qualities of the percepts. The projected fields of the electrodes (see Fig 1a and b) were located in digits 2-5 and at base of each of those fingers. Sensations were reported from 59 of 64 electrodes, and no painful sensations or paresthesias were reported. We also investigated the effect of increasing amplitude on perceived intensity. The relationship appeared to be linear ($R^2 = 0.98$) for the 5 electrodes tested (see Fig 1d).

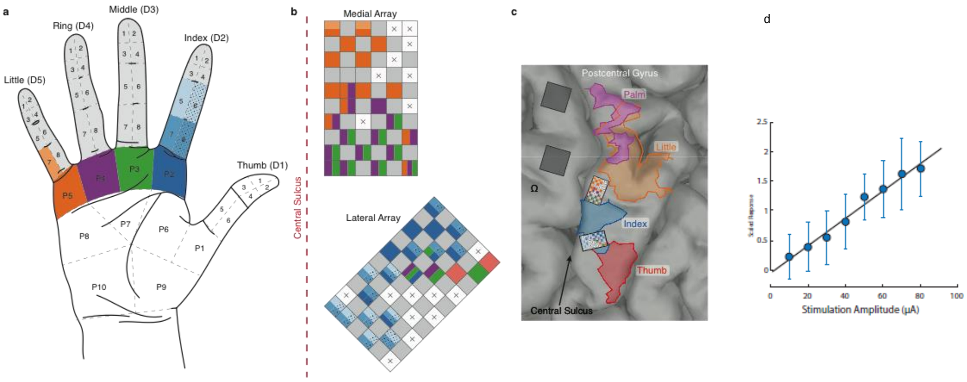

Figure 1. *Locations and intensity of percepts elicited by ICMS delivered to S1 a. A segmented hand was shown to the subject to document the projected fields elicted by ICMS. Colored areas represent locations of the hand where focal percepts were reported. Gray regions represent locations where percepts were reported as part of large, diffuse projected fields. b. Layout of projected fields on implanted arrays. Gray squares indicate unwired electrodes, while white crosses indicate electrodes that did not elicit any percepts c. Regions of cortex activated during presurgical imaging experiments. The locations of the arrays and projected fields are overlaid. d. The perceived intensity scaled with increasing stimulus amplitude. The averaged data from 5 tested electrodes are shown normalized to its mean response. Error bars represent one standard deviation from the mean. The black line shows the linear regression fit to the data.*

Discussion: These results demonstrate that ICMS delivered to area 1 of S1 has the potential to provide somatosensory feedback to people who use BCIs. We found that percepts were evoked at somatotopically relevant locations, and that the perceived intensity of stimuli scaled linearly over a large range. These features enable us to relay both the location and intensity of object contact, two sources of information that would be helpful for BCI users to interact with objects.

Significance: The ability to provide artificial somatosensory feedback to BCI users could improve the user's control and experience with the device. This is an important step towards a clinically relevant neuroprosthetic.

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Neurofeedback via intracranial depth electrodes

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Introduction: The use of deep brain stimulation (DBS) devices in a clinical setting for treating various neurological and psychiatric disorders is developing [1], which provides the opportunity to explore new BCI concepts, by using the stimulating electrodes as deep recording electrodes. As a test case, we focus on intracranial recording from the amygdala of patients with epilepsy that undergo intracranial mapping for the localization of the epileptogenic zones. In this preliminary study we demonstrated that subjects can learn to volitionally regulate the amygdala signal amplitude in a Neurofeedback (NF) setting while interacting with a complex multimodal environment.

Material and Methods: Our NF setting is a based on a visually realistic environment (implemented with the Unreal Development Kit game engine), which aims at supporting user engagement through a well-defined task, as well as maintaining arousal through multimodal output. Fig. 1 depicts the experimental overview.

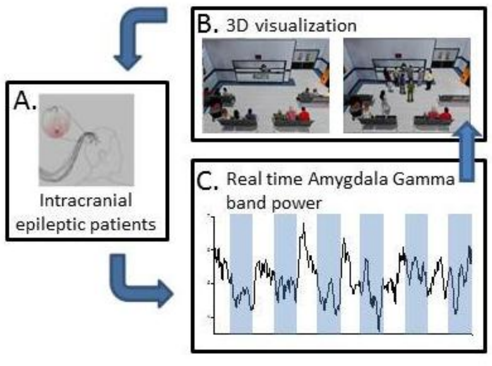

Figure 1. *System Overview and Experimental Setting: the user is instructed to appease the situation in the waiting room. NF is based on a Gamma band amygdala iEEG power: the level of unrest in the waiting room matches the subject's amygdala's activation. C, The amygdala activity is plotted during several short NF trials (white-baseline blue-NF).*

The NF task consists in controlling the level of unrest of a virtual crowd composed of characters in the waiting room of a hospital. Unrest is defined as the ratio between characters waiting and those protesting at the front desk, and is further emphasized by a matching soundtrack. Amygdala activity acquired through the depth electrode is mapped in real-time to the level of unrest, using a statistical distribution of virtual characters between waiting and protesting states.

Valid data were obtained from 3 patients with epilepsy (2M, 1F) implanted with Behnke-Fried depth electrode (AD-TECH). iEEG was sampled at 2 kHz and recorded using Neuroport (Blackrock microsystems). Each of the NF sessions included six to eight baseline epochs of passive viewing of the waiting room environment (60 sec each) and equivalent number of active NF blocks (60 sec each). The participants were instructed to "appease the waiting room using their brain activity" No preferred cognitive strategy was suggested to the subjects.

Results: Preliminary analysis of the iEEG recordings suggests that participants acquired the ability to down-regulate their amygdala's gamma band activity, even with little training. A successful relaxation session was defined as a block during which the probe values were significantly lower than those recorded in the baseline blocks (two-tailed Student's t-test; $p < 0.05$). Success was found in 50% of the relaxation sessions. We show that the response is specific to the Amygdala, i.e. other electrodes do not show correlated alterations to the gamma band activity. It is also specific in terms of band, as other frequency bands in the amygdala do not exhibit correlated activity with the Gamma band.

Discussion: Our preliminary results demonstrate that it is possible to train subjects to directly and specifically modulate their Amygdala's activity using depth electrodes as a signal acquisition device. Results obtained are encouraging, in particular the relatively high success rate considering minimal training received by subjects.

Significance: We presented a proof of concept of volitional control of local limbic activity recorded by depth electrodes in the Amygdala. This opens the way for further investigation of DBS electrodes for BCI applications. The NF setting we presented also supports various levels of personalization, or tailoring to specific conditions.

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Predicting Single-Trial Motor Performance from Oscillatory EEG in Chronic Stroke Patients

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Introduction: Machine learning methods allow for the decoding of ongoing brain states that provides valuable information about trial-by-trial behavioral performance variations of subjects. As a possible field of application, we analyze ongoing brain activity in a hand motor paradigm to predict motor performance on single-trial basis. The online prediction of motor performance can be utilized as an assistive technology for rehabilitation in order to enhance and speed up motor learning by causally influencing the training performance.

Material, Methods and Results:
Within the framework of a sequential repetitive hand force rehabilitation task for stroke patients (SVIPT, [1]), we studied the users brain activity by EEG (64 passive channels, BrainAmp DC). Pre-trial oscillatory power of the EEG was analyzed in terms of its correlation with a motor performance score of the upcoming trial, using a data-driven spatial filtering method called Source Power Comodulation (SPoC, [2]). The algorithm derives an oscillatory subspace (given by a spatial filter) whose bandpower activity is predictive for the motor performance of the upcoming trial. The method requires the data to be filtered to a narrow frequency band of interest. In our offline analysis, SPoC was trained within a 5-fold chronological cross-validation. The resulting filters were applied to unseen data in order to gain an estimate of the motor performance z_{est} for each trial entering the analysis. Since supervised spatial filtering methods are prone to over-fit the data, the meaningfulness and stability of any SPoC component needs to be verified by additional validation procedures [3]. Here, we report on results from a single session (about 200-240 trials) of three chronic stroke patients. The exemplary predictors shown in Fig. 1 were obtained by data of two subjects. They are based on a pre-go interval 800 ms before the *go-cue.* As performance metric, we chose the reaction time upon the go cue of the SVIPT task.

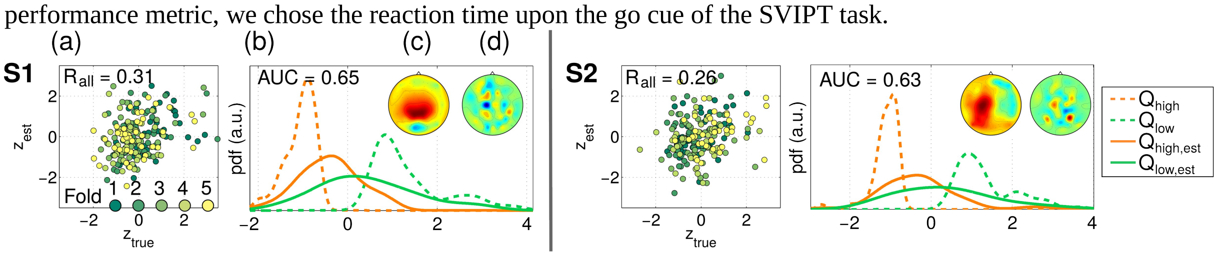

Figure 1. *Probing the predictive strength of two oscillatory components for subjects S1 and S2. The example given for S1 lives in the alpha-band (f=[10,12] Hz), the one for S2 is extracted from the beta range (f=[27,31] Hz) (a) Scatter plot of single trial performance prediction z_{est} as a function of the measured value z_{true} color coded by the temporal structure of the session. (b) Separability of the predictor by contrasting the upper and lower quartiles of z (dashed) with the corresponding quartiles according to z_{est} projected back to the z domain. In addition, the AUC value for a 50 percentile split is reported. Activity pattern (c) and spatial filter (d) extracted from SPoC.*

Discussion and Significance: In healthy subjects, the extraction of motor performance predictors delivers single-trial predictors which explain up to 25% of the variance [4],[5]. Our case study on three chronic stroke patients proposes that the same approach also allows to extract robust motor performance predictors under more severe conditions (less training trials, more artifacts). The resulting subspace features were derived from different frequency ranges (e.g. alpha and beta band) which corresponds to previous findings in healthy subjects. The subject-specific subspace components extracted for stroke patients may be used for brain-state dependent closed-loop experimentation in order to enhance rehabilitation training performance.

Acknowledgements: This work was (partly) supported by BrainLinks-BrainTools, Cluster of Excellence funded by the German Research Foundation (DFG), grant number EXC 1086.

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Treating attention deficits in chronic stroke patients using Slow Cortical Potential (SCP) Neurofeedback

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Introduction: Slow cortical potentials (SCPs) are slow polarization shifts measurable with electroencephalography (EEG) and lasting from 300 ms to several seconds. Negative polarization shifts represent cortical activation or excitability while positive shifts express cortical inhibition. SCPs can be brought under voluntary control by neurofeedback training and were successfully used for attention enhancement in children with attention deficit disorder [1]. As in chronic stroke patients attention deficits often remain after cognitive rehabilitation treatment is completed, we investigated the potential of SCP neurofeedback training for attention enhancement in this target population. We hypothesized people with chronic attention deficits after stroke to learn willful SCP control via neurofeedback training (H1) and willful shifts toward cortical negativity leading to attention and concentration increase being measureable on the behavioral level (H2).

Methods: Twenty-five chronic stroke patients with subjectively reported attention deficits, were included in this study. Ten dropped out and the remaining sample (N=15) was on average 62 years old (M=62.40, SD=8.73) and included four females. Participants' attention was tested using the Test battery of Attentional Performance (TAP), more specifically the subtests 'divided attention' and 'alertness'. Participants were trained to control their SCPs for 8 sessions over a time period of two to three weeks using Biotrace Software (MindMedia, the Netherlands). A circle presented in the middle of the screen had to be either increased (negativity) or decreased (positivity) in size. If accurate, the circle color changed from light grey to green. In case the participant willfully produced the requested SCP polarity for 80% of the time during the last 4 seconds of each 6 second trial, a smiley face was presented as a reward. Each session consisted of 10 training blocks including 50 trials. After the last training session, post training attention assessment was performed.

Results: Concerning H1, we found stroke patients to learn willful control over their SCPs via neurofeedback training. ANOVA suggested a main effect of block, (F=6.18, p=.01) qualified by a triple interaction of block, session, and condition (F=5.27, p=.02). Follow-up analysis indicated that, across all sessions, no difference between conditions could be found in the first block of each session, but that, beginning in the fifth session, stable differences between conditions emerged in the last block number. H1 was confirmed (see figure 1). We also found that patients could significantly increase their T-scores in TAP DA Omissions (t(14)=-3,461,p=.004). Therefore, our second main hypothesis was partially confirmed.

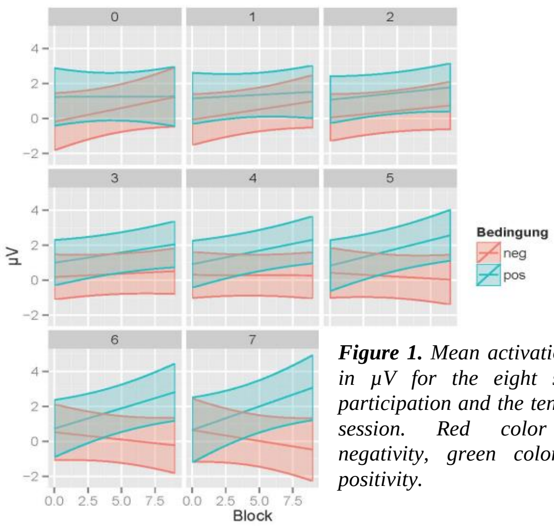

Figure 1. *Mean activation depicted in µV for the eight sessions of participation and the ten blocks per session. Red color indicates negativity, green color indicates positivity.*

Discussion: Ten participants of our original sample dropped out either because they were too exhausted, not compliant or had difficulties in understanding the instructions. Therefore, in the future, training sessions need to be adjusted to be shorter, using a more intuitive and possibly also entertaining feedback and the thresholds for reinforcement should be decreased to reduce frustration and strengthen learning.

Significance: Although the sample size needs to be increased, we cautiously conclude that SCP neurofeedback training is a promising new treatment possibility for chronic stroke patients with attention deficits.

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Volitional Control of Beta Band Power in Parkinsonian patients

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Introduction: Previous work has demonstrated that subjects can volitionally control the power of their endogenous local field potential signals given real-time feedback [1], [2]. Further work has demonstrated that volitional modulation of cortical motor beta band local field potentials prior to performance of a reaching task effects performance of the reach [3]. Specifically, reduction in beta power contributes to faster reaching, supporting the hypothesis that motor system beta power serves as an inhibitor of upcoming movements [4]. Since beta LFP signals are hypothesized to also be involved in motor symptoms related to Parkinson's disease [5], [6] we sought to replicate the sequential neurofeedback and movement task in PD patients implanted with a Medtronic Activa PC + S Neural Stimulation device. Here we present results from initial neurofeedback-only sessions from three patients.

Material, Methods and Results: We studied 3 subjects with diagnosed PD. Subjects all had one Activa PC + S devices, each that supports two four-contact leads. Subjects with bilateral therapy also had a separate Activa SC unit (for clinical therapy only). Subjects all had one lead laying over cortical areas approximately spanning premotor cortex to somatosensory cortex [7]. Subjects either came into the UCSF clinic (2 subjects) or completed the beta band power controlled neurofeedback task at home (1 subject) for a single 1-2 hour session. Subjects performed an instructed movement task as a baseline to assess the range of beta power. Table 1 summarizes the signal inputs used for neurofeedback control for each patient. All patients gave their written informed consent to participate in this study under a protocol approved by the Institutional Review Board.

Table 1: Signal Properties Driving Beta Cursor For Each Patient

Patient	**Home or UCSF**	**Stim On / Off**	**Time Domain vs. Power Channel**	**Beta Power Calculation Method**	**Cursor Prediction**
1	UCSF	Off	Time Domain	Multi-Taper	Linear Reg.
2	Home	On	Power Channel	n/a	Linear Reg.
3	UCSF	Off	Time Domain	Welch	Kalman Filter

For the neurofeedback task, a fixed mapping between subject neural activity and cursor position was calculated using the movement task as training data. The task required subjects to modulate the cursor to hit one of four instructed targets per trial.

We find that for all three subjects there were slight asymmetries in the mapping between neural activity and cursor position that made 1-2 targets challenging yet possible, and the other 2-3 targets either too easy or unattainable. For the targets that were achievable yet challenging, during late training all three subjects exhibited above chance performance, and one subject exhibit significant improvement in time it took them to modulate to that target (Chance calc. above bootstrapped distribution: Patient 1: $p<0.01$, Patient 2: $p < 0.01$, Patient 3 $p < 0.001$, Improved time to target two-tailed Student's t-test: Patient 3: $p < 0.05$).

Discussion: We found that subjects were able to improve performance for at least one neurofeedback target, demonstrating a proof of concept of volitional control using signals acquired by the Activa PC + S device in various modes of operation. These modes include subcortical stimulation on or off, power channel signals or time domain signals, and use of a linear regression method or a Kalman Filter to estimate cursor position (see Table 1). Moving forward, we will be completing longer training sessions with patients and eventually coupling the neurofeedback trials with bradykinesia-inducing motor tasks to investigate effects of modulation on disease-related motor symptoms.

Significance: This is the first demonstration to our knowledge of using the Activa PC + S device for volitional neurofeedback control using cortical leads.

Acknowledgements: The authors would like to acknowledge Medtronic Neuromodulation for their technical support in signal analysis and implementing these experiments.

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A New Statistical Model of EEG Noise Spectra for Real-time, Low-γ-band SSVEP Brain-Computer Interfaces

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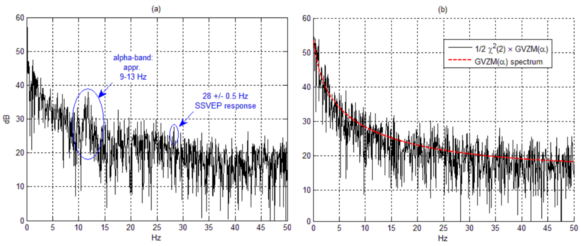
Introduction: A major impediment to practical real-time γ-band (≥ 30Hz) SSVEP BCIs is the high level of spectral noise which dramatically increases the error rates of frequency detectors/estimators (Fig. 1a). The standard "1/*f*-type" spectral model [1] of EEG noise is both theoretically unsatisfactory and too ill-defined for hypothesis tests. Based on our new theory of *quantum ion channel kinetics* [2], we model EEG noise spectra as random processes of the form $S_{\mathrm{EEG}}(f) = S_{\mathrm{GVZM}}(f)\cdot\Xi(f)$, where $\Xi(f)$ are independent $\chi^2(2)/2$ random variables at each frequency f and $S_{\mathrm{GVZM}}(f)$ is the *generalized van der Ziel-McWhorter* deterministic function whose inverse Fourier transform is $R_{\mathrm{GVZM}}(t) = P_0\int_{\tau_1}^{\tau_2}\left(1/\tau^{\alpha}\right)e^{-t/\tau}\,d\tau + P_1\delta(t)$ for tunable parameters $\alpha, \tau_1, \tau_2, P_0, P_1$ (Fig. 1b). We show such noise models have superior statistical characteristics for BCI and other neuroengineering applications.



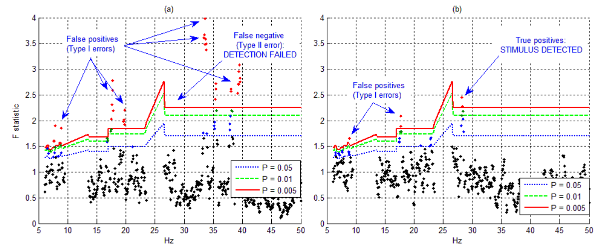


Figure 1. *(a) Raw single-trial EEG spectrum from 28Hz SSVEP BCI experiment showing a response peak which is nearly indistinguishable from background noise. (b) Synthetic GVZM* $\cdot\chi^2(2)/2$ *noise spectrum optimally- fitted to the data of (a).*

Figure 2. *(a) Critical levels for SSVEP detection/estimation using standard smoothed periodogram algorithm [4] and the data of Fig.1. (b) Detection/estimation using optimally-fitted GVZM* $\cdot\chi^2(2)/2$ *statistics.*

Material, Methods and Results: The model was tested on a 15-second, 28Hz SSVEP trial (Fig. 1a) from a publically-available BCI dataset [3]. Biosemi electrodes A14-A16, A21-A23, A25, A27-A29 were averaged to form a virtual visual electrode. Blink artifacts were estimated by linear regression onto the three frontal electrodes. A popular *F*-test SSVEP detection algorithm [4] was compared to the same algorithm with its pre-stimulus estimator replaced by our optimally-fitted GVZM $\cdot\chi^2(2)/2$ statistic. Each spectral value (excluding mid-α- and low-β-bands) was classified with respect to its *F*-test critical value calculated from the null hypothesis of no stimulus at that frequency. The results are shown in Fig. 2.

Discussion: The standard algorithm [4] failed to detect the 28Hz response spike in the noise background and also produced numerous false positives (Fig. 2a). On the other hand, our GVZM-based algorithm not only accurately detected the 28Hz response with $P < .005$, it also produced far fewer false positives (Fig. 2b).

Significance: This work proves that it is feasible to detect/estimate low-γ-band SSVEP spikes in real-time despite their poor signal-to-noise characteristics by using neurologically-appropriate statistics for EEG background noise. Such noise models will be essential for the development of future practical real-time SSVEP BCIs in the mid-γ-band.

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A Real-Time Neural Spike Based Data Reduction Platform

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Introduction: The research presented was motivated by a long term goal of monitoring the electrical activity of thousands of neurons, in an effort to decipher the brain activity. Recording thousands of neural signals may provide some insight in what Santiago Ramón y Cajal, called "the impenetrable jungle where many investigators have lost themselves"[1]. Monitoring the dynamic signals of thousands of neurons by increasing the number of recording channels in Micro-electrode-Arrays (MEAs) [2] is a breakthrough that might bridge the gap between the firing of neurons and motion, perception or even decision making. Increasing the number of recording channels, real-time data reduction becomes essential to limit the storage memory and transmission rate. Sending spike APs instead of raw data can achieve a data reduction ratio of 0.025 [3]. We present the design of a neural spike-based data reduction platform that can handle thousands of channels on Field Programmable Gate Arrays (FPGAs), making use of their massive parallel processing capabilities.

Material, Methods and Results: The Neural Spike Detection platform receives time division multiplexed serial samples from a high number of neural recording channels at the multi-gigabit receiver port of the FPGA. The receiver performs de-serialization of the data and ensures correct sample-word alignment. The system affiliates each sample to its source channel and performs spike detection. If a spike is detected the spike waveform along with its time stamp and channel ID are passed to an output buffer. The main building block of the design is a spike-based data reduction unit that handles 128 channels [4]. Although, the amount of data is significantly reduced, the system needs to integrate a high-speed communication link to transfer the AP waveforms to the host PC, accounting for transmission bottlenecks during periods of multi-channel neuron bursting [3]. A PCI express link limits queuing-based transmission latencies and saves queue memory during synchronized neuronal activity. The PCIe transmission was applied using a Xillybus IPcore [5].

The design was implemented on a Xilinx® Virtex-5 XUPV5-LX110T FPGA evaluation board and internal signals were monitored using Xilinx ChipScope. The scheduling process for data transmission among the channels was controlled by a Finite-State-Machine. The queue depth was monitored by sending it along with the spike data to the host PC. It was then extracted from the spike data and examined in MATLAB.

It was found that the maximum hardware usage percentage was for the BRAM. Each channel occupied 1120 bits. For the available FPGA boards, the MGTs can handle the maximum number of channels that can be handled by one chip based on the BRAM availability. The design bottleneck is the transmission through PCIe to a host PC at neuronal bursting activities. Further reduction will be needed to decrease the output data, for example by implementing spike sorting in hardware as well.

Discussion: The spike-based data reduction platform can be integrated with a data acquisition system at the interface to the Analog-to-Digital Converters ADCs, that represent the final stage of any neural signal acquisition system. A series of JESD standards have set a common language between fast high performance ADC and FPGAs making use of the high bandwidths SerDes can provide. Theoretically speaking, available ADC with MGTs can handle up to 10,000 recording channels sampled at 25 KSPS.

Significance: This research presented found solutions to some of the problems related to designing a real-time neuronal data reduction platform that can handle thousands of recording channels. It has integrated the application of MGT and autonomous data control to avoid interrupt latencies.

Acknowledgements: The authors would like to thank the NetS3 Lab in the Neuroscience department of the Instituto Italiano di Tecnologia (IIT) for providing the neuronal recordings used for testing the platform. The data was recorded from dissociated rat hippocampal cells (21 days in vitro) using high-density MEAs from 3Brain.

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CEBL$_3$: A New Software Platform for EEG Analysis and Rapid Prototyping of BCI Technologies

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Introduction: Version 3 of the Colorado Electroencephalography and Brain-Computer Interfaces Laboratory (CEBL$_3$) is a new software platform, written in Python, that is designed to support all phases of Brain-Computer Interface (BCI) research and development [1]. CEBL$_3$ is being developed by the Colorado State University BCI Group and currently supports a variety of standard and cutting-edge features, including modules for signal processing, visualization, machine learning and a fully-functional Graphical User Interface (GUI). A major design goal of CEBL$_3$ is to allow researchers to rapidly progress novel ideas from the early experimental and analysis stages to fully functional BCI prototypes.

Motivation: Current BCI software packages are typically designed with one of two primary goals: offline analysis or performing interactive experiments [2]. For instance, EEGLAB and BCILAB are written primarily in MATLAB and easily permit exploratory analysis using standard or custom methods. However, they are not equipped with an extensive framework for developing new user interfaces or performing real-time experiments. On the other hand, software packages like BCI2000 and OpenVibe are well-suited for performing interactive experiments. However, they are written in C++ and require significant time and effort to implement new methods. The goal of CEBL$_3$ is to bridge this gap by providing a single BCI software platform that supports all stages of BCI development in a flexible, feature-rich and high-performance environment.

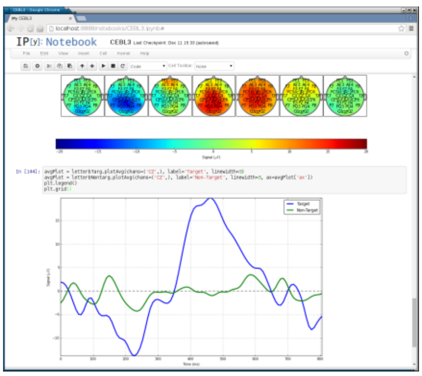

Figure 1. *A screen capture of CEBL$_3$ in an IPython notebook.*

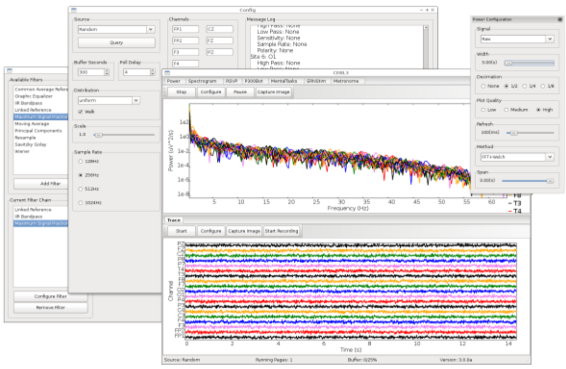

Figure 2. *A screen capture of the CEBL$_3$ graphical user interface.*

Results: In CEBL$_3$, researchers can begin by performing offline analysis in an IPython notebook, shown in Figure 1, using any of the provided analysis modules. CEBL3 also has integrated support for NumPy, SciPy and Matplotlib, which allows researchers to easily incorporate well-established and novel algorithms while maintaining computational performance. Promising approaches can then be placed into the GUI framework, shown in Figure 2, which is based on wxPython and a number of custom widgets. This allows for the rapid promotion of novel methods from offline analysis to fully functional BCI's. Presently, we have used CEBL$_3$ in a number experiments and demonstrations, including in-home experiments involving users with motor impairments.

Significance: CEBL$_3$ has the potential to increase the productivity of BCI researchers by promoting code-reuse and reducing the time required to place novel methods in an interactive framework. This may also encourage online experimentation and testing of novel BCI technologies in real-world use-cases.

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Classification of Visual Target Detection during Guided Search using EEG Source Localization

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Introduction: It is becoming increasingly common to use experimental paradigms that utilize synchronous eye-tracking and electroencephalographic (EEG) measures to explore the neural processes underlying visual search. In these paradigms, fixation related potentials (FRPs) are used to quantify early and late components of visual processing following the onset of a fixation. However, FRPs often contain a mixture of bottom up (e.g. sensory input from the stimulus) and top down (e.g. saccade planning) processes in addition to electrooculography (EoG) artifacts and unrelated neural activity. In this study we sought to isolate the neural sources of target detection in the presence of eye movements and concurrent task demands.

Material, Methods and Results: In this study we obtained simultaneous eye-movement and EEG measures during a guided visual search task. Participants were asked to identify visual targets (Ts) amongst a grid of distractor stimuli (Ls), while simultaneously performing an auditory N-back task with varying degrees of difficulty. First, we used independent components analysis (ICA) to separate EEG signals into neural and non-neural sources [1]. We then combined these sources, using simplified measure-projection analysis (MPA) [2], to isolate activity in six regions of interest (ROIs): occipital, fusiform, temporal, parietal, cingulate, and frontal cortices.

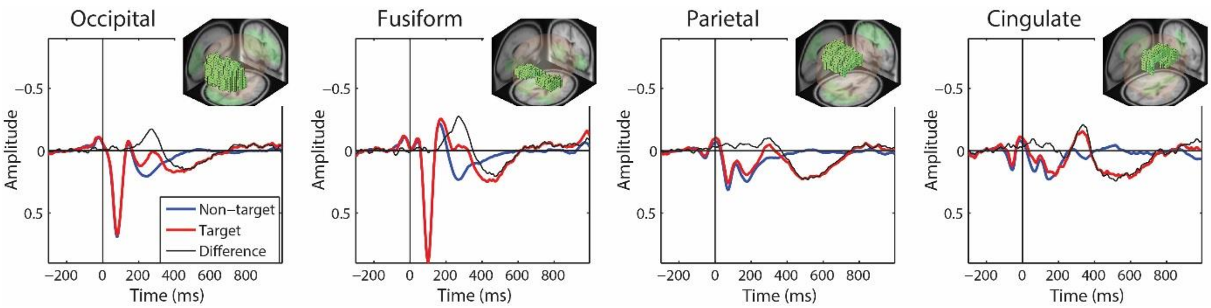

Figure 1. *Grand average neural response from four of the six ROIs. Each figure shows the average of the combined IC activations within the corresponding ROI for all target and non-target fixation. Inset shows the voxels included in each ROI.*

Time-frequency features were calculated from the combined sources on each fixation for all six ROIs. We then employed standard ridge regression with 5-fold cross-validation to construct linear discriminant classifiers for each ROI. Using this approach, we were able to classify target from non-target trials well above chance in all participants. Interestingly, by combining classification scores from each ROI, we were able to achieve classification accuracies significantly higher than those produced from the best ROI for each participant.

Discussion: Thus, our hierarchical approach successfully identified target detection trials across a range of concurrent auditory load conditions. Likewise, this approach was able to elucidate the contributions and time course of task-relevant neural activity from each ROI, in contrast to the majority of previous FRP studies [3], [4]. However, in this experiment saccade distances and fixation times were somewhat controlled. Future work is required to determine if this approach will translate into more real-world scenarios with complex stimuli.

Significance: The accurate, single-trial classification of FRPs would be a significant advance for BCI technologies whose goal is to interpret the neural response to presented stimuli (i.e. reactive BCIs). As visual search is a ubiquitous and natural behavior within humans-computer interaction, the approach described here would provide a less constrained framework for future BCI technologies.

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Comparison of a consumer grade EEG amplifier with medical grade equipment in BCI applications

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Introduction: The price of the hardware prevents the dissemination of non invasive BCI. Recently, more affordable EEG amplifiers appeared on the market. Among them, the OpenBCI board (http://www.openbci.com/) claims to bring BCI to the many. Enthusiasts and laboratories have started to use this board, but the quality of the recordings and the reliability of the resulting systems have yet to be assessed. In this study, we compare side by side the OpenBCI board with the g.tec g.USBamp amplifier (http://www.gtec.at/), a device commonly used in BCI research. Both OpenBCI and g.USBamp amplifiers can record up to 16 electrodes. This number of channels is sufficient to setup various BCI. We compared OpenBCI with g.USBamp for, on the one hand, P300 speller and, on the other hand, EEG-based workload monitoring using the n-back task [1]. Doing so, we could study respectively temporal and spectral features.

Material and Methods: As opposed to most of the literature, that compares electrodes (e.g. wet *vs* dry), in the present work we study amplifiers. Therefore, instead of complex montages [2] or between-subjects experimental designs [3], we used the same electrodes during simultaneous recordings to compare both. This setup ensures that the signal coming to each amplifier is exactly the same, avoiding any offset or bias regarding the source of the measures. For that purpose we crafted two adapters, with and without a circuit made of ideal diodes. We called those connections "direct" and "isolated" respectively. The ideal diodes montage, placed before amplifiers' inputs, prevented any current to flow in reverse direction from either amplifier to the adapter; it ensured that one set of recordings would not bias the other. One recording session occurred for each application and each condition. We acquired 16 EEG channels all over the scalp using the active g.Ladybird electrodes from g.tec – ground set to "bias" pin on the OpenBCI. Two kinds of analyses were performed. One compared how the amplifiers behaved in practice, when used for classification. The second then looked at the Pearson correlation between the acquired signals, on par with the literature – e.g. [4]. OpenViBE 1.0 was used to acquire signals for both amplifiers – 512Hz sampling rate for the g.USBamp, 125Hz for the OpenBCI. The visual P300 speller came from OpenViBE, with default settings. The protocol inducing workload was implemented following [1]. The signal processing pipeline for temporal and spectral features were analogous to [5].

Results: Direct connection: we tested classification accuracy for significance using Wilcoxon signed-rank tests – we repeated the classification ten times using randomized 4-fold cross-validation. There was a significant difference between amplifiers for the P300 tasks ($p < 0.01$, 48 target trials, 240 distractors). The AUROCC mean score for the g.USBamp was 0.961 *vs* 0.918 for the OpenBCI. There were no significance ($p = 0.079$) for the workload monitoring application, AUROCC scores were 0.89 *vs* 0.90 (180 trials in each 0-back and 2-back task). The Pearson correlation between temporal features of the P300 speller was statistically significant ($p < 0.001$), with a mean R score of 0.9965 over the 16 channels. There was also a significant correlation ($p < 0.001$) for the spectral features from the workload application, with a mean R score of 0.9983 for the 0-back task and 0.9979 for the 2-back task. Isolated connection: there was no significant differences between amplifiers' AUROCC scores, neither with the P300 speller nor for the workload application. As for the signals, there was significant correlations for temporal and spectral features ($p < 0.001$); R score of 0.8847 for temporal features, 0.9976 for spectral features during 0-back task and 0.9987 during the 2-back task. Note that for all applications and conditions AUROCC scores were far beyond chance level (which is 0.5).

Discussion: The correlation between temporal and spectral features tends so show that the signals acquired from the g.USBamp and the OpenBCI are, if not identical, very closely related. While there were no significant differences in classification of spectral features, the g.USBamp performed slightly better than the OpenBCI during the P300 speller task. The results with the "isolated" connections seems to support the similarities between both amplifiers. The weaker correlation compared to "direct" connections may be due to noise added by the ideal diodes circuit, as it did not translate into different classification accuracy – working BCI applications were produced still.

Significance: Overall, the results suggest that the OpenBCI board – or a similar solution also based on the Texas Instrument ADS1299 chip – could indeed be an effective alternative to traditional EEG amplifiers. Even though medical grade equipment possesses certification and still outperforms the OpenBCI board in terms of classification, the latter gives very close EEG readings. In practice, the obtained classification accuracy may be suitable for reliable BCI, widening the realm of applications and increasing the number of potential users.

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Comparison of session-to-session transfer between old and recent session data in motor imagery BCI

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Introduction: Zero training is an important issue in brain-computer interface (BCI), as it minimizes the time-consuming calibration phase in a user-oriented system. Typical approaches transfer pre-existing session data to new session data to reduce the difference between sessions [1-2]. In previous work [3], we proposed a new strategy that used on-site background noise and outperformed existing feature extractors. We showed improved session-to-session transfer using a regularized spatio-temporal filter (RSTF) and a bias correction (BC) without any new session data; however, we did not investigate fully when BC is significantly effective. In this paper, a comparative study was performed on session-to-session transfer between very old pre-existing data (over 3 months old) and data collected recently (within a month).

Materials, Methods and Results: We compared classification accuracies and classifier outputs for pre-existing (more than three months) and recent (within a month) session data using RSTF with offline (background noise from pre-existing data) and on-site noise, and RSTF with on-site noise and BC. For the pre-existing data condition, we tested 6 multi-session data from 3 subjects, and for the recent data condition, 14 multi-session data from 12 subjects were tested. Results showed that RSTF with on-site noise suppression was useful for classification accuracy in both the pre-existing and recent conditions (Figure 1-A), and output results (Figure 1-B). RSTF with on-site noise and BC showed significant improvement in performance in the pre-existing data condition only.

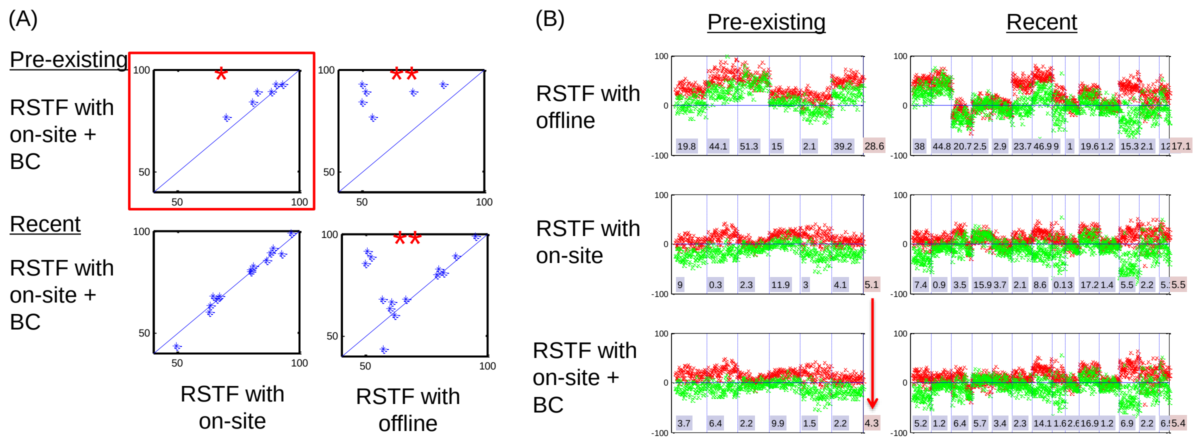

Figure 1. Comparison of three approaches to classification accuracy (A) and classifier outputs (B) with pre-existing (more than three months) and recent (within a month) session data. (A) Statistically significant pairs are marked with * (p<0.10) and ** (p<0.05). (B) Red and green dots indicate classifier outputs of different classes. Blue-shaded values are degrees of bias and red-shaded values indicate the mean of the degrees of bias defined in the equation.

Discussion: The bias correction method considers the Kullback Leibler distance between two different sources of background noise [3] and showed improved performance in the pre-existing data condition. It is likely that these interval sessions have a different spatial structure, while recent interval sessions do not.

Significance: Our proposed method showed improved session-to-session transfer for pre-existing session data more than three months old simply by using on-site background noise acquisition without new session data.

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Deep Transfer learning for Cross-Experiment Prediction of Rapid Serial Visual Presentation Events

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Introduction: Designing classifiers for robust cross-subject and cross-experiment prediction of brain activities in responses to cognitive events is a significant challenge in brain-computer interface (BCI) applications. We have developed previously a new EEG-tailored deep convolution neural network(CNN) model called CNN4EEG and showed its robust and superior performance than existing shallow algorithms including XDAWN for predicting Rapid Serial Visual Presentation (RSVP) target events. In this work, we investigate transfer learning (TL) [1-2] based on CNN4EEG for cross-experiment prediction.

Material, Methods and Results: We used the data from three different RSVP experiments (CT2WS and Static Motion, and Expertise RSVP [3-4]). For each, we extracted 1s EEG epochs with sampling rate 512 Hz obtained from RSVP experiments. First we trained a CNN4EEG with a data set containing 17000 training epochs obtained from combined epochs from CT2WS and Static Motion. A new RSVP dataset with 256 training and 1044 testing samples comes from Expertise data set. A CNN4EEG with seven hidden layers is trained. The input epoch size is 64×128 and the output of the deep convolutional neural network has 2 nodes for two class classification. The hidden layers characteristics are listed in the Table 1 (layers are defined as kernel width $\times$ kernel height / number of feature maps).

Table 1: Deep convolutional neural network hidden layers

Feature-maps	Max Pooling	Feature-maps	Max Pooling	Dropout	Fully-connected	Fully-connected	Fully-connected	Dropout
64×4/10	1×2	1×8/20	1×2	50%	400 nodes	200 nodes	100 nodes	50%

When we use the trained CNN for the classification of the new data set without any fine-tuning, AUC score for the classification of the 1044 testing samples is 68.84%. On the other hand, when the weights of the trained model is used as initialization weight and a fine tuning is conducted afterwards, with 256 training samples, the AUC score of the classification of the 1044 testing samples reaches to 78.57%. Apparently the fine tuning of the deep convolutional neural network causes a ten percent increase in classification performance. It is notable that TL with XDAWN result in 63.98% AUC score.

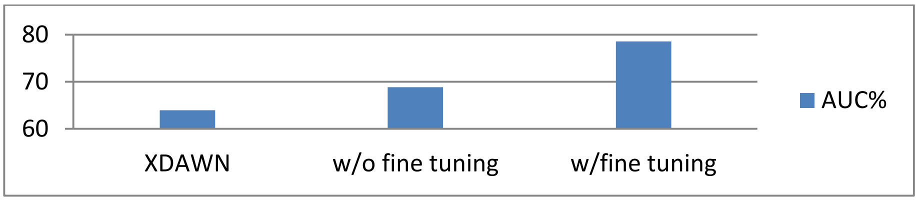

Figure 1: AUC of transfer learning for XDAWN and with and without fine tuning

Discussion: Our experimental results on EEG RSVP data are performed in two cases, using a pertained deep convolutional neural network as a feature extractor and also using its weights just as initialization weights and doing a fine tuning. The results clearly show that the TL with our deep model CNN4EEG can significantly improve the cross-experiment classification performance.

Significance: In this paper, we investigated the transfer learning for cross-experiment prediction of RSVP target events. We show that TL can reduce the over-fitting phenomenon when we implement DL algorithms on a target RSVP dataset; finally, we provided this CNN model trained from a large source RSVP dataset as a transferable model for other RSVP BCI tasks to use.

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Improved estimates of BCI accuracy with hierarchical Bayesian models

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Introduction: Recent replication failures in psychology [1] and the prevalence of low-powered studies in neuroscience [2] have prompted calls for reform of statistical practices, with the current situation even being characterized as a "statistical crisis" [3]. One commonly identified problem is the over-reliance on null hypothesis significance testing (i.e. p-values), and a commonly proposed solution is to move towards parameter estimation and towards Bayesian methods [4]. Although hierarchical Bayesian models of accuracy have already been proposed for brain decoding studies [5], they have not been directly compared to their non-hierarchical Bayesian versions. In this abstract we present a simulation study of Bayesian models of accuracy, and show that hierarchical models improve subject-wise estimates of accuracy, compared to non-hierarchical models.

Material, Methods and Results: The hierarchical model of accuracy is shown in Fig. 1.A. In the non-hierarchical model subject-wise accuracies ψ_i are considered as directly observed, without sampling error, and their values are set at y_i / T_i; the non-hierarchical model is otherwise identical to the hierarchical model. The simulated accuracies were obtained using the hierarchical model as a generative model. We simulated 2500 experiments, with the number of subjects per experiment uniformly sampled between 5 and 20, and the number of trials per subject uniformly sampled between 20 and 200. The group-wise accuracy μ_α for each experiment was uniformly sampled between 0.55 and 0.95 on the probability scale, and std. dev. σ_α was uniformly sampled between 0.2 and 0.8 on the log-odds scale. The Bayesian inference was performed using Markov chain Monte Carlo simulation. The errors in subject-wise accuracy estimates for the two models are shown in Fig. 1.B.

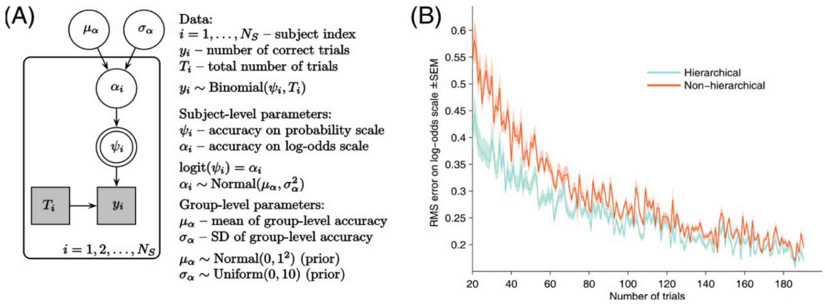

Figure 1. *(A) The hierarchical model of BCI accuracy in a group of users. (B) Root-mean-square (RMS) error in the subject-wise accuracy estimates on the log-odds scale, depending on the type of the model and the number of trials for the subject.*

Discussion: The subject-wise estimates of accuracy are improved using the hierarchical model, especially for subjects with low number of trials, without the loss of accuracy at the group-level estimates (group-level results omitted here for space). The reason for the improvement is the pooling of information across subjects. Moreover, using the Bayesian hierarchical model, a full posterior distribution for subject-wise accuracies is available, rather than just a point estimate such as sample accuracy used in the non-hierarchical model.

Significance: We demonstrate the effectiveness of the hierarchical Bayesian model of BCI accuracy, and show it to be superior to the non-hierarchical model in estimating subject-wise accuracy. The improvement is particularly evident when a low number of trials is available for a subject, which is a common situation in BCI research.

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M3BA: New Technology for Mobile Hybrid BCIs

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Introduction: Over the last decade, the range of Brain-Computer Interface applications has substantially been enlarged by combining BCI with other physiological or technical signals [1]. Also, comparatively new technologies like functional Near-Infrared Spectroscopy (fNIRS) joined the modality set used for multi-modal BCI or for the enhancement of EEG based BCI [2]. To contribute to the progress in this new generation of hybrid approaches, we designed modular hardware specialized for new approaches of hybrid BCI in and outside the lab.

Material, Methods and Results: Based on our previous work on modular mobile open source fNIRS technology [3], we designed a highly miniaturized next-generation device for Mobile (Bluetooth) Modular Multimodal Biosignal Acquisition (M³BA = "MEBA"). The M3BAs are fully stand-alone battery powered modules, each providing 4-6 EEG/EMG/ECG channels (@500Hz/24Bit), 4-6 fNIRS channels (@16,66Hz/24Bit, 750/850nm LED) and a 3-axis accelerometer. In a novel approach, the Texas Instruments ADS1299 integrated EEG circuit with its outstanding electrical characteristics (e.g. 1µVpp input noise) was used for combined EEG- and NIRS acquisition hardware design. Figure 1 depicts a M3BA module and raw EEG, ECG, fNIRS and accelerometer data simultaneously recorded with one device in a session including open/closed eyes (alpha) and deep breathing.

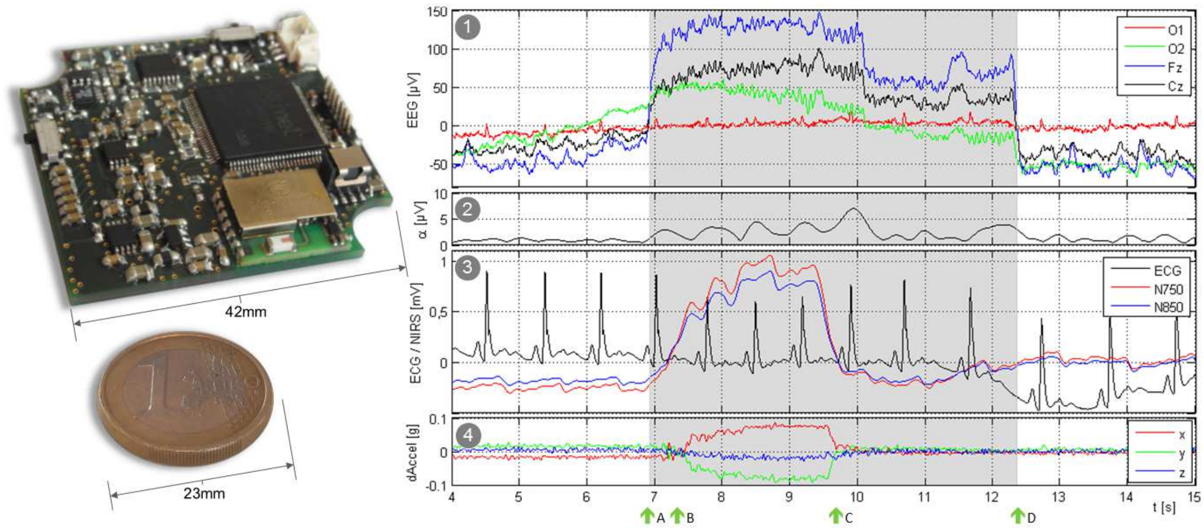

Figure 1. *M3BA Device (left) and multiple signal modalities [(1): EEG, (3): ECG and NIRS, (4): Acceleration] acquired during simple relaxation (white) and trial (grey) period. Distinctive points in trial: close eyes (A), deep breath in (B), breath out (C), open eyes (D). Signals (1,3,4) are raw signals without any filtering/ pre-/post processing except mean offset removals. (2) shows the average envelope of bandpass filtered (4th o. butterw., 10-13Hz) EEG channels O2, Fz, Cz for mean alpha visualization.*

The raw data in the figure exemplifies some advantages of using multiple modalities for further signal analysis, as several obvious interrelations are easily observable: ECG artifacts in EEG (esp. O1, an electrode with bad skin contact), ECG and pulse wave artifacts in the optical NIRS signal, EOG induced EEG voltage offsets and optical artifacts /slow NIRS signals during breathing (movement/accelerometer signal), amongst others.

Discussion: M3BA is a new customizable research tool designed for the use in multimodal mobile BCI in and outside the lab and is aimed to facilitate a better identification and use of common and complementary information in multiple (bio-)signals. By this, we hope to improve the robustness against non-stationarities and artifacts in our signal analysis and machine learning based BCI approaches. Currently, in collaboration with the Physikalisch-Technische Bundesanstalt Berlin, the EEG- and NIRS hardware characteristics of the device are extensively evaluated and first BCI studies are on the way.

Significance: The use of multiple modalities measured by miniaturized mobile hardware could contribute to bringing (hybrid) BCI technology further out of the lab and into real-world scenarios – clinical or non-clinical, where potential users can benefit from it the most.

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NPXLab Suite 2016: tools for BCI signal analysis

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Introduction: The NPXLab Suite is a collection of easy to use free software tools aimed at analyzing physiological signals acquired during either clinical or experimental protocols. Brain-Computer Interfaces could also benefit from this framework as several facilities are provided, such as ICA, CSP, ERP and spectral analysis, classification, statistics and metrics computation. The main guidelines that inspired their implementation and some of their features are here briefly outlined.

Material, Methods and Results: There are several frameworks aimed at handling BCIs protocols, such as BCI2000, OpenVibe, BF++ [1] to name few, but because they do not share a common functional model they can hardly interact, especially in real-time: today it is really difficult to have widely accepted standards that allow to mix BCI software modules from different frameworks as this would require to rewrite relevant portions of the software, breaking existing implementations. However, a different approach could be to try to share at least some off-line analysis tools, thus standardizing just the “static” functional model and not also the “dynamic” mechanisms that would permit to share information across modules in real-time.
NPXLab goes in this direction, as it allows to analyze different bio-signals (e.g. EEG, ERP, MEG, NIRS, etc...), from different acquisition devices and vendors (it supports more than 15 different file formats) with a very friendly user interface. It implements a native file format (NPX, based on XML) which can be easily extended without breaking the backward compatibility so that it can be extended in a painless way. It also comes with 7 different classifiers for BCI (SWLDA, SVM, BLDA, Neural Networks, SRLDA, RLDA, FLDA), several time domain and spatial filters, including ICA (Fig. 1), Laplacian and CSP (Fig. 2), and can perform classical and advanced analyses on protocols like P300, N400, Steady State EP and all kinds of ERPs. A previously released version was also adopted by several laboratories in the EU Decoder Project for performing ERP analysis, metrics computation and statistical validation of the analysis results from NIRS, fMRI and ERPs. An Italian EEG systems manufacturer (EBNeuro, Florence, Italy) has also integrated the NPXLab Suite within its system through a commercial plug-in mechanism. Completely written in C++ programming language it implements the functional model described in [2] and performs faster than many similar and expensive commercial products.

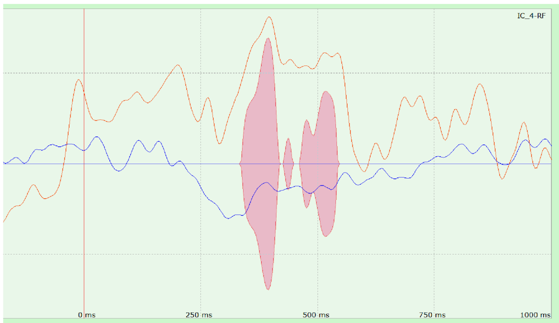

Fig. 1 – ERP module view in which an averaged ICA component relative to target (orange) and non-target (blue) stimuli in a P300 protocol of a patient are shown. Dark pink bubbles indicate statistical significance ($p<0.05$) after sample by sample t-test and False Discovery Rate statistical correction for multiple comparisons.

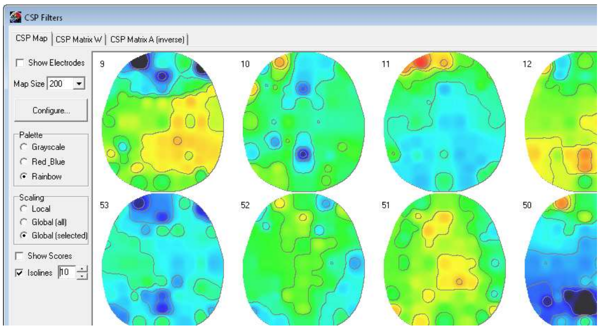

Fig. 2 – A partial screenshot from the common spatial pattern tool. All the supported file formats could take advantage of it after conversion to native NPX format. This operation can be easily performed with the File Converter software facility.

Discussion: The NPXLab Suite is a features rich and easy to use collection of tools for the analysis and processing of physiological signals. It allows to quickly perform classical analyses (e.g. Averaging, Spectral Analysis, time domain-filtering, etc...) as well as more advanced ones (e.g. ICA, Common Spatial Patterns, classification, etc...). In the BCI research field it has been successfully used in several laboratories to pre-process, review, remove artifacts and classify signals from various systems and to compute various metrics.
It can also be used to compare the performances of BCI systems from different protocols [3] and acquisition devices (e.g. EEG, fMRI, ERP, NIRS, etc.) in a simple way as it is based on the model described in [2].
Born in 2002, this project is continuously improved, updated and extended, and it will be also supported in the following years. It is available for downloading at http://www.brainterface.com.

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Pilot Study on Using Fractional Order Calculus-Based Filtering for the Purpose of EEG Signals Analysis

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Introduction: Analysis of Electroencephalography (EEG) signals has recently awaken increased interest of numerous researchers all around the world - caused by the rapid development of BCI-related research areas. The EEG signals are applied in most of the BCI systems as they provide necessary information in regards of brain's activity. In this paper pilot study on implementation of filtering based on fractional order calculus (Bi-Fractional Filters - BFF) for the purpose of EEG signals' classification was in short presented.

Material, Methods and Results: The application of EEG signals in BCI, especially from cost effective sensors is a difficult task, as it relies on real time analysis and interpretation of low quality data and its interpretation depends on the applied method of signal processing [1]. The concept of using of fractional calculus in technical application has become popular in recent years, however the theory was developed already in the 19th century. One of rapidly developing area is implementation of fractional filters for bio-signals processing, as it allows great flexibility in filter shaping [3]. In this paper fractional filtering process was carried out with the Laguerre impulse response approximation implementation [4]. The Fig. 1 illustrates: (a) time series of the analysed 'mu'-waves recorded from the right hemisphere of the brain (C3) using the gaming (not medical) headset Emotiv, so the obtained data is not really 'raw'; (b) is this signal's spectrum. One can observe damping of 28 dB/dec, which is not possible while using traditional filters; (c) Comparison (another, sample time-interval) of using a basic band-pass (8 and 12 Hz) filter and a fractional - BFF filter (with the given parameters:α=0.7, b=11.1688, c=124.7412).

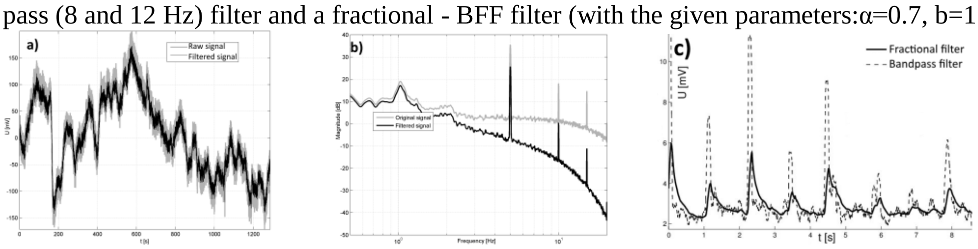

Fig. 1. a) time series (sample 1); b) spectral analysis (sample 1); c) fractional and band-pass filtering (sample 2).

Discussion: The research is currently of initial study stage and the idea of using BFF filtering is being tested. The results are promissing and show wide range of filter design possibilities. Implementation of such filtering in fractional form is numerically impossible – so the approximation has to be taken into account due to occurence of numerical errors. The high order of approximation enables more accurate filters' response, but it may provide less numerical stability.

Significance: The implementation of BFF Filtering is not very popular yet, but the authors assume that it will become widely used in the near future due to its efficiency and wider potential in development of frequency filters' characteristics. The proposed method also offers more flexible adjustment of the frequency characteristics [5]. The previous applied methods were in more detail presented in: [1,2].

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Pipeline for ECoG electrode localization on brain surface: towards a one click approach

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Introduction: Electrocorticographic (ECoG)-based Brain-Computer Interface (BCI) systems require to accurately localize implanted cortical electrodes with respect to the subject's neuroanatomy. Electrode localization is particularly relevant to understand the area recorded from, hence providing an optimal control of neuroprosthetic devices. Yet, this problem has been shown to be non-trivial, especially due to the brain surface shift that is likely to occur after a craniotomy [1]. Several procedures have attempted to solve this problem [2-3], however current procedures require either a time-consuming detection and transcription of the electrodes coordinates from the CT volume scan or combining several different software programs. Here we propose a new pipeline that automatically detects electrodes on the post-operative high-resolution 3D CT scan using AFNI (http://afni.nimh.nih.gov/afni) and projects the electrodes on the cortical surface by applying a brain shift correction [3] using a FreeSurfer (http://surfer.nmr.mgh.harvard.edu) individual anatomy surface. We are working on developing a completely integrated Matlab® GUI interface that would provide an automatic and standard tool of particular relevance for the BCI community.

Material, Methods and Results: The current pipeline consists of the following steps: 1) high-resolution post-operative CT alignment to the pre-operative MRI anatomy (Figure 1A) using the local Pearson correlation cost function implemented in AFNI; 2) automatic electrode localization on the aligned CT scan using 3D clustering detection function provided by AFNI (Figure 1B); 3) electrode coordinates extraction obtained by computing the center-of-mass of each cluster; 4) electrode labelling according to the electrodes leads layout; 5) brain shift correction by projecting the electrodes on the surface of the cortex [3] obtained by the FreeSurfer segmentation; 6) projected electrodes visualization on the brain surface rendering. Validation of the pipeline was carried out in five patients with intractable epilepsy implanted with standard clinical grids. Results were compared to the ones obtained with the currently available method developed by Hermes et al. [3] on the same subjects (e.g., Figure 1C). Mean Euclidean distance and standard errors between electrodes position were 1.03±0.10mm, 2.08±0.11mm, 1.39±0.11mm , 1.52±0.14mm and 2.7±0.1mm , for each subject respectively.

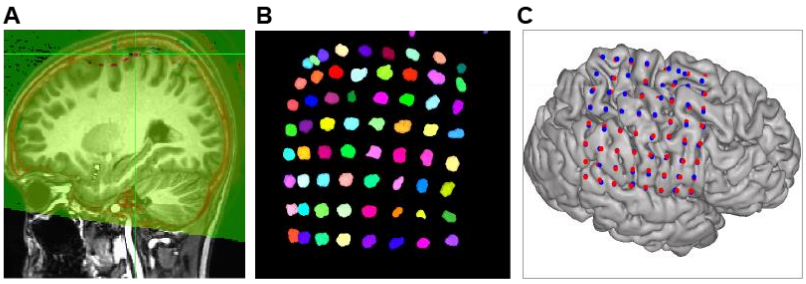

Figure 1. *Two steps of the coregistration pipeline. A) Post-operative CT aligned (red and green) to pre-operative MRI anatomy (gray scale). B) 3D clustering detection of the electrodes. C) Example of electrode prediction using both new (blue) and currently available (red) pipeline, for a representative subject.*

Discussion: The pipeline allows for automatic detection of electrodes position using high resolution post-operative CT and will ultimately consolidate the different software components into one Matlab® GUI interface. There are several limitations that still need to be tackled, such as faster extraction of clusters center-of-mass and labelling. However, the method has excellent potential to automatically detect electrodes on high-resolution ECoG grids using the post-operative CT scan, allowing for a more accurate projection.

Significance: We are developing a straightforward tool that allows the accurate localization of ECoG electrodes on the brain surface. This procedure will provide an important tool for ECoG in neuroscience and for the BCI field for developing optimal neuroprosthetics.

Acknowledgments: The authors thank Richard Reynolds and Daniel Glen for their support on the AFNI components of the pipeline.

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Predicting Serial Visual Presentation Events from EEG Using Spatial-temporal Convolution Neural Network

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Introduction: An important problem concerning BCI applications is event prediction based on EEG data. Past research has identified a host of event-related potentials (ERPs) such as P300 and N1 that are indicative of different basic sensory, cognitive, and motor events. However, the ERPs can change in both magnitude and timing with subjects and experiments, making cross-subject prediction based on ERPs less reliable. Additionally, significant improvement in spatial and temporal resolution of EEG has tempted us to predict much more complex cognitive events that can produce a variety of EEG patterns highly convoluted in space, time, and frequency. To address these issues, we investigate deep learning (DL) solutions in this paper. Recently DL has shown more and more widely applications on BCI tasks (H Cecotti, et al., 2011) and the key to DL's success is its ability to automatically discover discriminate feature representations (Y Bengio, et al., 2013) that are essential for accurate prediction from raw signals. However, designing an appropriate DL model is most of the time hinders further usage. The key factor complicating this process is there are numerous nuisance hyper-parameters from DL model require fine-tuning. Therefore, in order to take full advantage of the learning ability from deep learners for RSVP signals and lighten DL model designation workload, we have investigated several architectures of DL and tested their performances on a time-locked rapid serial visual presentation (RSVP) dataset for comparison.

Material, Methods and Results: In this study, we considered an RSVP experiment called the Cognitive Technology Threat Warning System (CT2WS) [1-2]. We performed leave-one-subject-out test involving 15 subjects with in total about 10,400 epochs (~700 epochs per subject). Considering different DL architectures, we investigated deep neural network (DNN) modules, which are consists of several fully-connected layers; a proposed hierarchical DNN (HDNN) modules which tries to capture the local temporal correlations in raw EEG signals; and the proposed spatial-temporal convolution neural networks (STCNN) which is designed specifically to capture both spatial and local temporal correlations using multiple filters or kernels. Additionally, we also performed tests on three existing DL architectures designed for EEG recognition, named as CNN with 2 temporal filters (CNN2TF, P. W. Mirowski, et al., 2008); CNN with 1 spatial filter (CNN1SF, H Cecotti, et al., 2013); and CNN with 1 spatial filter and 1 temporal filter (CNN1SF1TF, H Cecotti, et al., 2011). Moreover, inspired from image recognition, we also tested our RSVP dataset on classical CNN for computer vision: ImageNet (A Krizhevsky et al., 2012) and GoogleNet (C Szegedy et al., 2014) which also surprising can achieve performable accuracy even better than some of the specific architecture designed for EEG signal processing. Overall, our proposed STCNN achieved the best performance with 89% AUC of ROC, followed by CNN1SF1TF with 88% and then ImageNet with 86% of AUC. DNN has the worst performance (84% of AUC) among all DL algorithms, similar to xDAWN (84% of AUC), which is the state-of-art algorithm for RSVP.

Discussion: In this paper we have tested 8 different DL architectures, including two proposed DL models for EEG based event classification, which are designed to improve the representation of spatial and local temporal correlations in EEG. We showed almost all DL have a significant improvement over other shallow learning algorithms, which is consistence with other works conclusion that deep learners have better capability on feature representations. Besides, models designed to capturing both spatial and temporal features outperforms other DL algorithms which is also consistence with our hypothesis that a specify design in the convolutional layer to exploit local correlations can significantly improve the performance. Finally, to explain the performance of ImageNet and GoogleNet, we believe on the one hand, these networks also captures the spatial and temporal correlation of EEG signals therefore they are better than DL models without using such designation; and on the other hand, since EEG epochs arrange all channels on a 1D vector which smears the spatial filtering from capturing the correct local correlation, they are not the ideal model to use either.

Significance: We have achieved several unique features specifically tailored for RSVP BCI tasks. First, we have investigated the existing DL models for EEG signals and our proposed STCNN which have achieved the best performance in the RSVP dataset. Second, we showed that DL models designed specifically to capture spatial and temporal features will benefits RSVP classification performance. Finally, our trained STCNN model on RSVP dataset can be extended as a feature extractor for other RSVP tasks. Since the architecture of STCNN is applicable for general EEG classification, additional effort in the future to investigate its performance for various BCI tasks is desirable.

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Relevant Frequency Estimation in EEG Recordings for Source Power Co-Modulation

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Introduction: Non-invasive neuroimaging techniques as EEG and MEG allow measuring oscillatory sources related to different cognitive processes. On the sensor level, these techniques deliver a mixture of the underlying source activity, which is caused by volume conduction and impedes the analysis and interpretation of measured brain data. Spatial filters determined by the Source Power Co-modulation algorithm (SPoC) [1] allow to extract sources whose band-power values correlate with a given target variable in single trial. However, SPoC requires prior knowledge about the frequency band of interest, which may contain such co-modulating sources. As brain signals vary between individuals, prior knowledge about optimal frequency bands may not be available or require a full search over the spectrum.
As a remedy, we present the SPEC-SPoC algorithm, following the idea of the SPEC-CSP algorithm introduced in [2]. SPEC-SPoC co-optimizes not only spatial filters as in standard SPoC, but in addition it determines a spectral filter, which defines a suitable frequency band. SPEC-SPoC is tested on EEG data of a steady-state auditory evoked potential (SSAEP) paradigm, for which the optimal frequency is known.

Material, Methods and Results: SPoC optimizes a set of spatial filters by first weighting the trial-wise spatial covariance of the EEG signals with the target variable and then decomposing it into its main components. This first step allows to extract the components or sources which have the strongest (anti-) correlation between their band-power and the target variable. To estimate the frequency of interest, this SPoC-step is alternated with second step to computation for each frequency bin the correlation between the band-power of the decoded sources and the target variable. As the frequency bins of the original data are re-weighted using the obtained relevance value, this second step enhances the most relevant frequency components and suppresses irrelevant ones. The described two-step procedure is repeated until convergence. For the SSAEP datasets collected from seven healthy subjects, the target variable corresponded to the loudness of the auditory stimuli, whereas the ground truth frequency of interest was the SSAEP stimulation frequency of 40 Hz.
Fig. 1(a) exemplifies the spatial and spectral patterns for one of the subjects (S1), where the spectral pattern shows that the identified relevant frequency is exactly at 40 Hz. Furthermore, Fig. 1(b) compares correlation coefficients of sources yielded by SPEC-SPoC (red) versus those obtained by standard SpoC (blue), which was applied after a 40 Hz band pass filter.

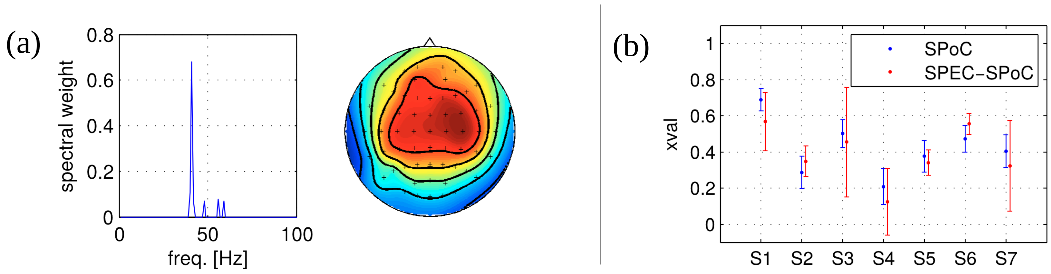

Figure 1. *(a) Example of spectral filter (left) and spatial (right) pattern obtained via SPEC-SPoC for subject S1. The target frequency (40 Hz) is successfully identified. (b) Mean correlation values and standard deviations of sources with the performance metric, achieved by SPoC (blue) and SPEC-SpoC (red), for each of the studied datasets. Performance of SPEC-SPoC is comparable to the one achieved by SPoC, with SPEC-SPoC inferring the relevant frequency band from the data.*

Discussion and Significance: Determining the frequency band informative for a phenomenon under study is a problem which has not been addressed for the SPoC algorithm. With SPEC-SpoC, the automatic tuning of a spectral filter to identify the optimal frequency band becomes possible in a purely data-driven approach. SPEC-SPoC yields results which are not statistically different to those obtained by SPoC ($p=0.8048$). While the latter makes use of *a-priori* knowledge about the informative frequency-band, SPEC-SPoC was able to infer this information from the data. Compared to a brute-force grid search, the new algorithm may reduce run time and the need of user interaction, thus contributing to more accurate, faster and reliable results.

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Skipping BCI calibration: fundamental investigations on Restricted Boltzmann Machines

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Introduction: Operating a brain-computer interface (BCI) that decodes spontaneous electroencephalogram (EEG) rhythms is a skill that users have to learn [1,2]. Feedback is essential for skill learning. EEG is typically recorded from users prior to BCI use and used to train pattern recognition models (calibration). During online operation, the model output is commonly presented as feedback. We aim at developing BCIs that do not require calibration. To this end we study between-user model transfer and online co-adaptation. The former allows providing feedback from the start and the latter enables user-specific finetuning of model parameters to enhance performance. The aim of this offline study is to evaluate the usefulness of the Restricted Boltzmann Machine (RBM) model as a generative classification framework [3] for the above mentioned purposes.

Material, Methods and Results: Dataset 2a from BCI competition IV [4] was used (N=9 healthy users; 2 days; 4 motor imagery classes). Only left hand and feet trials were included in this offline single-trial analysis (72 trials per class per day). Six logarithmic band power [2] features (8-15 Hz, 16-30 Hz; Laplacian channels C3, Cz and C4; 2s estimation window) were extracted and adaptively normalized [1] before training.
Leave-one-user out cross-validation was applied to evaluate between-user model transfer. Recordings of N-1 users were used to train the RBM via contrastive divergence learning [5]. It was then applied to the Nth user's data of day two. The first row of table 1 summarizes mean accuracies achieved. User-specific finetuning was assessed by adapting the model to the held out user's recordings of day one via backprop-learning − see row two. Row three summarizes results for a conventional user-specific shrinkage regularized linear discriminant analysis (sLDA) classifier, which was trained on the Nth user's data of day one and applied on day two.
The RBM performed significantly above chance level for 8 out of 9 users with an average accuracy of 73% in the between-user scenario (sLDA was also evaluated for between-user transfer yielding slightly lower but not significantly different accuracies). After finetuning to the user the mean performance increased by 9% to 82%.

trainings-set	model	accuracy per user [%]									overall accuracy [%]
		1	2	3	4	5	6	7	8	9	
other-users	RBM	91	59	81	69	57	69	82	61	89	**73±13**
day 1	RBM	92	81	89	72	56	82	95	77	94	**82±13**
day 1	sLDA	94	79	89	72	52	79	95	77	95	**81±14**

Table 1. Average classification accuracies for the held out user's 2nd day and mean and standard-deviation across all users. The 95% confidence interval for chance level is [-0.42,0.58].

Discussion: As expected, there was no significant difference between the sLDA classifier and the RBM for log-bandpower features. However, we demonstrated that the RBM model is capable of extracting information, which is inherently stored in the model parameters, from a mixture of users. Unlike sLDA, learning can be seamlessly continued on a single trial basis for a new user. Moreover, since the initial model performs above chance level for many users one can directly start with co-adaptive feedback training.

Significance: The results presented indicate that our RBM based approach is suitable for providing feedback from the start and can be adapted on a single-trial basis. We are currently working on an online implementation.

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Toward a simulator for the development of BCI applications in children: Preliminary steps in validating age-specific EEG simulation in BCI applications

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Introduction: Recently, brain-computer interfaces (BCI) have been demonstrated as powerful tools in assistive technology and neurorehabilitation (NR) applications [1]. However, these applications have yet to be fully realized and demonstrated for use with children. Simulating realistic, age-specific electroencephalography (EEG) activity could facilitate the development of BCI for children. To do so, we propose using the neurophysical model developed in [2,3,4] in conjunction with generated *mu*-rhythm stimulations to investigate differences in BCI processing applications at various developmental ages. This paper reflects ongoing work towards such a simulation environment.

Material, Methods and Results: The general model described in [3] was implemented in MATLAB with key age-dependent parameters extracted from [4] through random normal distributions. The model is generative and imitates corticothalamic neuronal interactions through biologically relevant parameters (for a full description see [2,3,4]). Spontaneous EEG time series was simulated for several ages, both pre and post-adolescence, with parameters decided by the original validation datasets in [3,4]. The total power for each simulated EEG decreases with age, while the prominent spectral band shifts towards higher frequencies, illustrating a development consistent with literature reports [5]. Time series for several ages are presented in Figure 1, with relative spectral band power given in Table 1.

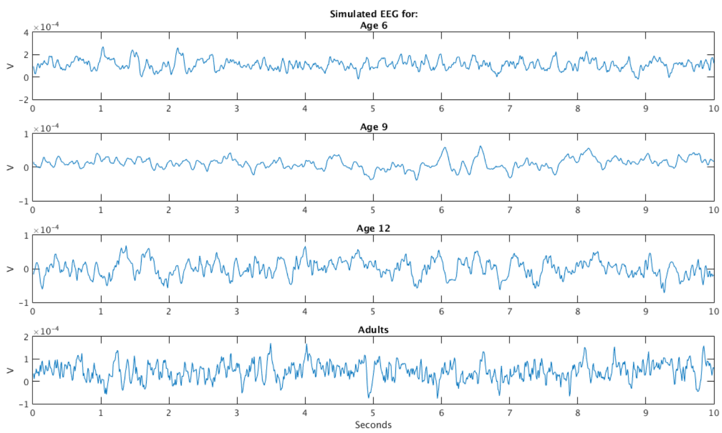

Figure 1. *Time series simulated EEG for ages 6,9,12 and adults (from top to bottom).*

	Relative Power			
Age (years)	**6**	**9**	**12**	**25**
Delta (0.5-4 Hz)	0.960	0.894	0.72	0.863
Theta (4.5-8 Hz)	0.026	0.081	0.159	0.054
Mu (8.5-12 Hz)	0.009	0.016	0.060	0.044
Beta (15.5-30 Hz)	0.004	0.03	0.042	0.027

Table 1. *The relative power for frequency bands for each age in the simulated EEG spectra.*

Mu-rhythm stimulation can be introduced to the model as an impulse stimulus through including a delta-impulse function [3]. Distributing the *mu*-stimulation in controlled age-specific EEG simulations can then mimic motor imagery (MI) paradigms, allowing the simulation to potentially be processed in MI-BCI applications.

Discussion: Simulating age-appropriate EEG data with the option to define evoked-responses, such as *mu* stimulus, provides a critical tool currently unavailable. These simulations provide a flexible environment for examining standard BCI processing chains in children and highlighting areas of improvement in BCI applications on a scale not feasible using direct user recording. Optimizing the MI-BCI tool-set for the developing brain with age-specific simulated EEG data could expand the BCI user base. Further investigations include validation of the EEG simulation and *mu*-rhythm imitation through comparison to real EEG data, with age-specific evaluations done when possible. Additional work includes implementing conditions to translate this model to reflect neurological deficits, potentially allowing access to NR-BCI applications for children via MI-BCI [6].

Significance: The details presented here are a work in progress. Using age-specific, biologically relevant EEG simulations with controlled stimulations allow the optimization and validation of BCI tools for children of various ages. Validating BCI applications for use with children via simulation would help facilitate translation of BCI to children, potentially impacting children suffering from neurological deficits, who may benefit from NR-BCI applications.

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Transfer Learning with Large-Scale Data in Brain-Computer Interfaces

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Introduction: Brain-computer Interfaces (BCIs) have been developed for translating specific patterns of brain activities into comprehensible commands to control computers or external devices. To deal with individual differences in human electroencephalogram (EEG), BCIs often require a significant amount of training data to build and calibrate a reliable model for each individual. This user-specific training/calibration is not only labor intensive and time consuming, but also hinders the applications of BCIs in real life [1]. To alleviate this problem, transfer learning (TL) has been employed to leverage existing data from other sessions or subjects to build a BCI for a new user with limited calibration data [2, 3]. However, the TL approaches still require representative training data under each of conditions to be classified, which might be problematic when the data of one or more conditions are difficult or expensive to obtain. This study proposed a novel TL framework that could leverage large-scale existing data from other subjects and a very limited amount of calibration data from the test subject. This study also demonstrated the efficacy of this method through a BCI that detected lapses during driving.

Material, Methods and Results: For each new target (test) subject, the proposed TL approach fused a set of existing classification models built upon other source subjects' data into a new model for the subject. The weights of the source models were optimized according to 1) the generalizability of each source model to other source subjects, and 2) the similarity between the subject's calibration data (first 10 trials of the experiment) and data from other subjects. The TL framework was evaluated on a large-scale dataset of a lane-keeping driving task (46 sessions from 28 subjects) within a realistic driving simulator, in which subjects were asked to quickly respond to lane-departure events by steering the car back to the cruising position. The duration from the onset of a lane-departure event to the onset of subject response was defined as reaction time (RT) [4, 5]. In this study, the BCI is developed to classify alert (with RTs <1.5 times of the 5^{th} percentile RT) and lapse trials (with RTs >2.5 times of the alert RT). Figure 1 shows the performance of the TL approach in terms of required calibration data and accuracy of detection, compared to that using within-subject cross-session classification. TL marginally outperformed the within-subject approach (87.62±7.32% vs. 84.55±9.12%, p=0.24 assessed by paired t-test) across 11 target subjects who had multiple sessions. Most importantly, TL required much fewer calibration data than the within-subject approach (1.51±0.23 vs. 85.97±22.57 min, $p<10^{-17}$).

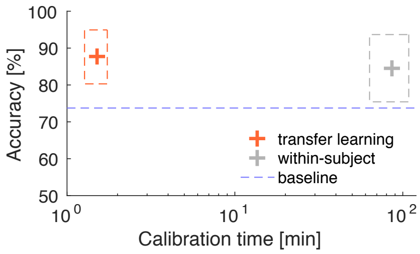

Figure 1. *The proposed TL framework achieved marginly better accuracy of lapse detection (red cross) than the within-subject cross-session prediction (gray cross). The results were obtained from 11 target subjects who had multiple sessions. The TL approach required significantly fewer calibration data than the within-suject approach. Blue dashed line indicates the average blind classification baseline (73.75%) across the 11 target subjects.*

Discussion: Current within-subject and TL approaches both require training data under all study conditions from each individual [2, 3]. These approaches may not be feasible for the detection of lapses because a subject might remain alert across the entire pilot session, resulting in very limited amount of data under the lapse state, making the approaches impossible to build an effective BCI. Thus, it is imperative to develop a novel TL approach that does not rely on the availability of individual's pilot data yet accounts for inter-subject variability.

Significance: With the help of large-scale existing data, the proposed TL approach outperformed the within-subject approach while considerably reducing the required calibration data for the target subject (only ~1.5 min of data from each individual as opposed to ~90 min of a pilot session used in the within-subject approach). The TL approach can enable and facilitate numerous real-world applications (not limited to lapse detection) of BCIs.

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Turbo-Satori: A novel real-time fNIRS data processing and analysis toolbox

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Introduction: Turbo-Satori is a novel real-time processing and analysis tool for functional near-infrared spectroscopy (fNIRS) data which was acquired using a NIRx recording device [1]. The software is optimized for real-time applications such as neurofeedback and brain computer interface (BCI) applications. It supports online oxy/deoxy concentration value calculations from raw wavelength data and provides advanced in-built incremental statistical analysis (RLS GLM), filtering and trend removal procedures, neurofeedback options as well as network interface solutions to export data to 3rd party applications using the TCP/IP network protocol.

Material, Methods and Results:
The software calculates and shows oxy and deoxygenated haemoglobin concentration values in real-time and provides this values for time course displays and neurofeedback / BCI procedures. Oxy/deoxy concentration values are calculated from the raw wavelength in real-time. A moving average filter can be used to remove physiological confounds like heart-beat fluctuations or high frequency noise. The filter settings can be set in hertz and are internally converted into the moving average filter length. Additionally linear trends can be removed incrementally in raw and oxy/deoxy concentration values. A RLS GLM is calculated incrementally for each data point and the resulting statistics are indicated in the row headers in the channel selection area of the software using received triggers or a predefined protocol containing the different conditions and timings. This allows the user to immediately inspect the channels with the highest statistical significance which are e.g. therefore promising to use for neurofeedback and BCI applications. The contrasts used in the t-test can be changed during and after the experiment to support the channel selection procedure. An important aspect in real-time fNIRS applications is the processing time. In an optimal setup this time should be constant during the whole experiment to be able to present real-time neurofeedback or BCI information. Therefore Turbo-Satori is based on incremental procedures which can be performed in a run time of O(1) for each data point. We measured the processing time using two different datasets, the first datasets using 20 channels and the second using 64 channels. For the first experiment a mean processing time of 2.22 milliseconds (sd=1.47ms) per data point, sampling rate 10,42Hz (~98ms)(20 Channels), was measured. The second dataset performed similar: mean processing time 2,76ms (sd=2.57ms) for each data point, sampling rate 7,81Hz (~128ms) (64 Channels). To fulfill the real-time condition a processing time below the sampling rate is required.

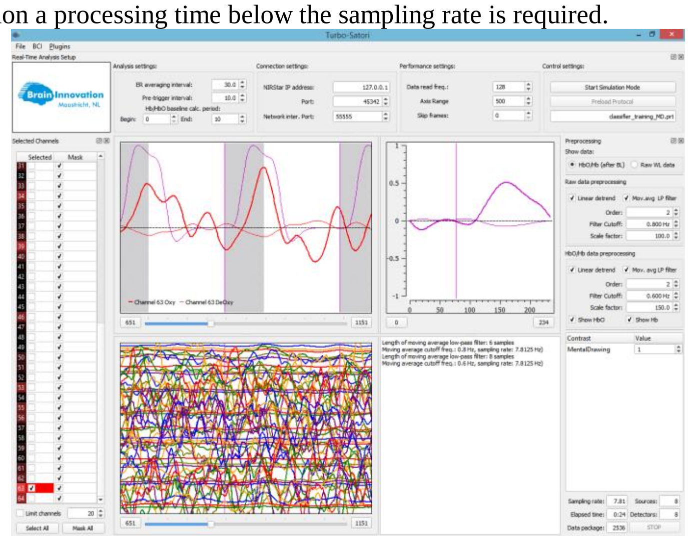

Figure 1. *User interface of Turbo-Satori. The user is able to inspect channels in detail and combine them in one view. All preprocessing parameters can be adjusted in on-line and are accessable during data acquisation. A log window shows current information.*

Discussion: Different filter types need to be tested and applied in real-time fNIRS conditions to evaluate the improvement in filtering quality and allow more filtering options. This would allow to correct for stronger artefacts and signal fluctuations in real-time.
Significance: A novel fNIRS toolbox was introduced performing different preprocessing and analysis procedures in real-time with a processing time for each data point of O(1).
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References: [1] NIRx Medical Technologies, LLC

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Word networks for BCI decoding purposes

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Introduction: In a previous work [1] we demonstrated that the beneficial properties of hidden Markov models (HMM) can be used to extract additional information without further classifier training efforts. For data from a complex visual paradigm, HMMs could be used to decode the type of the stimulus (picture category) and additionally predict its duration with high accuracy when trained on category information only. There is no analogous approach for the widely used static classifiers (e.g. SVMs). However, due to the small amount of training data available and low signal-to-noise ratios, parameter estimation for HMMs is difficult and therefore, the achievable decoding accuracies are slightly lower than for static classifiers. Here, we show how the use of word networks (Fig. 1a) - a technique from the field of speech decoding (where HMMs represent the gold-standard) - can be used to conveniently incorporate prior knowledge into the decoding. This information boosts the decoding accuracies reached with an HMM approach up to the level of SVMs. Considering the additional information that can be extracted due to the dynamic nature of HMMs, the routine turns out superior overall.

Material and Method: The analysis is performed on two electrocorticography (ECoG) datasets as described in [1]. High gamma features are computed using Matlab implementations as described in [1,2]. The paradigm design (Fig. 1b) causes some trials to contain multiple stimuli, thus providing a challenging dataset for HMMs. We compare the accuracies for a standard HMM decoder as used in [1] ('Standard'; this represents a single-word recognizer) and three setups using WNs (semi-continuous decoding) with increasing levels of prior knowledge:

(1) 'WN default': No prior knowledge. Here, the longest consecutive interval determines the decoded category.

(2) 'WN first word': For trials modeled by multiple HMMs, we assign the label of the first model. This setup reflects that all trials start with the original stimulus (i.e. on which the trial label is based).

(3) 'WN FW + no short': Use the first model's label, but ignore sequences shorter than 20 samples ($\triangleq$ 375 ms). This adds the information that no such stimuli (i.e. shorter than 300 ms) appeared in the paradigm.

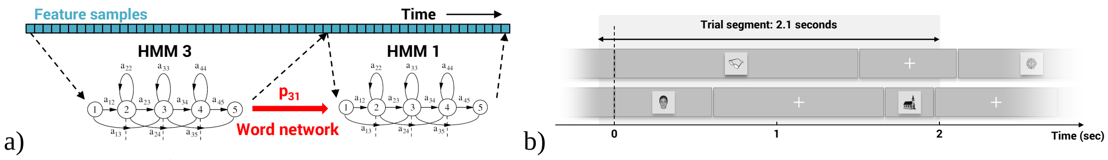

Figure 1. *a) Principle of HMM decoding using word networks [3]. Contrary to the 'Standard' case, in which each trial must be modeled by a single HMM, the time series of feature values of a trial can be modeled as a combination of multiple HMMs using WNs. b) Visual paradigm: pictures from three categories (objects, faces, watches) were presented for 5 different durations (300ms-1500 ms). Note, that some trials (esp. with short first stimulus) contain an additional stimulus at the end of the time segment.*

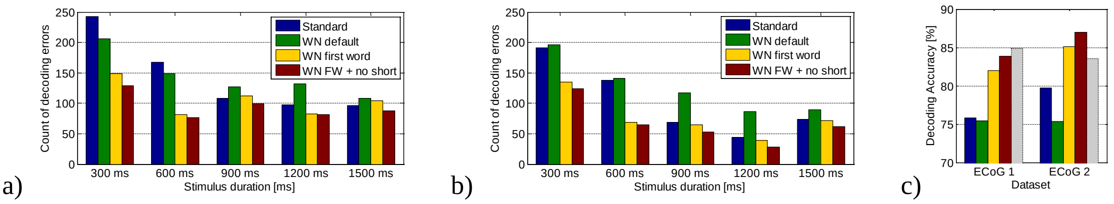

Figure 2. *Count of category decoding errors using different decoding strategies for both datasets (a) ECoG 1, b) ECoG 2). c) Decoding accuracies for both datasets and all decoding strategies (chance level: 33.3%; dashed gray bar: SVM results).*

Results and Discussion: In the 'Standard' case, most decoding errors occur for shorter stimuli (Fig. 2a,b). This is likely caused by additional stimuli appearing within these trial segments. A single HMM cannot compensate for this and misclassifies the trial eventually. WNs allow combinations of HMMs within a single trial but increase the complexity of the decoding routine. For the 'WN default' case this results in decreasing accuracy, especially for longer stimulus durations. However, with increasing level of prior knowledge, decoding accuracies rise significantly. With the combination of both prior knowledge aspects, the 'FW + no shorts' case consistently leads to the best results. The gain in decoding accuracy is 8.1 % and 7.2 % (ECoG 1 and 2) with respect to the 'Standard' case. Thus, the routine can catch up (ECoG 1) or even outperform (ECoG 2) respective SVM results while preserving the benefits of dynamic classifiers (see introduction).

Significance: We show that the use of WNs facilitates the incorporation of prior knowledge. This can significantly improve decoding accuracies and offers huge potential for more sophisticated analysis.

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2-D analog like control of a cursor by means of SSVEP acquired with two dry electrodes and elicited by 4 LEDs

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Introduction: In this study we propose a new SSVEP-based BCI approach [1] for 2D cursor control. Our goal is to allow a subject to gaze at a point on a PC screen and move a cursor on it, not fixing a flickering LED but gazing between 4 LEDs. The result is a dependent BCI which provides a mean ITR of 21 bit/min (SD: 3 bit/min). Data were collected using a wireless electroencephalograph with just two dry electrodes (O1, O2) and analyses were performed offline.

Material, Methods and Results: This study included 12 subjects (5f, 7m). We used 4 white flickering LEDs whose frequencies have been set, using Arduino UNO board, to 8.5 Hz – 9.5 Hz – 10.5 Hz – 11.5 Hz (see Fig. 1). Every subject had to gaze at 64 different target locations (red circles, fig. 1), while every trial was divided into 3 epochs: Inter-Trial Interval (1s), Cue (2s), during which the subject was instructed to the target location to gaze, and Performance (4s) during which the subject had to fixate the previously requested site. Targets were displayed on a PC screen within a square whose side was 21.7cm and whose vertices were populated by the four LEDs (Fig. 1) that were mounted on a fixed frame positioned on top of the PC screen. Subjects were positioned at a distance of 80cm from the center of the screen. Two EEG signals (O1, O2) were recorded by means of dry electrodes using a Bluetooth wireless communication electroencephalograph (NE StarStim).

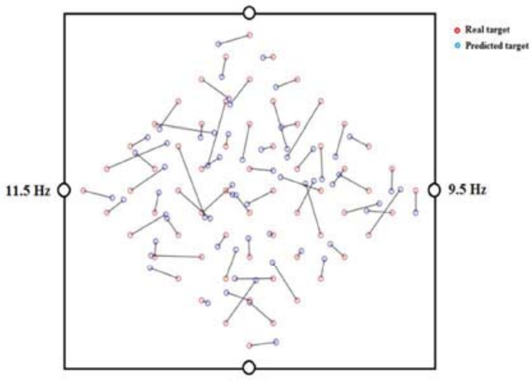

***Fig 1.** LEDs position and errors for the best performing subject. Each segment represents the distance between the real (red) and estimated (blue) target.*

Spectral features (amplitudes and phases) were computed during the performance epoch of each trial by means of FFTs computed over 4s, thus obtaining a resolution of 0.25Hz. Those in the [5-99Hz] band were used to built 8 linear models, two for each LED, that linked spectral features with polar coordinates of the targets, centered at each LED location, after a pre-selection procedure which reduced the available features from 1504 to 48. Thus, from each LED, a model pair was built, one for the modulus and one for the phase, that identified in polar coordinates the location of the targets. A total of 4 models pairs, one for each LED, were then built. It should be noted that the same trial was then modeled by 4 different model pairs, thus according to 4 different polar systems.

For each of the 8 models, the choice of the best one (and so of the features set that composed it) was carried out according to Akaike AICc coefficients, computed iteratively 48 times while removing at each iteration the least significant spectral feature. We tested, using a leave-one-out approach, the proposed method by predicting each target location by estimating it from the 4 different models pair and after averaging across them.

The average error, computed as the difference between real and estimated target location, from all the targets and for all the subjects was 2.3cm (mean bit-rate 21±3 bits/min). For the best performing subject we obtained an average error of 1.8cm, and a theoretical bit rate of 27 bits/min.

Discussion: The results show that it could be possible to have an analog-like control of a cursor in 2D and with just 4 flickering LEDs. This can be obtained by building a model that relates spectral features of the elicited SSVEPs signal with the polar coordinates of a target having as origin a flickering LED. The BCI system we propose is particularly practical and comfortable, thanks to the use of only two dry electrodes. The stimulation is minimally annoying for the user, who can use the interface without directly gazing at a flickering LED.

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A surgeon's brain switch: cortical dynamics of cognitive load in surgeons

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Introduction: A surge in medical robotics has widened the variety and complexity of tools available to surgeons. In a pressurised environment, where split-second decisions are often required, the cognitive demands on surgeons are enormous. Intelligent operating suites comprising cognitively-controlled robotic platforms, may help reduce the surgeons' mental workload and improve technical performance [1-2]. However, such an advanced system requires streamlined switching between traditional and robotic tools, depending on the surgeon's cognitive workload. To study haemodynamic markers of surgeons' workload [3-4], we present results from an authentic surgical environment where surgeons experienced an escalating cognitive demand during a bimanual surgical task. Our findings show the presence of between-subject variability in cortical haemodynamic data and technical performance, suggesting that workload states are dissociable and relate to surgical performance.

Materials & Methods: 28 surgeons performed a laparoscopic suturing exercise in a box trainer (iSurgicals, UK). Subjects created 5 knots under two conditions: 1) self-paced (SP) (max. 300s per knot) 2) time-pressure (TP) (max 120s per knot). A 48-channel functional near-infra-red spectroscopy (fNIRS) system (ETG4000, Hitachi Medical Corp) was used to acquire haemodynamic data from the prefrontal cortex (Fig. 1a). Subjective workload was quantified using the validated Surgical Task Load Index (SURG-TLX) and performance was measured using task progression scores, accuracy scores, leak tests and knot tensile strengths.

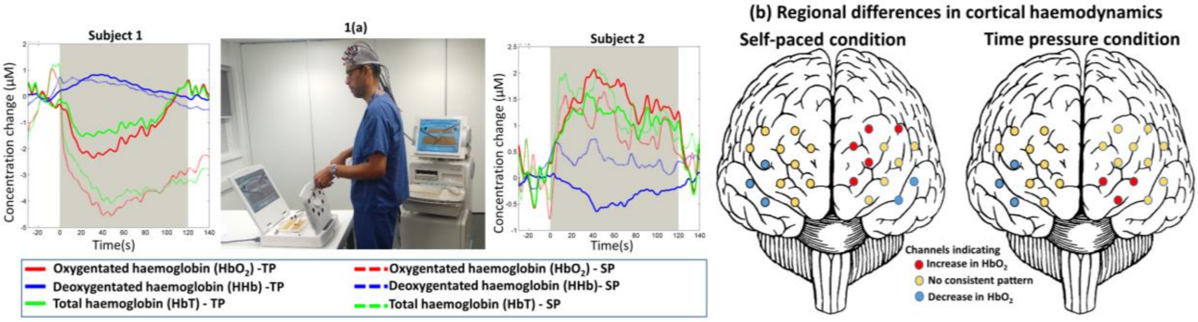

Figure 1. *a) Experimental set-up and mean oxygenation changes for two subjects in self-paced (SP - dotted) and time pressure (TP - solid) conditions. Shaded area depicts task duration with uniformed duration (120s) for both tasks. b) Graphic representation of group trends in channel-wise cortical oxygenation changes exhibiting regional differences in HbO_2 for the two conditions.*

Results: Time courses of mean concentration change in oxygenated haemoglobin (HbO_2) indicate dissociation between the SP and TP conditions. For example, a larger HbO_2 decrease during the SP condition is seen in subject 1, who experienced a greater increase in perceived load under TP and exhibited a larger deterioration in performance (Fig. 1a, Table 1). Conversely, subject 2 showed reverse haemodynamic patterns to subject 1 with a larger HbO_2 increase in TP. Subject 2 experienced less perceived load under TP and exhibited less performance deterioration (Table 1). Condition-wise investigation reveals regional changes in oxygenated haemoglobin. Visual inspection of time courses reveal a general increase in HbO_2 in medial frontal channels in the TP condition, and in ventromedial channels in the SP condition (Fig. 1b).

Table 1: Performance metrics for 2 example subjects

	Self-Paced					Time Pressure				
Subject	**SURG TLX (a.u.)**	**Task Progression Score (a.u.)**	**Accuracy Score (mm)**	**Leak Volume (ml)**	**Tensile Strength (N)**	**SURG TLX (a.u.)**	**Task Progression Score (a.u.)**	**Accuracy Score (mm)**	**Leak Volume (ml)**	**Tensile Strength (N)**
1	59	5.4	2.8	16	47.154	160	2.4	5	25.4	0
2	152	5	1.3	17.6	41.096	196	3.6	3	18.8	20.398

Discussion: The data presented is novel for its subject population, paradigm and the target application. Haemodynamic changes during the two conditions have dissociable trends, indicating the surgeon's cognitive state. Data shows regional variations, indicating the role of inherent cortical structures in processing workload, which may be better revealed by image reconstruction. Further analysis can highlight neural markers of high and low performance, potentially leading to a training intervention for surgical trainees.

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A visual BCI system using mild peripheral visual field stimulation

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Introduction: Traditional visual Brain-Computer Interfaces (BCIs) often use intense and flickering stimuli in the central visual field to elicit strong brain responses[1,2]. However, for a long-term use, these visual stimuli could be irritating and lead to visual fatigue, headache and mental anxiety. Furthermore, in the scenes of virtual reality and augmented reality, the flash in the central vision would pose a challenge for users to perform other visual tasks. This study aims to develop a visual BCI system that could give users a flicker-free central vision by only presenting weak stimuli in the peripheral visual field.

Material, Methods and Results: Forty alphanumeric characters were arranged as a 5×8 matrix displayed on a computer screen in front of subjects. Stimuli were a white dot that would appear either in the bottom left (defined as digit ‘0’) or right (digit ‘1’) peripheral area (1.1 degrees from the center) for every 100ms for a duration of 33ms. Two basic binary units I and II were designed as a sequence of digits ‘0101’ and ‘1010’, respectively. According to a time-domain coding strategy, 6 units were required to code 40 characters. As the two kinds of digits ‘0’ and ‘1’ would elicit different visual evoked potential (VEP) patterns, target characters could be decoded by finding the best match between VEP and templates. To select a target character, subjects just need to focus their attention on the center of the character while passively receive a sequence of stimuli appearing in the peripheral field. One subject performed an online test to spell 39 characters in a random sequence after ten-minute training, and achieved an information transfer rate of ~50 bits/min.

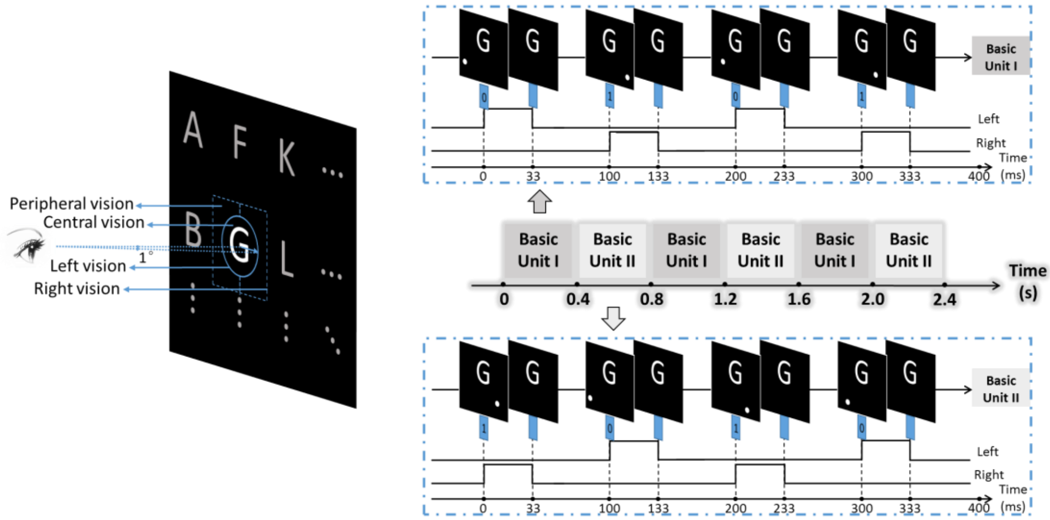

Figure 1. *(Left) Central, peripheral, left and right visions of the target character defined in this study. (Right) Timing sequence of a completed trial for letter ‘G’ are displayed with the discription of the two basic units.*

Discussion: The study results demonstrated that the peripheral visual BCI system was effective in spelling characters. Moreover, it gave users a more comfortable interface, as the peripheral visual stimulation was weak and mild. Furthermore, in the scenes of virtual reality and augmented reality, the flicker-free central vision could provide users with a clear sight on the outward environment.

Significance: This study develops a new visual BCI system that codes characters with inconspicuous stimuli in the peripheral visual field. It opens a new and promising direction for the research of BCIs.

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Attention in Complex Environment of Brain Computer Interface

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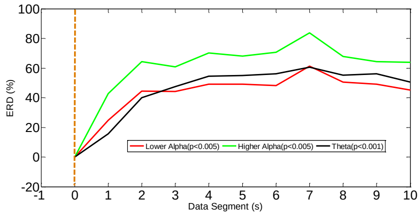
*Introduction: E*lectroencephalogram (EEG) power is related to human cognitive processing, but in a complex and non-linear way. Attention is one of such fundamental human cognitive processes. EEG power in alpha band is positively related to it, whereas EEG power in theta band simultaneously shows the inverse relation [1]. It has been reported in past studies that if EEG power in lower (8-10Hz) and upper alpha (10-12Hz) supressed than opposite holds true for theta (4-7.5Hz) in attentional process [2]. The main purpose of this study is to explore the hidden nature of attention while involving a video game with high attentional need. This game creates a scenario in which subjects need to pay attention on both of the game and designed task. The attentional changes like handling sequential and random targets in our daily life - one complex environment.

Material and Method: EEG data were collected from 10 right-handed subjects (male; 24.5 years; AD: 500Hz; 32 electrodes; 1-50Hz). A visual match-three puzzle game was used in which stimuli presented randomly 6-8 times in each session (total 6 sessions; played approximately 90 minutes). Subject needed to increase attention for 10s when target appears. The score was given by calculating and quantifying alpha power recorded online from EEG during 10s [3]. For analysis, EEG data from 1s prior as a reference interval and 10s following the onset stimulus were segmented. A power spectrum time series was calculated using the fast Fourier transform (FFT) which was squared and averaged for individual frequency band to obtain a measure of the power spectral density (PSD) from frontal channel (Fz) for each subject [4]. Event related desynchronization (ERD) was also calculated on obtained PSD based on Pfurtscheller method [5]. It is important to note that positive value of ERD indicates power suppression while negative ERD means decrease in power.

Results: Previous studies [1-2] suggested that visual attention is the main factor for suppression of lower and upper alpha band power as well as increase in theta band power. But in the present study, alpha and theta activities as well event related changes in respective power shows yet another pattern of result and complex nature. Our results in ERD (Figure. 1 (a)) and event related spectral perturbation (ERSP) (Figure. 1 (b)) revealed that theta, lower alpha and upper alpha power desynchronized simultaneously during attentional processing.



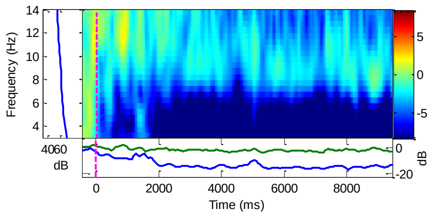


Figure 1 (a) Event related desynchronization (Left); (b) Event related spectral perturbation (Right)

Discussion: The primary result presented in this paper raised a question on current attention brain computer interface (BCI) which is based on alpha and theta inverse relationship. Our result indicated that this inverse relation is not always stable in the complex condition. Therefore, there is a need to design a more precise indicator for monitoring human attention (including resource allocation/attention switching). This finding can be an important step for generalizing and applying for BCI in real-world environment instead of laboratory.

Significance: This work can be applied to improve the development of attention/concentration based BCI.

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Autocorrelation based EEG Dynamics depicting Motor Intention

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Introduction: Movement intention detection is useful for intuitive movement based Brain-computer interfacing (BCI). Various oscillatory cortical processes are involved in voluntary movement generation. We explore the fundamental brain processes underpinning movement intention by studying the temporal dynamics of EEG. A novel autocorrelation based feature was used to identify movement intention on a single trial basis. Autocorrelation analysis results were compared with well-established Event Related Desynchronisation (ERD) and Movement Related Cortical Potential (MRCP) neural correlates of movement.

Material, Methods and Results: A voluntary index finger tapping task was chosen for EEG experiments on fourteen individuals (26±4 years, 7 female, 2 left handed). In each of the 40 trials recorded, an instruction to make a right/left tap or rest was displayed. Participants were given a 10 s window to perform the finger tap at a random time. Bipolar channels F3-C3, Fz-Cz, F4-C4, C3-P3, Cz-Pz and C4-P4 were used for analysis.

The autocorrelation function estimates the temporal dynamics of EEG by describing how it relates to itself. Previous studies have suggested that the autocorrelation function changes during movement [1]. To capture the evolution of autocorrelation, an exponential curve was fitted to the autocorrelation estimated from a 1s window of the EEG and the procedure repeated for each window shifted by 100 ms. The exponential curve represented the relaxation process captured by the autocorrelation and its decay constant (an estimate of how fast or slow the autocorrelation decayed) was used as a feature for classification (see Fig. 1a). ERD [2] and MRCP [3] features were also extracted from single trials for comparison. Autocorrelation and ERD was extracted from five frequency bands because they span a wider range whereas MRCP was extracted from its' range of 0.1 to 1Hz.

Table 1. LDA classification sensitivities

Method	Left Tap %	Right Tap %
Autocorr 0.5-30Hz	78.25 (±9.58)	78.48 (±8.36)
ERD 8-13Hz	88.27 (±7.54)	84.54 (±9.43)
MRCP 0.1-1Hz	70.60 (±5.93)	68.90 (±5.26)

(a) (b)

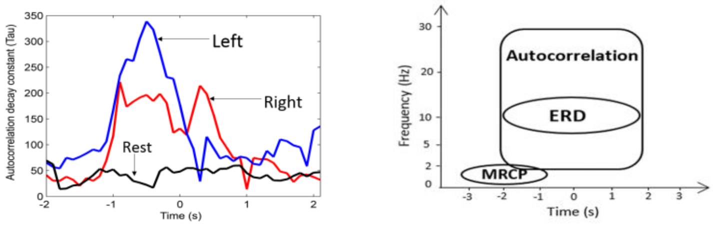

***Figure 1.** (a) Autocorrelation decay constant (C3-P3) - right tap (red), left tap (blue) and rest (black). Movement at 0s. (b) Autocorrelation, ERD, MRCP feature space.*

Autocorrelation decayed slower during movement intention and execution and faster otherwise. Table 1 shows the comparison of the grand average classification sensitivities for all the participants obtained using a Linear discriminant analysis (LDA) classifier. All results were significantly better than chance ($p < 0.05$).

Discussion: ANOVA indicated that the sensitivities of the autocorrelation, ERD and MRCP were significantly different ($p < 0.001$). Low MRCP sensitivities suggest that it may not be suitable for single trial. Autocorrelation performed equally well across all frequency bands whereas the performance of ERD was best in the μ band (8-13Hz). The movement prediction timings and spatial locations for autocorrelation, ERD and MRCP are different. Fig. 1b shows the spread of features with respect to frequency and time. The features also exhibit different spatial distributions; ERD and MRCP are restricted to the motor cortex, while autocorrelation has a broader spread, predominantly over central and parietal cortical regions. This shows that autocorrelation occupies different space, providing information about movement intention complementary to that contained in ERD or MRCP.

Significance: We have introduced a new neural correlate of movement intention, depicting different information from ERD and MRCP. These autocorrelation features could be used, along with ERD and MRCP, in a hybrid classifier for constructing a robust online BCI with improved accuracy. Autocorrelation reflects slow dynamics of the amplitude decay of EEG and the modulations of oscillations. Different morphologies of the autocorrelation could also be indicative of different metastable-states in the brain, which will be investigated further.

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Can SSVEP be modulated by tDCS?

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Introduction: Steady-state visual evoked potential (SSVEP)-based brain-computer interface (BCI) is one of the representative reactive BCI paradigms [1]; however, it has been frequently reported that non-negligible numbers of individuals have difficulty in using SSVEP-based BCI systems due to the low signal-to-noise-ratio (SNR) of SSVEP responses for specific stimulation frequencies. Many studies have strived to overcome the so-called "BCI illiteracy" issue by introducing new visual stimuli or classification algorithms, but it still remains a challenging issue to be addressed for the commercialization of SSVEP-based BCI. In this study, inspired by a recent report that transcranial direct current stimulation (tDCS) can modulate visual evoked potentials [2], we investigated whether the representative features of SSVEP-based BCIs such as SNR, amplitude, and canonical correlation analysis (CCA) coefficient can be modulated by tDCS, especially for individuals with low-SNR SSVEP.

Materials, Methods and Results: Twenty healthy subjects volunteered to participate in our study, three of whom were excluded due to severe noises and artifacts included in the recorded EEG data. Each participant participated in two double-blinded experiments - an actual tDCS experiment (2-mA anodal stimulation for 20 min, anode: Iz, cathode: Cz) and a sham tDCS experiment (2-mA anodal stimulation for 1 min) - conducted on different days. The second experiment was conducted at least one month after the first experiment in order to avoid any possible training effect and post-tDCS effect. On each day, SSVEP responses were recorded right before and after the randomly assigned actual or sham tDCS session, using six EEG electrodes (Oz, O1, O2, POz, PO3 and PO4). In each SSVEP session, one trial consisted of 2-s fixation, 10-s SSVEP stimulation, and 7-s resting periods. Checkerboard pattern-reversal visual stimuli with frequencies of 5, 6, and 7.5 Hz were presented 15 times in a randomized order for each frequency. After high-pass filtering at 1 Hz, amplitudes, SNR values, and CCA coefficients for three stimulation frequencies were evaluated, and then each feature was averaged over channels.

Total 204 datasets (17 subjects x 3 frequencies x 2 sessions (pre- and post-tDCS) x 2 conditions (actual and sham tDCS)) were processed according to the procedure explained below. First, we gathered pairs of pre-tDCS and post-tDCS SSVEP datasets of which the initial SNR (i.e., SNR of pre-tDCS SSVEP) was lower than a certain threshold (e.g., SNR < 1.6). We then evaluated the statistical differences in the amplitudes, SNR values, and CCA coefficients of the SSVEP datasets recorded before and after the actual/sham tDCS using the paired t-test. We repeated this procedure while varying the threshold value from 1.5 to 2.5.

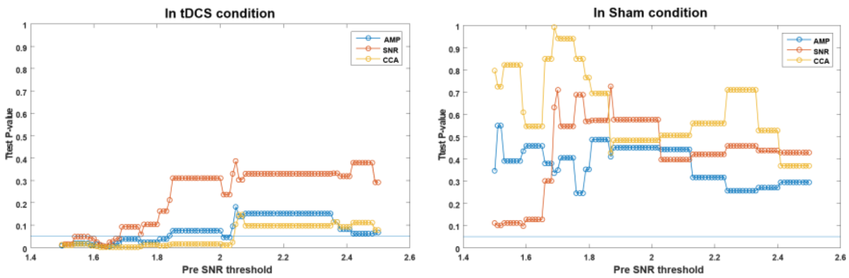

Figure 1. *Changes in p-values with respect to the pre-SNR threshold: (Left) actual tDCS; (right) sham tDCS*

Results: Experimental results showed that 20-min anodal tDCS can significantly enhance not only the spectral power, but also SNR and CCA coefficient of SSVEP responses especially when the SNR of the initial SSVEP is low (Figure 1). The difference in the CCA coefficients remained statistically significant even for SNRs as high as 2. No SSVEP features showed statistically significant changes after sham tDCS.

Discussion: tDCS has the potential to be used to enhance the overall performance of SSVEP-based BCI systems, especially for individuals who do not respond to specific visual stimulation frequencies.

Significance: To the best of our knowledge, this is the first study that reported the enhancement of SSVEP responses after tDCS.

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Combination of EEG and fNIRS for the (Un)Conscious Discrmination during Anesthesia

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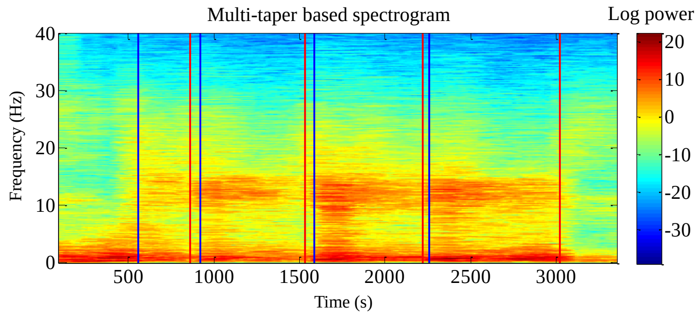
Introduction: Recently, electroencephalogram (EEG) and functional near-infrared spectroscopy (fNIRS) which are commonly used in Brain-Computer Interface (BCI) systems have been utilized into anesthesia study in neuroscience field to monitor depth of consciousness [2,3]. The objective of this paper is to show a feasibility of multi-modality based on EEG and fNIRS in experimental protocol of anesthesia and demonstrate the effect of brain dynamics of related with (un)conscious stage in the spectral domain of EEG data.

Material, Methods and Results: To investigate the relationship between EEG & fNIRS activity and depth of consciousness when the subjects' lose/recovery their consciousness, we recorded EEG with 62 channels and fNIRS with 14 channels acquired from 4 sources and 10 detectors simultaneously. Furthermore, we also measured bispectral index (BIS^{TM}, Covidien, Mansfield, MA) and extra vital signals such as blood pressure, end-tidal CO_2, etc. Throughout the experiment, subjects have to respond to prerecorded auditory stimuli by button per every 9-11s with closed eyes. When pressing the button, anesthetic agent (propofol) is infused into his/her vein by patient-controlled sedation application (see Figure 1-(a)). To evaluate brain dynamics, multi-taper time-frequency spectrum was utilized to estimate the brain dynamics under anesthesia with the filtered data from 0 to 40Hz in the frequency domain [4].

(a)



(b)

Figure 1. *(a) Experimental setup with EEG and fNIRS systems, (b) Grand average EEG spectrogram based on multi-taper analysis over 5 frontal area with 19 subjects. Vertical blue and red line indicate time points related with loss of consciousness (LOC) and recovery of consciousness (ROC), respectively.*

Figure 1-(b) which only uses the trigger information by button demonstrated that according to the depth of consciousness, transition points related with LOC and ROC have specific differences in some frequency ranges such as alpha and beta oscillations.

Discussion: In our study, we found discriminative EEG/fNIRS patterns in the spectral domain, especially, alpha and beta oscillations. EEG has increased/decreased specific frequency bands at LOC/ROC point, while fNIRS has gradually increased oxy-hemoglobin concentration level aligned to LOC.

Significance: We proposed a novel paradigm in anesthesia study using a hybrid EEG and fNIRS measurements to find specific signatures related with depth of consciousness.

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Comparison Between Discrete and Continuous Motor Imageries: toward a Faster Detection

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Introduction: A large number of Brain-Computer Interfaces (BCIs) are based on the detection of changes in sensorimotor rhythms within the electroencephalographic signal [1]. Moreover, motor imagery (MI) modifies the neural activity within the primary sensorimotor areas of the cortex in a similar way to a real movement [2]. In most MI-based BCI experimental paradigms, subjects realize a continuous MI, i.e. one that lasts for a few seconds, with the objective of facilitating the detection of event-related desynchronization (ERD) and event-related synchronization (ERS) [3]. Currently, improving efficiency such as detecting faster a MI is a major issue in BCI to avoid fatigue and boredom. In this regards, a recent article showed that a brief intention of movement corresponding to a 2s-MI, leads to more informative ERS features than continuous motor imageries [4]. Thus, in this study, we are investigating differences between continuous MIs and discrete, i.e. simple short, MIs.

Material, Methods and Results: 17 healthy subjects carried out real movements, discrete and continuous MIs, in the form of an isometric flexion movement of their right hand index finger. Each subject realized first a session of real movements, and then a discrete and a continuous sessions of motor imageries in a randomized order. Each session is divided into runs for a total number of 100 trials. Beeps were used as go and stop signals. Finally we computed ERD/ERS% for 9 electroencephalographic channels (FC3, C3, CP3, FCz, Fz, CPz, FC4, C4, CP4) using the "band power method" [3] (Fig. 1), topographic and time-frequency representations.

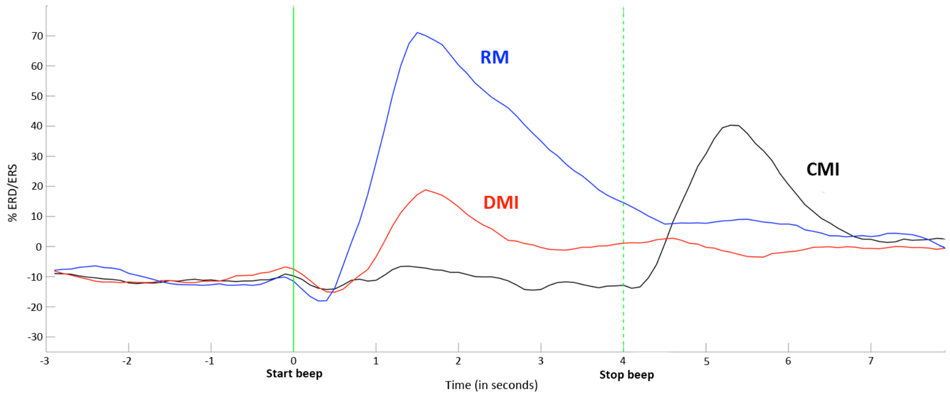

***Figure 1**. Grand average (n = 17) ERD/ERS% curves estimated for the real movement (blue), the discrete motor imagery (red) and the continuous motor imagery (black) within the beta band (18-25 Hz) for electrode C3.*

Discussion: When subjects imagine a continuous movement for several seconds, it usually corresponds to a succession of imagined movements. In this case, several ERD and ERS seem to be generated. Thus, the temporal contraction of several ERD and ERS generated can be less detectable by a system [4]. Moreover, continuous MIs generate a delayed ERS compared to a discrete MI. Nevertheless, it appears that a longer imagined movement increases the power of the beta rebound.

Significance: Results show that both discrete and continuous MIs modulate ERD and ERS components. Both ERSs are different but ERDs are close in term of power of (de)synchronization. These results show that discrete motor imageries may be preferable for BCI systems design in order to faster detect MIs and reduce user fatigue.

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Comparison of Hierarchical and Non-Hierarchical Classification for Motor Imagery Based BCI Systems

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Introduction: Motor imagery (MI) based BCI systems record and analyze the brain activity to determine users' intentions while imagining moving some parts of their body [1]. In order to build systems that are able to detect several commands, multiclass schemes need to be applied. Hierarchical methods allow solving multiclass problems by using a tree of binary classifiers, whose root discriminates between two groups, each one containing a half of the classes. Each succeeding node includes again only one half of the classes from the selected group, and the process is recursively repeated until each node contains a single class, from which the final decision can be inferred. In this study we compare a series of multiclass approaches to assert the benefits of hierarchical classification. The compared methods are based on two effective techniques for MI-discrimination, namely, Common Spatial Patterns (CSP) and Riemannian geometry, for which the hierarchical and non-hierarchical approaches have been considered. We include the CSP by Joint Diagonalization method (CSPbyJAD) [2], which corresponds with a non-hierarchical approach; and its hierarchical counterpart, namely, Binary CSP [3]. In addition, the non-hierarchical Minimum Distance to Riemannian Mean method (MDRM) [4] is also evaluated, together with its analogous hierarchical approach; a contribution of the present work called Hierarchical MDRM algorithm (HMDRM). All these methods have been applied on dataset 2a of the BCI competition IV to facilitate their comparison.

Material, Methods and Results: Dataset 2a contains 22 EEG recordings from two different sessions of 9 healthy subjects performing four MIs (left hand, right hand, feet, and tongue). Signals were filtered using a Butterworth filter within the frequency range [8-30 Hz]. For each trial, a 2s-window starting 0.5 s after the task cue was considered for classification. Data from session 1 were used to train all the compared methods, which were subsequently evaluated with data from session 2. For the implementation of the HMDRM algorithm, the features of each trial correspond to the coefficients of its estimated covariance matrix, and every choice to select the next node of the decision tree is based on the MDRM algorithm. The performances achieved with all methods are shown in Table 1. For comparison purposes, we also include the winner of the competition, named Filter Bank Common Spatial Patterns (FBCSP) [5].

Table 1

Kappa value achieved with all methods using the dataset 2a of the BCI competition IV.

Method	S1	S2	S3	S4	S5	S6	S7	S8	S9	AVG
BCSP	*0.77*	*0.56*	*0.77*	*0.57*	*0.49*	*0.47*	*0.83*	*0.69*	*0.68*	***0.65***
HMDRM	*0.74*	*0.37*	*0.75*	*0.56*	*0.40*	*0.36*	*0.64*	*0.58*	*0.70*	***0.57***
FBCSP	*0.68*	*0.42*	*0.75*	*0.48*	*0.40*	*0.27*	*0.77*	*0.75*	*0.76*	***0.57***
MDRM	*0.75*	*0.37*	*0.66*	*0.53*	*0.29*	*0.27*	*0.56*	*0.58*	*0.68*	***0.52***
CSP by JAD	*0.65*	*0.40*	*0.77*	*0.50*	*0.44*	*0.19*	*0.25*	*0.72*	*0.50*	***0.49***

Discussion: The highest accuracies were reached by the BCSP and HMDRM methods, confirming the effectiveness of hierarchical algorithms. The BCSP algorithm achieves an accuracy that is improved by 8% compared to the winner of the competition, and by 16% compared to the CSPbyJAD method. The HMDRM approach also improves the accuracy with respect to the non-hierarchical MDRM algorithm by approximately 5%, and reaches the same results as the winner of the competition.

Significance: The present work shows that it is advantageous to split the original multiclass task into groups and hierarchically perform the corresponding binary classification, presumably due to an overtraining reduction. Moreover, it contributes with the implementation of a hierarchical method based on Riemannian geometry.

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Decoding auditory attention using behind the ear EEG

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Introduction: Brain computer interfaces are promising for the active and passive control of hearing device settings. For every day BCI applications alternatives to the classical EEG cap electrode placement are needed. We have developed the cEEGrid, a behind-the-ear electrode grid (Fig A-C) designed for concealed EEG acquisition over the course of a day [1]. Here we explored the possibilities of decoding auditory attention to different concurrent music streams using the cEEGrid. We used a previously established auditory attention paradigm of [2] and compared attention decoding for high-density scalp EEG and cEEGrid EEG data acquired concurrently.

Material and Methods: From 20 participant 84 scalp cap EEG and 18 behind-the-ear EEG channels were recorded simultaneously. Three concurrent music streams (duration 3 s) were presented, differing in the music instrument, the direction (front, left, right) and the number of beats (3,4,5 respectively). Listeners were instructed to pay attention to either the left or the right stream (but never the central stream) and to indicate with a (post-stimulus) button press whether the melody of that stream was ascending, descending or alternating. ERPs were computed for the two conditions and a classifier (LDA) was trained on the data.

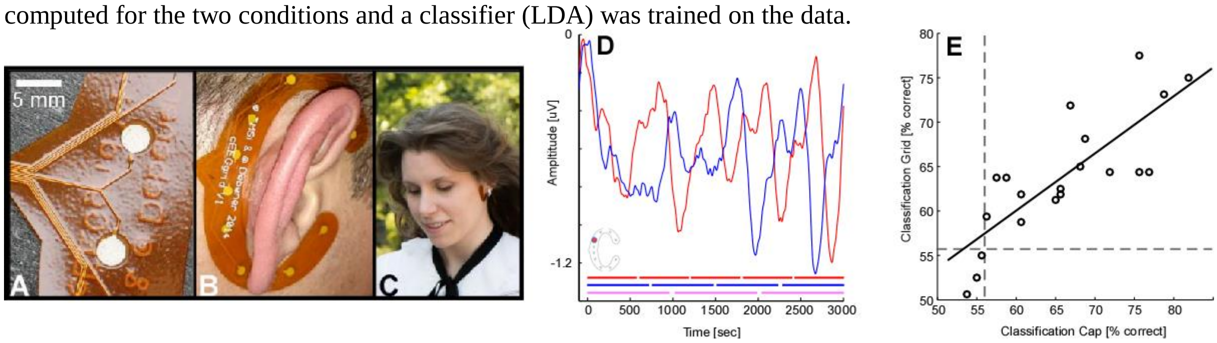

Figure 1. *The cEEGrids are designed as semi-disposable electrode grids. The flexprint material includes several layers of a biocompatible polymide, the conductive parts consist of gold plated ends, pure copper traces, and conductive Ag/AgCl based polymer thick film ink. B) The ten electrodes per ear are arranged in a c-shape and positioned around the ear using an adhesive. A small amount of electrode gel assures a low impedance electrode-skin contact. C) The cEEGrids do not attract attention when worn outside the lab. D) Grand average ERP of the left (blue) and the right (red) attended stream for one cEEGrid electrode (indicated in inset). The horizontal markers indicate the sounds in the three streams (pink: center stream - 3 notes, blue: left stream - 4 notes, red: right stream – 5 notes). E) Classifcation accuracy for scalp EEG and cEEGrid. The dashed lines show the 56% chance level.*

Results: The grand average ERP for the cEEGrid electrodes indicated the number of tones in the attended stream (Fig. D). On average classification was above chance-level with an accuracy of 64% (range 51% - 78%; chancel level 56%) for the cEEGrid and 66% (range 54%-82%) for the scalp EEG. 17 of the 20 datasets were classified above chance for both setups (Fig E). Task performance for identifying the melodic content of the attended stream varied between 45% and 99%. A non-significant correlation between cEEGrid classification accuracy and task performance was found (r=0.43, p=0.06). Better task performance led to a higher classification accuracy.

Discussion: The data recorded with the cEEGrid allowed the identification of the direction of attention above chance level in 3 seconds long music segments. The accuracies between cEEGrid and scalp EEG data are comparable. From a usability standpoint the classification accuracies should be increased, which could be achieved by implementing artefact attenuation, longer trials and advanced classification procedures.

Significance: Unobtrusive and convenient placement of EEG electrodes improves the user acceptance of BCIs. Here we show for an auditory BCI paradigm that informative signals can be extracted from the behind-the-ear cEEGrid electrodes.

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Design of Duty-cycle Screening Paradigm for Steady-State Somatosensory Evoked Potential

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Introduction: Steady-state somatosensory evoked potential (SSSEP) has been developed by several brain-computer interface (BCI) research [1-2]. However, the recent SSSEP-based systems showed the low performance for controlling the external devices efficiently. Hence, we suggest a screening technique that can reflect subject-dependent frequency and duty-cycle. In this study, we compared the proposed screening method with normal screening method (frequency only) for demonstrating the necessity of the proposed screening method.

Material, Methods and Results: Electroencephalogram signal was recorded using 17 channels following the international 10-20 system. In the screening session, tactile stimuli was attached on the index finger at a time (left or right). First, the fixation cross (+) appeared during 5 seconds for obtaining the SSSEP in the resting state which means that tactile stimuli were still activated but there was no attention to the stimuli. Then, subjects were instructed to concentrate to attention cue during 3 seconds. During screening session, tactile stimuli consist of nine frequencies (15-33 Hz in 2 Hz steps) and each frequency has nine duty-cycles (10-90% in 10% steps) with 5 times iteration. Total 450 trials were conducted on each hand in this experiment. Increase of spectral power (from attention to rest) was calculated by Fast Fourier Transform (FFT) analysis for finding optimal stimuli. We selected optimal stimuli when the SSSEP had the highest increase of spectral power in the obtained frequency and duty-cycle. In the test session following screening session, subjects conducted simple task to concentrate on the vibration stimulator corresponding to the visual cue (left or right). We extracted spectral and spatial features using the FFT and Common Spatial Pattern (CSP), respectively. The extracted features were classified using linear discriminant analysis with 10-fold cross-validation. Table 1 shows the optimal stimuli that have the specific frequency and duty-cycle. It also compares the accuracies of the proposed screening method and the accuracies of the normal method. We can see that increases rate of spectral power in our proposed screening method is higher than normal screening method only considering frequency.

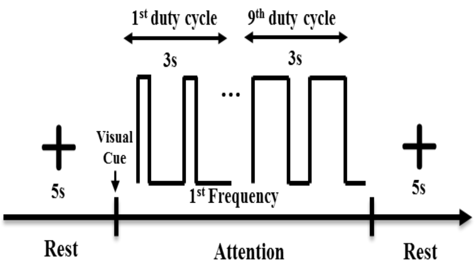

Figure 1. *Illustration of the screening paradigm*

Table 1*. Optimal stimuli and accuracy of two methods*

Sub	Screening method	Frequency (Hz)		Duty-cycle (%)		Increase rate of spectral power (%) (Proposed-Normal)		Accuracy (%)	
		Left	Right	Left	Right	Left	Right	FFT	CSP
A	Normal	15	23	50	50	+17.3	+15.8	66.3	88.7
	Proposed	15	25	90	60			73.2	94.2
B	Normal	23	19	50	50	+10.6	+21.4	50.7	49.3
	Proposed	15	19	70	30			60.3	58.2
C	Normal	25	21	50	50	+17.7	+21.6	77.5	93.2
	Proposed	27	21	70	90			75.4	98.1

Discussion: We found optimal stimuli in the screening session and evaluated performance in the test session. The increase rate of spectral power (attention to rest) in proposed screening method are higher than normal screening method. It means that we need to consider not only frequency, but also duty-cycle in the screening session. Our proposal was to finding optimal stimuli states spin simple methods (FFT). However, we will apply the advanced method such as lock-in analyzer system [1-2] in the future work.

Significance: In this paper, we analyzed the SSSEP responses using the proposed screening method. To our best knowledge, our study is the first investigation for applying the subject-dependent stimuli that have optimal frequency and duty-cycle simultaneously in SSSEP. Hence, the optimized stimulus can be used for SSSEP-based BCI applications with the performance improvement.

Acknowledgements: This work was supported by ICT R&D program of MSIP/IITP. [R0126-15-1107, Development of Intelligent Pattern Recognition Softwares for Ambulatory Brain-Computer Interface].

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Detection of errors using multiple spectro-temporal features related to distinct post-error neural processes

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Introduction: Detection of different types of errors (e.g., user's own errors (or execution errors), interaction errors, and feedback errors) based on brain signals immediately following errors, has been increasingly studied in brain-computer interface (BCI) community [1], with the aim to improve the performance of BCI devices or developing novel BCI systems [2]. Here, we focused on the detection of execution errors using noninvasive electroencephalography (EEG) signal. Beyond the well-known error-related negativity (ERN) in previous studies [3-4], the present study investigated multiple spectro-temporal EEG features related to distinct post-error neural processes, given that different neural and behavior responses could be triggered by errors under the performance monitoring system [5-6]. We expected better detection of execution errors can be achieved by including as many as error-related EEG patterns.

Material, Methods and Results: 128-channel EEG data from 18 healthy subjects was previously recorded in a color-word matching Stroop task (details of the experiment and data, as well as preprocessing procedures, can be found in [7]). Subjects made 73 (±29) error responses out of 720 trials. To extract distinct neural processes, a group-wise independent component analysis (ICA) procedure was applied on preprocessed EEG data that were temporally concatenated across all subjects [6]. Spectro-temporal features were extracted from four neural processes (i.e., independent components, ICs; Fig. 1) that were characterized with well-known event-related potentials (ERPs) [6]. Statistical comparisons demonstrated that errors show significantly enhanced theta power at early time (around 0-300 ms) and decreased alpha/beta power at late time (around 150-500 ms), at all four ICs (Fig. 1). Thereafter, single-trial classification of error or correct responses was performed using a linear discriminant analysis (LDA) classifier by using different combinations of features. With features selected from spectro-temporal signals from 0 to 300 ms post-response after band-pass filtering from 1 to 10 Hz and down-sampling (25 Hz) for all four ICs, LDA achieved a mean accuracy of 93.6% (error: 70.0%; correct: 96.2%) and a mean area under curve (AUC) of 0.88.

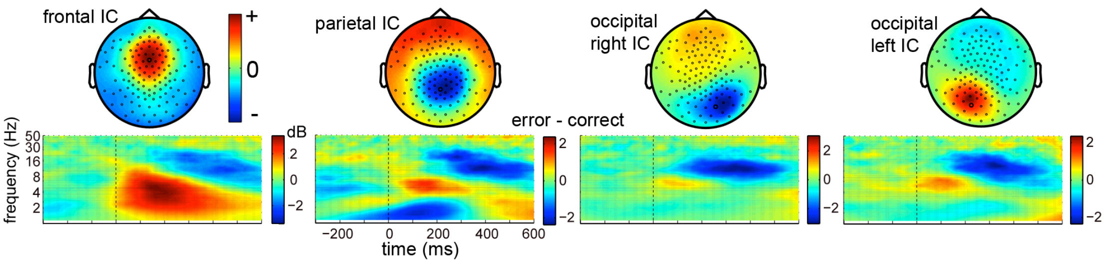

Figure 1. *Four ICs represented post-error neural adaptation. Top: scalp maps; bottom: response-locked time frequency representations of the difference between error and correct responses.*

Discussion: A series of EEG spectro-temporal patterns related to distinct cognitive and sensory neural processes were uncovered following error responses made by subjects. By combining as many as features related to post-error neural responses, better detection of execution errors has been achieved.

Significance: This study unveiled multiple spectro-temporal features over distinct neural processes related to errors, which can potentially be used to improve the single-trial detection of errors in the application of BCI.

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Disentangeling working memory load – finding inhibition and updating components in EEG data

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Introduction: Recently, passive BCIs have been used for the estimation of working memory load – a quantity describing the used amount of an individual's memory capacity. A well-known theory by Miyake et al. [1] distinguishes three executive functions (updating, shifting and inhibition) as differential factors imposing load onto working memory's central control structure. Most BCI-related research, however, considers working memory load as a unitary construct. The closer investigation of the individual workload components in terms of their neural signatures and the feasibility of their EEG-based classification was addressed by this work. The focus was on two functions updating and inhibition.

Material, Methods: A dataset consisting of EEG recordings of 22 subjects performing an n-back task with the simultaneous presentation of flanker-items formed the basis of the analysis (Scharinger *et al.* [2]). The n-back task imposes demands on updating, whereas the flanker task imposes demands on inhibition. The n-back was performed on sequentially presented strings of seven letters, to which the subjects had to respond with a button press. 'Yes' – the central letter of the string equals the central letter presented *n*-steps before (with three different levels of n manipulating updating demands: 0, 1 and 2) or 'No' the letter is not equal. The flanker accompanying the central letter for the n-back task consisted of six identical letters, three presented on the right, three on the left side of the central letter. The six letters could either be the same (congruent flanker: no inhibition demands) or different (incongruent flanker: inhibition demands) to the central letter. No reaction concerning the flanker was required by the subject. Features in the time and frequency domain have been evaluated for all correct updating and inhibition trials (correct button press). A support vector machine with a linear kernel and a 10-fold cross-validation was used for classification. In the time domain, the one second time frames of all correct trials (from stimulus onset) and all midline EEG channels (*1, *2, *3, *4, *Z positions) were used for classification. In the frequency domain, power spectra between 4-13 Hz for the same set of EEG channels were used. The calculation of the power spectra was done via Burgs maximum entropy method using a modelorder of 32.

Results: Classification on time domain features did not provide good results, which is why no values are reported. Classification based on the power spectra were more promising as can be seen in Table 1. Inhibition vs Baseline (and Updating vs Baseline) was tested in a 10-fold cross-validation to evaluate if the component can be differentiated from baseline trials in which the component was not required. Additionally, Updating vs Inhibition was tested to find out whether both workload components can be distinguished from each other (also cross-validated). The two individual classifiers (vs Baseline) were also tested on trials containing only the opposing component to evaluate if they share strong similarities, which would be an indicator for working memory as a unitary construct instead of a construct based on distinguishable functions.

Table 1. *Classification accuracy averaged over all 22 subjects. Upd. (Updating) refers to all trials in the 1-back condition with congruent flanker. Inh. (Inhibition) to trials in the 0-back condition with incongruent flanker. BL (Baseline) refers to 0-back trials with a congruent flanker. 2- vs 1-back and 2- vs 0-back were also evaluated but are not reported here due to shortage of space.*

Trainset	Inh. vs BL	Upd. vs BL	Upd. vs Inh.	Upd. vs BL	Inh. vs BL
Testset	Inh. vs BL	Upd. vs BL	Upd. vs Inh.	Inh.	Upd.
Accuracy	72.07 %	65.36 %	71.66 %	59.75 %	55.12 %

Discussion: The results indicate that inhibition and updating demands can be classified with accuracies sufficient for the use in passive BCI applications. They corroborate the hypothesis that workload consists of different components, which can be distinguished by their neural signatures. The fact that a classifier trained on either of the two components does not perform well on a dataset containing only the opposing component sustains the assumption that updating and inhibition are two different processes. Confounds due to task design and stimulus presentation can be ruled out as the two functions were executed simultaneously in one experimental setup. For the detection of workload the combination of different classifiers specialized on the individual executive functions might therefore be a good alternative to using one general workload classifier.

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Effect of a cognitive involving videogame on MI task

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Introduction: Researcher and developers have to face with performance variation in motor imagery[1] across and within subjects and its fluctuations over time. In addition MI achievement variations within subjects are closely correlated to neurophysiological variables[2]. In our study a MI task was submitted to a group of healthy subjects before and after playing BCIGEM videogame for 90 minutes. Some EEG features were found, suggesting a different pathway of activation inside MU rhythm during Motor Imagery (MI) after a mentally challenging activity like playing a videogame.

Material, Methods and Results: BCIGEM is a videogame derived from popular ‘Gem swap’ that includes some additional subroutines including a MI scheme. A 32 channel AgCl cap and a Neuroscan (Fs 500Hz, extracephalic reference) device was applied to acquire EEG data while subjects are playing pc version of BCIGEM videogame. Subjects performed calibration sessions and game session alone in a soundproof room under control of a video surveillance system. In a different day participants already performed a training procedure while on experiment day they received once more instructions about gaming. Each candidate (11 subjects, age range 22-27, all male right-handed) answered to a questionnaire before starting the game to collect self-reported motivation, tiredness and attention level. Analysis was focused on calibrations sessions before and after playing the game for 90mins. Subjects were instructed to imagine a brief hand movement (near 1s) according to an arrow’s direction shown on screen in front of him (at 0s time, 10 MI right/10 MI left). Near 1s before arrow appearance a cross come out on center of screen to prepare the subject for the task. According to previous findings[3] ERD seems unaffected by movement durations and brief movement imagery has a larger impact on pre-movement mu ERD rather than continuous movement. For this reason analysis window was extended from -1s before arrow onset to 1s after its appearance. EEG was preprocessed to extract epochs (-3s to +5s from arrow appearance marker) and filter data (7-30Hz) with a two-way least-squares FIR. A preliminary screening on calibration data running a combination of CSP spatial filter for feature extraction and LDA as classifier was performed to include only participants able to perform MI task. During this offline procedure only who scored at least 70% of accuracy was included in the study (4 subjects was excluded). To analyze EEG features only the MU band (8-13Hz) was isolated from data and only C3 or C4 contralateral to movement was taken in consideration. Time interval between -3s to -1s before onset of movement (i.e. time 0s) of each epoch was considered as baseline and average power spectrum across subjects was calculated for each second. While before playing BCIGEM the motor imagery related mu-band power decrease is sustained along all interval -1s to +1s (-1s to 0s 45% of ERD, 55% in 0s to +1s) , after 90mins of BCIGEM playing the motor imagery ERD is concentrated in interval 0s to 1s (-1s to 0s 10% of ERD, 90% of ERD in 0s to +1s). In both situations at +2s EEG returned at the level reached in baseline. Focusing on 10-12Hz Mu band same phenomenon is described with an ERD ending at +2s in calibration data after playing BCIGEM, while before playing the game still a little ERD is present ($p<0.03$ L:-38% R:-66%).

A study on baseline power composition was performed: in 8-14Hz band on Cc electrode after playing the game a relative decrease of lower mu representation (8-10Hz) was found after playing BCIGEM(L:-22%,R:-13%). If frequencies include upper theta (6-8Hz), upper theta and lower mu decrease (T L:-15%, R:-11% lower MU L:-7.5%,R:-4%) in comparison to upper mu bands (10-12Hz and 12-14Hz) after playing BCIGEM. In fact dividing ERD in two sub-bands (8-11Hz and 11-14Hz), still ERD is less evident after playing BCIGEM in 8-11Hz ($p<0.035$, L:-30% R:-76%) band but an inverse behavior in 11-14Hz is present compared to results before playing BCIGEM ($p<0.05$). In 11-14Hz there is a power decrease more evident after playing the game (L: +28%, R: +14%) reflecting higher frequency representation found in baseline.

Discussion: Results presented show a different behavior inside mu band before and after 90mins of involvement in a mental activity. As presented different ERD architecture could influence the motor imagery performance during time. MI tasks suffer of limitations in performance caused by user-dependent factors[4] and this further change in SMR attenuation phenomenon could be relevant in contexts where mental fatigue is an additional element. As consequence a recalibration to adapt BCI algorithms to identify an ERD with different characteristics could be a solution to maintain a stable BCI performance.

Significance: BCI outcomes could benefit of understanding brain dynamics in mentally challenging situations.

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Effect of visuomotor coordination and relaxation repeated interventions for Sensorimotor Brain Computer Interfaces

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Introduction: Sensorimotor-rhythms based brain computer interfaces (SMR BCIs) allow a user to send commands to a device by the modulation of brain activity in the sensorimotor cortex. After decades of investigation on the topic, we still find that 10 to 50% of users do not achieve control of the device [1]. The current study investigates within a pre-post design the effect of training of previously identified predictors on SMR-BCI performance, namely, visuomotor coordination ability [2,3] and relaxation [4].

Methods: N=39, BCI-naïve participants were randomly assigned to 3 intervention groups (n=13 per group): "Relaxation group": listening to a Progressive Muscle Relaxation audio file. "Visuomotor group": the goal was to steer a point through narrow paths on the screen with two knob controllers. "Reading group": participants were given a book to read (control). Intervention lasted 23 minutes on each of 4 consecutive days (session 1 to 4). EEG was recorded from 64 active electrodes. SMR BCI sessions were conducted on day 1 (prior to training) and on day 5 after training using the Berlin BCI Matlab Toolbox with co-adaptive calibration [5]. Participants performed right and left hand motor imageries to move a cursor on a horizontal axis during 320 trials (1s fixation cross, 1s directional cue, 4s feedback, 4s ITI). Performance was the ability to move the cursor in the cued direction. Questionnaires were answered prior and during the BCI session and assessed "self-regulation" (SR trait) and "state-mindfulness scale" (SMS state, mindfulness of sensations). Visual analogue scales (VAS 0 to 10) for relaxation were filled out after interventions.

Results: A significant effect of time on BCI performance was found ($p<.05$, M_{pre}=65.3%, M_{post}=68.3%, see figure 1), but no effect of group or interaction. There was an improvement in the visuomotor precision (reduction in the critical mean duration) between day 1 and day 4 ($M_{d5\text{-}d1}=-1.17$, $p<.01$). Critical mean error duration during the last visuomotor training session was negatively correlated with BCI performance post (rho=-.62, $p<.05$). Participants in the relaxation group had higher relaxation levels (M=8.5) after intervention compared to visuomotor (M=6.8, $p<.01$) and reading (M=7.4, $p<.05$) groups. State mindfulness (SMS_{post}) was positively correlated with post BCI performance (rho=.47, $p<.01$) and self-regulation was negatively correlated with post BCI performance (rho=-.32, $p<.05$).

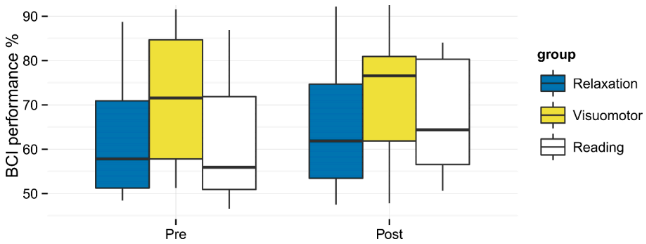

Figure 1. *BCI performance % (n=13 per group)*

Discussion: Confirming results from previous studies [2,3] for the 3rd time, the visuomotor coordination ability was positively associated with BCI performance. However, we found no effect of training, neither for the visuomotor coordination abilities nor for relaxation, albeit both predictors improved with training. We may speculate that the improvements were not large enough to affect BCI performance. In line with current research [6,7], mindfulness was positively correlated with BCI performance.

Significance: One week of daily repeated interventions could not improve BCI performance. Mindfulness was confirmed and self-regulation appeared new as correlates of SMR-BCI accuracy.

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Effects of Off-Site Attention on SSSEP Amplitude

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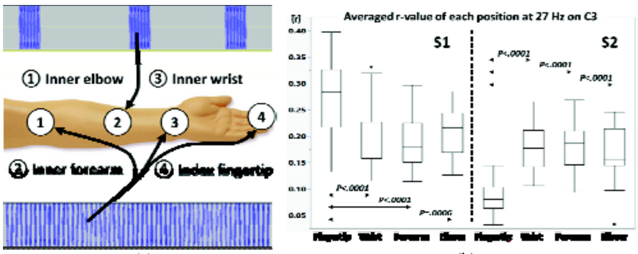
Introduction: Tactile-based BCIs have a potential to help visually-impaired and blind groups. Steady-State Somatosensory Evoked Potentials (SSSEPs) can be elicited on the contralateral areas of the brain with tactile stimuli [1]. Recently, tactile-based BCIs have been hybridized with SSSEP and tactile-P300 to improve BCI classification accuracy, and increase the number of usable classes [2], [3]. This is a preliminary research study to investigate the feasibility of using unattended flutter stimulation (SSSEP) with attended random pulse (tactile P300) via separate tactors on different positions, and how different spatial attention affects SSSEP response.

Material, Methods and Results: We used the same solenoid tactor setup as presented in our previous study [3]. Vibrational stimuli were presented on subjects' fingertip, wrist, forearm, and elbow of dominant side: one tactor presenting random pulses on one of four positions with SSSEP stimulation presented on the other three positions (see Fig 1a). A subset of three of the four locations were chosen as SSSEP stimulation sites to find both the characteristics of nerve pathway and individual differences. This was used to find the most important positions for SSSEP stimulation, which should not be selected for P300 but selected for SSSEP, and vice versa. To generate a random pulse, a 100 Hz sine wave was presented for 250 ms, while SSSEP stimulation was generated by modulating a 27 Hz square wave atop a 100 Hz sine wave. Five healthy subjects conducted 100 pseudo-randomly distributed trials by locations and pulse patterns. Each trial consisted of a 5s rest, 2s reference, and 8s stimulation, during which the subjects were asked to focus only on counting the number of random pulses, which was used as a mental distraction task. EEG signals were recorded with a g.USBamp amplifier using a large Laplacian montage around C3 and C4. BCI2000 was used for data acquisition and stimulus presentation, with EEG signals sampled at 512 Hz and band-pass filtered from 20-56 Hz, then analyzed using Canonical Correlation Analysis (CCA) from 20-29 Hz. The average CCA values showed higher Pearson's correlation (r-value) on the contralateral brain area for 27 Hz, with no differences on the ipsilateral brain area at the same SSSEP frequency. ANOVA of different positions at 27 Hz on C3 for each subject showed S1 had a significantly higher r-value on the fingertip than other positions ($p < .0001$), while S2 showed a significantly lower r-value on the fingertip than other positions ($p < .0001$) (see Fig 1b). S3 ($p = .0619$) and S4 ($p = .0763$) showed marginal significance, and r-value of fingertip was lower than that of the elbow for S3, while there were no significant differences for S4 in post-hoc Tukey tests. S5 showed no significant differences between positions.



(a) (b)

Fig 1. (a) Diagram for tactor positions and stimuli for random pulse
(b) Averaged r-value of each position at 27 Hz on C3 for S1 and S2

Discussion: The results showed unattended flutter sensation could elicit SSSEP on the contralateral brain area by only attending to random pulses presented on the same nerve pathway. Moreover, there were individually different effects of spatial-selective attention on the nerve pathway. Based on these results, this paradigm will be extended to a multi-class tactile hybrid BCI, which will have multiple tactors for P300 and SSSEP for each class. By doing so, we will validate if the result would be the same when extended to multiple classes with multiple tactors for P300 and SSSEP on both forearms.

Significance: We have validated that SSSEP can be evoked through off-site attention. This is important because if P300 and SSSEP are presented on separate tactors at different positions, while asking the subjects to attend only on random pulses, this may reduce the mental workload needed to focus on both flutter and random stimulation for a tactile hybrid BCI system. In addition, these results can potentially improve the performance of a tactile-based BCI system by utilizing user-specific stimulation sites for improved SSSEP response. These features will be used for future research to develop a hybrid BCI for behaviorally non-responsive patients.

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Efficient Transfer Learning in Brain Computer Interfaces using Spectral Meta Learning

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Introduction: Recent advances in signal processing and machine learning techniques have enabled the application of Brain-Computer Interface (BCI) technologies to fields such as medicine, industry and recreation.. Despite the recent progress, the non-stationary nature of EEG, as well as user-to-user and session-to-session variability require most BCI systems to employ time-consuming and costly calibration sessions. The use of transfer learning techniques to minimize or eliminate this need for calibration data is an area of on-going interest for the development of practical BCI systems. This study aims to eliminate the need for calibration sessions and develop a user-independent BCI using an unsupervised ensemble technique called the Spectral Meta-Learner (SML) [1]. We apply the SML as a fusion algorithm to combine the predicted outputs of several training subjects subject whose individual classifier models were developed using information geometric classifiers (Minimum Distance to the Riemannian Mean- MDRM [2]). The effectiveness of this approach is demonstrated in a single-trial ERP detection for a rapid serial visual presentation (RSVP) task.

Material, Methods and Results: Thirty-two subjects were analyzed with a leave-one-out method where 31 subjects were used as training data to transfer to the left-out subject. MDRM models from the 31 training subjects made individual predictions to the test subject and the SML algorithm was used to fuse the output of the ensemble in an unsupervised fashion. Figure 1 shows the balanced accuracy (the average of sensitivity and specificity) of the SML as a BCI transfer method compared to several other ensemble based transfer learners. Figure 1 also shows the ceiling performance of traditional within-subject learner where 10 minutes of training data are used to build an MDRM model and the rest of the remaining data from that subject is used for testing.

The pairwise transfer method, where the model from a single training subject is transferred to the test subject performed the worst from all the methods analyzed with an average balanced accuracy of 61%. The SML method achieved performance comparable to the within subject classifier and outperformed all of the tested transfer methods including the traditional un-weighted (majority vote) and the Riemannian-distance based ensemble where the Riemannian distance was used to weight the individual models in the ensemble.

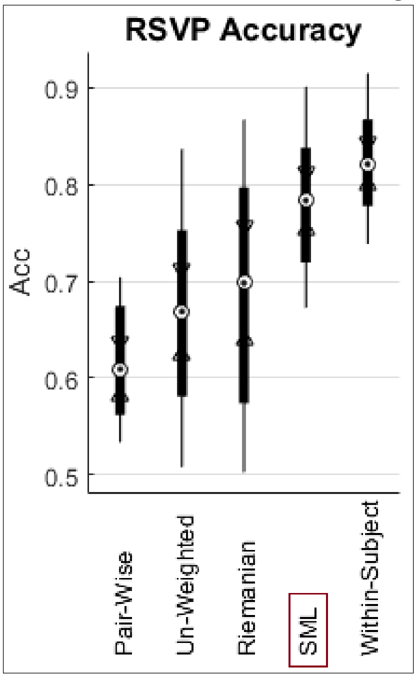

Figure 1. *Single trial RSVP balanced accuracy for the proposed SML method compared to other ensemble learners and the traditional calibration learner.*

Discussion: The proposed SML ensemble technique for transfer learning was able to achieve single trial ERP detection with a performance that is comparable to traditional within-subject calibration. Additionally, this method outperforms existing ensemble techniques for BCI transfer including the traditional majority voting scheme and the recently developed Riemannian distanced based transfer learning technique.

Significance: This study shows that unsupervised transfer learning for single-trial detection in ERP based BCIs can be realized to achieve practical performance levels that are comparable to within-subject classification. This represents a step-forward in the goal to completely eliminate the need for BCI calibration for a user-independent BCI system.

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ERP Features Correlate with Reaction Time in a Posner-Like Covert Attention Task

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Introduction: Spatial hemineglect (unilateral neglect) is a deficit typically developed after right-hemispheric stroke. It affects attention and awareness processes for one side of a patient's space [1]. The feasibility of BCI-based systems to support rehabilitation of cognitive deficits – such as neglect – remains an unexplored field, but BCI-systems making use of overt and covert visual attention to control applications have been explored [3,4,5]. A pilot study with three normally aged control subjects was carried out to study behavior (reaction time upon stimulus presentation) and event-related potential (ERP) responses of the EEG elicited during the execution of a modified Posner task [6]. Testing visual spatial covert attention, this task is a common diagnostic tool in the context of neglect, but trial-to-trial reaction time performance varies strongly. We study the relation between this behavioral performance and brain signals in single trial analysis, using BCI methods.

Material, Methods and Results: Three healthy subjects aged 49, 56 and 51 participated in a single-session EEG study. Fixating the center of the screen, a directional cue indicated to covertly direct their visual attention to one side of the screen at the beginning of each trial. After 2000 ms to 3000 ms, a visual stimulus (gray square) appeared on the cued side of the screen in 90% of the trials, upon which the subject were asked to react by a button press (detection acknowledgement). The remaining 10% were null trials and did not require any action. A sketch of the task can be seen in Figure 1(a). Per subject, 800 trials (20 blocks of 40 trials each) of 64 EEG channels were recorded..

Average ERP responses of channels Cz (solid) and Pz (dashed) are visualized in Fig. 1.b and 1.c. The ERPs of the left plot are windowed relative to stimulus presentation at time t=0 ms. The positivity at 650 ms to 900 ms is stronger for faster responses, as indicated by blue ERP curves and enhanced signed r^2 values in the horizontal bars. ERPs centered relative to the button press at t=0 ms (right plot) reveal a stronger early negativity for fast responses around -100 ms. These two temporal features per channel allowed an average classification accuracy of 0.69, 0.75 and 0.66 (with a chance level of 0.5) for the three subjects. Using only the first feature per channel, the classification values are slightly reduced to 0.63 and 0.70 for subjects 1 and 2, and slightly increased to 0.71 for subject 3.

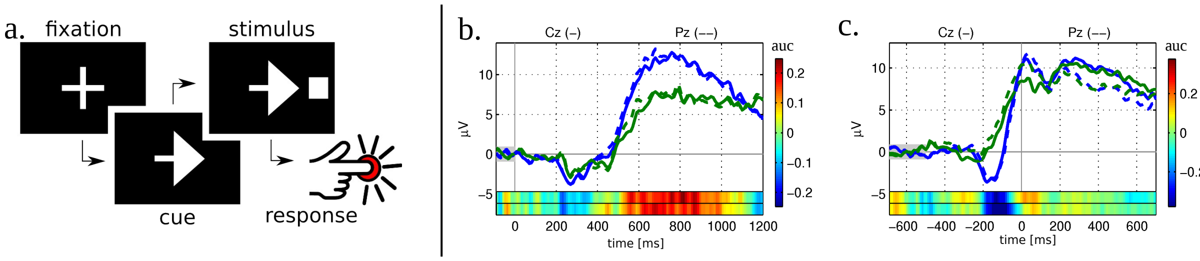

Figure 1. *(a) Sequence of a covert-attention task. (b/c) Averaged ERP responses for two channels. (b) ERPs relative to stimulus presentation (Subject 2) and (c) relative to button press (Subject 1). Blue trials mark fast responses, green slow responses.*

Discussion and Significance: The assessment of a subject's ability to react either rapidly or slowly to a covert stimulus in single trial and based on EEG signals only is challenging. Data of the first three subjects indicate, that an informative neuronal marker for reaction time can be obtained for single trials based on ERP responses. This objective metric may allow to set up novel experimental paradigms for the assessment of patients with neglect, where visuo-spatial attention and visuo-motor interaction shall be studied online without requiring open behavioral responses.

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ERP Responses of the Elderly for Bisyllabic Word Stimuli

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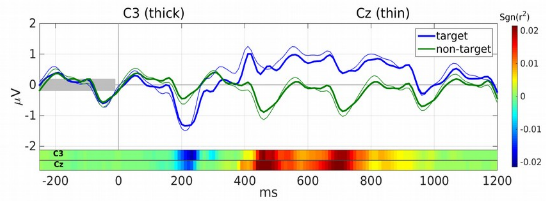
***Introduction**:* Brain-computer interface (BCI) based on auditory event-related potentials (ERPs) are investigated to establish communication for patients with motor impairments [1]. ERPs of the electroencephalogram (EEG) evoked by external stimuli provide information about a subject's attentional state. Most auditory-BCIs use tones stimuli [2], but also paradigms with natural sounds [3] and words [1] have been used. Working towards an attention-constrained rehabilitation paradigm, a setup with monosyllabic word stimuli has been evaluated for young healthy participants [4]. Although the elicited ERP components differ in latency from those of artificial tones [2], monosyllabic word ERPs can be classified on a comparable level in single trial [4]. Based on normally aged subjects, who match in age with patients with aphasia induced by (first) stroke, the present study aims at evaluating the feasibility of single-trial target versus non-target decoding for even more complex bisyllabic word stimuli.

***Methods**:* Twenty elderly native German speaking subjects (mean age 60.20±8.04 years, normal hearing, no history of neurological deficits) were familiarized with 6 word stimuli (see Fig. 1B) and matching sentences prior to a single offline EEG session (64 channel passive Ag/AgCl electrodes). Seated in a ring of 6 loudspeakers (AMUSE paradigm, [2]), the target word and direction of each trial was cued by a matching sentence. A trial contained 90 stimuli (15 iterations of 6 word stimuli). Six runs with 6 trials each were recorded, adding up to 540 target EEG responses and 2700 non-target responses within a single session. Word stimuli were presented in pseudo-random order from 6 directions at an stimulus onset asynchrony (SOA) of 250 ms. Additional conditions with a single loudspeaker and headphones were conducted but will not be reported on here.

Results: Fig. 1 shows (A) the grand average (GA) *target* and *non-target* ERPs in two selected channels and (B) GA classification accuracies. Two colored rows in Fig. 1(A) indicate the signed *r*-squared value between the two classes for the selected channels. An early class-discriminative negative response (*N200*) followed by a prolonged discriminative positive response is observed. From each channel, the amplitudes of eleven time intervals (ranging 100ms-1200ms) were extracted after baseline correction. The GA classification accuracy when combining all words, using these 704 features, evaluated via chronological 5-fold cross-validation with a shrinkage-regularized LDA, was 72.85% (with 62.20% chance level). Using only 7 early time intervals from 100ms to 400ms resulted in an GA accuracy of 68.79%, which demonstrates that the early negative response alone contains substantial information about the attended word. Specialized classifiers for each word performed on similar levels (Fig. 1(B)), showing neither significant differences (*t*-test, *p*-value>0.05) among each other nor relative to the combined classifier.

(A)


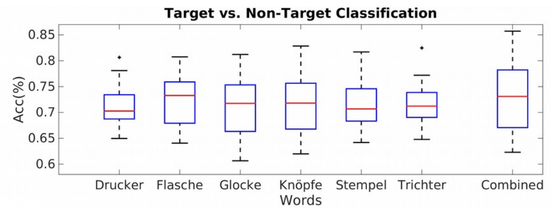
(B)


Figure 1. *(A) GA target and non-target ERP responses for channels C3 and Cz. (B) classification accuracy of word-specific classifiers.*

***Discussion and Significance**:* The ERPs of the elderly people upon bisyllabic words are slightly prolonged and delayed compared to those reported for monosyllabic words in [4]. A similar age-related effect was reported by van Dinteren et al. [5]. Nevertheless, also the delayed ERPs upon our more complex and slightly longer natural stimuli are sufficiently discriminative for an online paradigm for rehabilitation of aphasic patients, with accuracy close to those of monosyllabic words (71.2%) [4] and artificial tones (68.5%) [2].

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Extraction of motor patterns from joint EEG/EMG recording: A Riemannian Geometry approach.

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Introduction: The combined analyses of brain and muscle signals can be very useful in assessing the cortico-muscular connectivity and reorganization in brain injury. A basic approach would be to assess the sensorimotor (SMR) rhythms with electroencephalography (EEG) during the muscle activation in a pinch-and-hold task. For this paradigm, a cue is presented to the subject to initiate and stop the pinch-and-hold. However, we have found that this simple task can become quite challenging to perform repeatedly and robustly in children with hypertonic or hypotonic muscles, such as in hemiplegic cerebral palsy (HCP). We observed that many children found it difficult to respond immediately to a cue, hold and maintain the pinch on a force gauge, with a specific force, for the length of a trial for multiple trials. In these cases, a self-paced movement execution task appears more appropriate, albeit without an EEG-EMG time-locking event. Inspired by these experimental challenges in assessing the cortico-muscular connectivity in children with HCP, we developed a novel approach to extract SMR spatial patterns from EEG signals using the dynamic information of the corresponding EMG activation. Essentially, in this method the aim is to find EEG sources that can explain the variation of muscle activity. However, due to the different nature of frequency components between EEG and EMG, usual cross decomposition algorithms (CCA, PLS) are not easily applicable towards this goal. Recently, mSPOC was proposed as a novel approach to solve such an issue employing a complex iterative procedure to find components that maximized the envelop of correlation between sources of two sets of multivariate signals. Here, we introduce a simpler alternative methodology, based on Riemannian geometry, that allows to objectively extract EEG spatial patterns that explain variations of EMG power. We show a proof-of-concept in healthy subject's dataset.

Material: 4 healthy subjects participated to this study. 31-channel referential scalp EEG was recorded at 4096 Hz. Differential EMG was recorded at 1200 Hz, using bipolar electrodes at the FDI and ABP muscles of each hand. EEG and EMG streaming data were tagged with a TTL pulse, using hardware triggers, and synchronized offline. EEG and EMG were recorded while the subject engaged in a real-time EMG-controlled video game that presented cues and pinch force feedback, for 20 minutes (executing approx. 40 trials per hand).

Method: EEG signal was filtered between 8-15 Hz and EMG signal was filtered between 30-500 Hz. For both modalities, spatial covariance matrices were estimated using a sliding window of 1.5s with 85% overlap. This procedure produced two sets of covariance matrices that were then projected in their respective Riemannian tangent space using logarithmic mapping. Because of the property of invariance by affine transformation of the Riemannian metric, the tangent space obtained was a rotated representation of the source power. This reduces the problem of extracting sources that match EEG and EMG power, to simply finding rotations in the tangent space that explain the maxima of variance between the two signal sets. This can be achieved by applying a Canonical Partial Least Square (PLS) method. Once the coefficients of the rotations are estimated with PLS, they are back-projected using an exponential map, and diagonalized to produce a set of spatial filters and patterns ranked by their importance. For validating the effectiveness of the spatial pattern extraction, we apply a commonly used method to epoched data -- common spatial patterns (CSP).

Results: A comparison of the patterns extracted with the CSP algorithm and the proposed method is presented in Figure 1. The two methods converge toward the same solution, proving that our method can effectively extract spatial patterns in the same manner as the well-known CSP method.

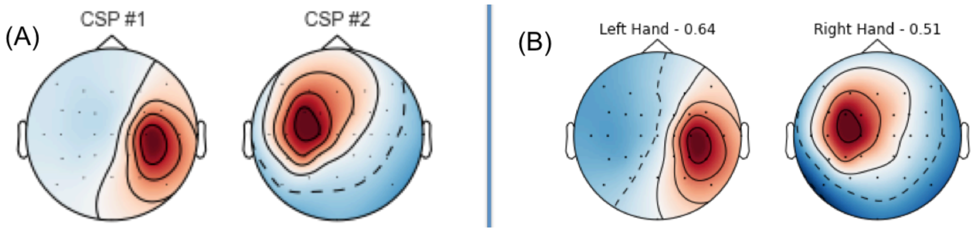

Figure 1. *(A) Spatial pattern extracted by Common spatial patterns. (B) Spatial pattern extracted by the proposed method*

Significance: This document introduces a simple framework to extract spatial patterns corresponding to movement execution, using EMG signal as a reference, without relying on the time-locking of the cue presentation and the subject's response. This can be very useful in assessing cortico-muscular connectivity in challenging subjects with movement disorders. Furthermore, this method can also be generalized to various types of datasets where spatial patterns may be related to power relationship between two sets of multivariate signals, for example: EEG and audio, and the like.

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Fatigue Evaluation through EEG Analysis Using Multi-scale Entropy in SSVEP-based BCIs

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Introduction: Fatigue is a big challenge when moving a steady state visual evoked potential (SSVEP) based brain-computer interfaces (BCIs) from laboratory into real-life applications [1], as it not only harms the system performance, but also causes users' discomfort. Towards eventually fatigue reduction, an accurate and objective evaluation of fatigue level is the first and also a crucial step. On the other hand, multi-scale entropy (MSE) can describe the complexity of physical and physiologic data and has been successfully applied to the analysis of human health states. Inspired by [2–4], we proposed an index based on MSE of electroencephalography (EEG) signals, for fatigue evaluation when a user is operating a SSVEP-based BCI. Experimental results showed that it performed better than other objective indices based on EEG spectral analysis.

Material, Methods and Results: 12 subjects performed a standard SSVEP-based BCI test. During the experiment, they were asked to gaze at the flashing stimuli for 30 trials in 6 sessions with EEG signals recorded. All participants finished a self-reported fatigue questionnaire based on the Chalder Fatigue Scale (CFS) before and after the visual task, to provide a subjective reference. Meanwhile, their fatigue levels in 6 different sessions evaluated by several methods, were calculated as the objective indices. The change between the first and sixth session is shown in Table 1, and the correlations between the subjective index and different objective indices are given in the third row.

Table 1. Comparison between the subjective index and objective indices of fatigue level changes between the first and sixth sessions.

Index	δ	θ	α	β	θ/α	θ/β	α/β	(θ+α)/β	θ+α	θ+α+β	SNR	Entropy	MSE
Change in percent	31%	-18%	-35%	-44%	20%	32%	12%	24%	-25%	-29%	-25%	-58%	-75%
Correlation to subjective scores (R^2)	0.001	0.012	0.020	0.034	0.014	0.022	0.021	0.030	0.036	0.007	0.424*	0.106*	0.369*
Number of fatigue levels distinguished	6	2	6	6	3	4	2	4	6	6	2	6	6

From Table 1, it can be seen that the index based on MSE performed better than the others. It provided the largest change during experiment, which could make fatigue evaluation more sensitive. Moreover, it distinguished all six levels of fatigue and has the second largest correlation coefficient to subjective fatigue score.

Discussion: Fatigue is a serious problem related to SSVEP-based BCIs, however there is no systematic study on this topic. A common practice is to evaluate the fatigue using self-reported questionnaires provided to the users for feedback about the feelings of fatigue in operating the systems, which are subjective and cannot be done in real time. MSE, as a new approach to measuring the complexity of physical and physiologic signals, may provide us a promising alternative to evaluate the fatigue related to SSVEP-based BCIs.

Significance: A new objective index based on multi-scale entropy was proposed to evaluate the fatigue when using SSVEP based BCIs. Experiments proved its effectiveness in comparison with other commonly-used EEG-based objective indices.

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How is subject-to-subject transfer probable in motor imagery BCI?

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Introduction: Subject-to-subject transfer is an ultimate goal of zero-training. We investigated how subject-to-subject transfer is probable in motor imagery (MI) brain computer interface (BCI) by comparing individual accuracies and subject-to-subject transfer rates for 156 subjects.

Materials and Methods: For this study, our team's left/right hand MI dataset of 52 subjects (100 trials for each class) [1] and open dataset of 104 subjects (about 20 trials for each class) [2-3] were used. Common spatial pattern (CSP) and linear discriminant analysis were applied. Individual accuracies were calculated by mean of cross-validations within each subject. For estimating of subject-to-subject transfer rate, 13-fold cross-validations on subjects were conducted. Each dataset were divided into training subjects (48 or 96 subjects) and testing subjects (4 or 8 subjects). For training filter and classifier, good subjects (individual accuracy > max{median accuracy, random chance level}) among training subjects were selected to use.

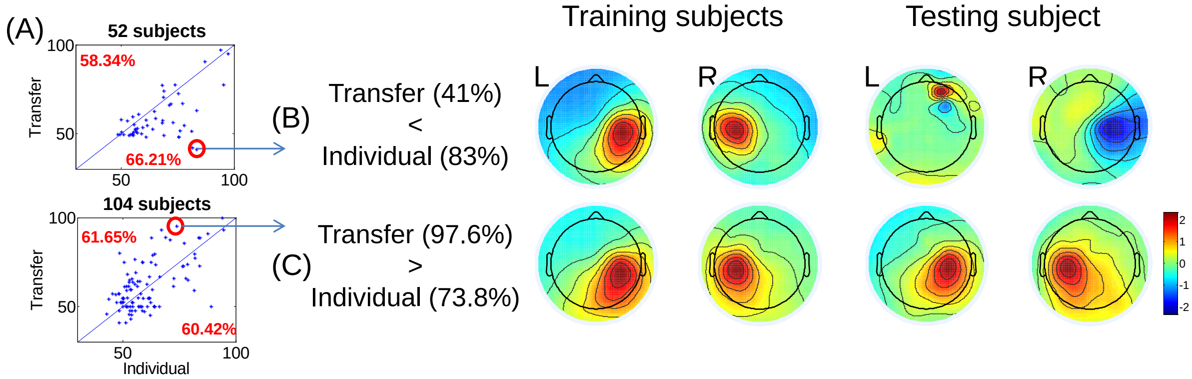

Figure 1 Individual accuracies and subject-to-subject transfer rates were compared on left/right hand motor imagery data and estimated source locations of MI by CSP filter. (A) Comparisons on 52 subjects (100 trials) and 104 subjects (20 trials). (B) a failure case of subject-to-subject transfer. (C) a successful case of subject transfer.

Results and Discussion: By the averaging effect, multi-subject data yielded quite fine CSP filter patterns as Figure 1(B-C). As Figure 1(A), mean of individual accuracies was higher than subject transfer rate on our team's MI data (52 subjects), however, individual accuracies and subject transfer rate were comparable on open MI data (104 subjects). It may be due to smaller number of trials (20 trials) in open MI data than in our team's MI data; weak individual information may produce low individual accuracy. It is found that when standard features extracted from multi-subjects are different from individual features of a subject, individual accuracy is likely higher than subject transfer rate. In such cases, estimated MI source locations extracted by CSP filters were far from somatosensory area, as depicted in Figure 1(B). It is quite doubtful if these are true MI features; it needs adaptive method. When individual features are similar to standard features, subject transfer rates are significantly higher (or at least comparable) than individual accuracies, as depicted in Figure 1(C).

Significance: There is tradeoff between generality and transfer rate [4]. Using fusion techniques [5], generality may be achieved, while subject transfer rate may be decreased. It is believed from this study that reasonable approaches for subject-to-subject transfer are neurofeedback method [6] (let user learn) and co-adaptive way [7] (let user and computer learn both).

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Hyperparameter Optimization for Machine Learning Problems in BCI

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Introduction: Pipelines for BCI data analysis comprise several building blocks, such as signal preprocessing, feature extraction, decoding of features and output shaping for the BCI application at hand. These components contain many hyperparameters, such as frequency bands, time intervals, regularization factors, adaptation parameters, etc., which need to be chosen carefully in order to obtain optimal overall performance. As even simple BCI setups comprise tens of mutually dependent (discrete or continuous) hyperparameters, the search space is too large for a full grid search. Even though experts can tune most parameters based on experience, the inter-subject variability inherent to BCIs is likely to reward a subject-dependent optimization strategy.

Material, Methods and Results: 20 healthy volunteers participated in a cued isometric force task of the hand (SVIPT, [1]) while EEG signals were recorded (64 passive channels, BrainAmp DC). A full setup is described in [2]. Comparable to a motor imagery processing pipeline, oscillatory EEG bandpower of a narrow frequency band within a (pre-trial) time interval was investigated. The analysis aimed at extracting supervised EEG subspaces (SPoC, [3]) which maximize the predictive squared correlation of their bandpower with continuous labels. The latter were obtained from a task-related motor performance metric. Overall, the processing pipeline comprised one nominal and three integer continuous hyperparameters resulting in 242,730 possible configurations. We investigated the performance and time requirements of four automatic methods for hyperparameter learning (SMAC [4], TPE [5], Spearmint [6], and random search). The first three perform Bayesian optimization, which iteratively fits and updates a probabilistic model to predict the performance of all parameter settings and uses this model to determine promising configurations to evaluate next. The mentioned methods ran 4 hours of CPU time, enough to evaluate up to 300 configurations (almost a factor of 1,000 less than the overall number of configuration). The results of the automatic methods are given in Fig. 1. Except for very short time budgets, the optimizer SMAC delivered best correlation values (lowest loss), followed by TPE and random search.

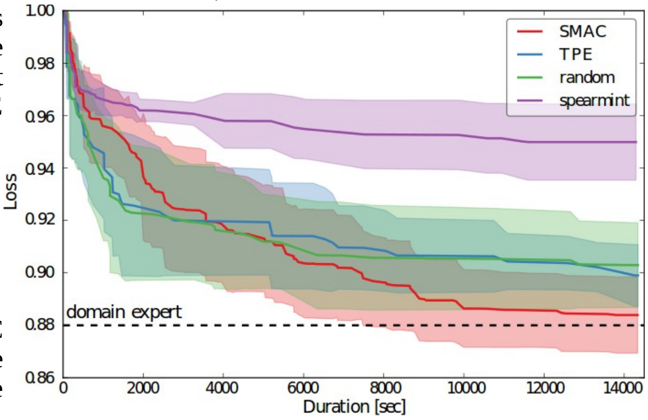

Figure 1. *Comparison of four hyperparameter optimization strategies wrt. the best obtained parameter set. The y-axis represents the (1-r²)-loss minimized (mean +/- stddev), the x-axis shows the runtime (CPU time budget).*

The best hyperparameter sets discovered by SMAC were very plausible and closely resembled those determined by the expert, with frequencies in the alpha band and short time windows within [-1000ms, 0ms] relative to the go cue of the hand force task.

Discussion and Significance: Since modern hyperparameter learning strategies outperform grid search by orders of magnitude and do not require human expert time, they can substantially facilitate progress in BCI. Although their application can be expensive for involved machine learning pipelines, they can also be parallelized for inclusion in an online system.

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Image and Neural Classifier Co-Training for Improved Classification in Rapid Serial Visual Presentation

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Introduction: One of the major difficulties in machine learning is the acquisition of sufficiently large sets of labeled data. Semi-supervised techniques allow a classifier to take data that it has confidently labeled and add them to its training set. Yet, sometimes a classifier can gain more informative training samples from another classifier. Co-training exploits the situation when two learners have fundamentally different views of the training data in order to get these more informative data samples [1]. Some prior work has used co-training to help train image classifiers using audio and visual data as the two different feature sets [2] or linguistic and visual data [3]. In this work we investigate the co-training of computer vision and neural classifiers for discriminating target images in a rapid serial visual presentation (RSVP) brain-computer interface (BCI) system.

Material, Methods and Results: 18 subjects participated in an RSVP experiment with an image database of common office objects and environments. Images belonged to one of five target classes: stairs, doors, containers, posters and chairs. A sixth class of non-target background images not containing any of the five target classes was used as the baseline (Figure 1). Subjects performed five RSVP sessions, where in each session subjects were instructed to identify one of the five target classes against the non-target images. 256-channel EEG was recorded using a Biosemi ActiveTwo system, the RSVP presentation rate was 5Hz and the target/non-target ratio was approximately 5/95. We used the xDAWN spatial filter together with a Bayesian LDA as the neural classifier [5]. The computer vision (CV) classifier is the AlexNet Deep Learning system [6], as implemented in the BVLC Reference Caffenet. Co-training consists of training both classifiers, next re-training the CV classifier with the most confident target images as labeled by the neural classifier, and then retraining the neural classifier with the CV classifier's most confident target images.

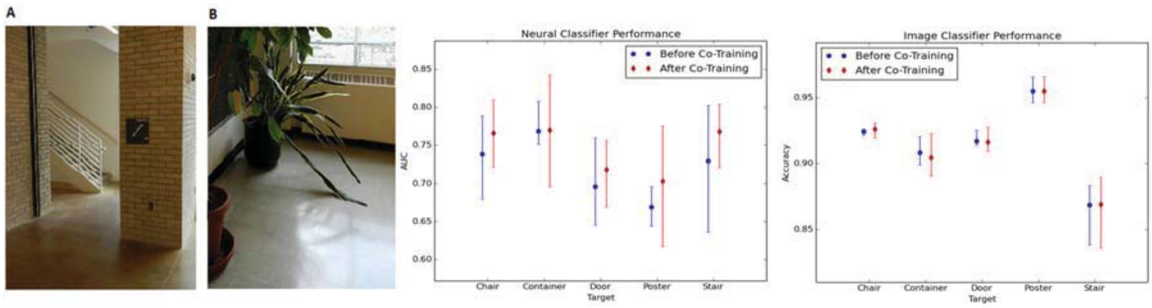

Figure 1. *(Left) Sample images of the target class Stair (A) and the background nontarget class (B). (Center and Right) Co-Training Performance of the Neural and CV Classifiers for detecting target classes versus the background images. Datapoints are average results over 5 trials, with error bars indicating maximum & minimum results.*

Discussion: We show that co-training the CV and neural classifier can markedly improve the performance of the neural classifier.

Significance: Our results suggest that co-training neural and computer vision classifiers can significantly improve the performance of future RSVP-based BCI systems.

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Investigating Depth of Cognitive Processing in the Brain Dynamics of Oscillations

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Introduction: Human-Computer Interaction (HCI) may benefit from accessing implicit information about the user state as it allows a fluid adaptation to the current situation. As one piece in this undertaking, we have studied the feasibility of quantifying how deeply presented information is processed in the brain by tapping the corresponding components of brain activity. The neural components arising from cognitive processes have been considered in the event-related potentials [1] and are here investigated in the spectral domain. The long-term goal is to estimate the momentary level of cognitive processing from the ongoing electroencephalography (EEG), and dynamically adapt the corresponding BCI application. The applicability ranges from human-computer interaction, like information seeking, to industrial workplaces (e.g. operator monitoring).

Material, Methods and Results: We developed a specific visual stimuli paradigm [1] in which we modulated the required amount of cognitive processing by task instructions in three domains: memory, which required visual/auditory memory recall of stimuli; language - which considered phonemic representations of the words that represents the stimuli, such as syllables; and visual imagery - which used quantitative measurements for differentiation. A shallow level of processing is given by short-term retention of information, e.g. color appearance, and a deep process level requires intense processing of the stimuli, e.g. semantic correlations.

The data was recorded from 17 participants using 64 channels EEG (Brain Products). We applied artifact removal techniques for muscular artifacts, eye blinks and loose electrodes. Subsequently, we assessed changes in the oscillatory power generated at different frequencies by extracting the spectrum (3-40Hz) with Fourier transform using Kaiser window (Fig. 1).

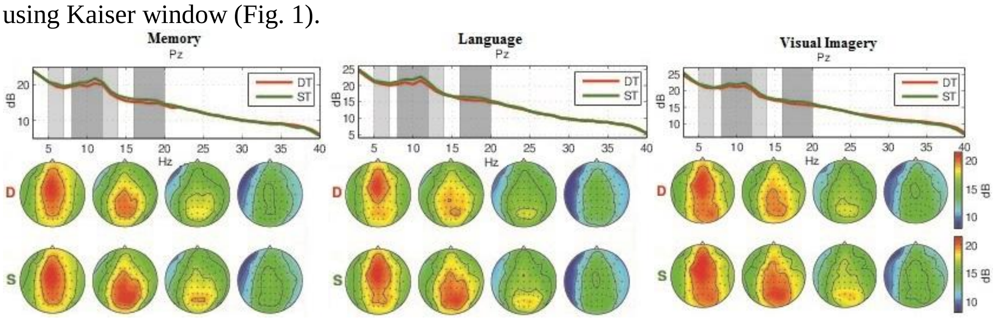

Figure 1. *Spectral analysis on grand average for deep (D) and shallow (S) processes in memory, language and visual imagery, over Pz. The top plots show the power log at different frequency bands and the grey shaded areas refer to the bottom scalp maps.*

We investigated the neurophysiological markers that represent the cognitive processes by evaluating the neural activity generated in theta (5-7Hz), alpha (8-10Hz) and beta (12-20Hz) frequency bands. Discriminative information can be observed over the alpha and low beta (12-14Hz), showing desynchronization (2-3 dB less) during deep processing with respect to the shallow processing. This corresponds to complex mental activities, such as concentration, focus and memory access. Theta (5-7Hz) and mid beta (16-20Hz) bands do not show significant difference.

Discussion: The log power spectrum shows that the levels of cognitive processes in different modalities can be distinguished, demonstrating the feasibility of monitoring the depth of cognitive processing for neuro-technological applications in BCI. Future developments will consider a regression approach to estimate ongoing level of cognitive processing.

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Movement Related Cortical Potential based on Multi-Class Motor Imagery

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Introduction: The movement-related cortical potential (MRCP) is one of the slow negative cortical potential generated during voluntary motor execution or imagery (MI). The MRCP has physiological 4 components during about 2 s at intervals of about 0.5 s [1]. The components are premotor positivity (PP), motor potential (MP), reafferent potential (RP), and P+90 [1, 2]. In the previous study, the MRCP showed the higher classification results than the event-related (de)synchronization in MI of patients groups [2]. However, MRCP-based multi-class classification and signal analyzing did not implement due to small amplitude and low frequency of the MRCP [3]. This study proposes the optimal feature extraction method for MRCP-based multi-class MI classification.

Material, Methods and Results: In our experiment, 5 healthy subjects participated. At the beginning of a trial, a fixation cross appeared on the black screen. After two seconds, a cue in the form of an arrow pointing to the left-right, and down direction (corresponding left-right hand, and foot) appeared and stayed on the screen for 5 s. The subjects performed 30 trials per tasks (left-right hand, and foot). The EEG data were acquired by the sampling rate 250 Hz based on 16 channels (F3, Fz, F4, F5, FC1, FC2, FC6, C3, C4, CP5, CP1, CP2, CP6, P3, PZ, and P4) in the international 10/20 system. The data were band-pass filtered at 0.1-1 Hz for pre-processing and segmented into 2 s long epochs according to the events. And then, the features of MRCP were extracted by mean values of time intervals of physiological components (PP, MP, RP, and P+90) for enhancing the multi-class classification performance. The 20 epoch intervals (0: 0.1: 1) were used to feature extraction in previous study. However we propose 4 epoch intervals (0-0.5; 0.5-1; 1-1.5; 1.5-2) based on the 4 physiological components, with heuristic decision. The regularized linear discriminant analysis was used to 5-folds cross-validation for our experimental results. The BCILAB toolbox was used to EEG signal processing. For comparison analysis, additional experiments were also implemented using 2 epoch intervals (0-1; 1-2), 3 epoch intervals (0-0.6; 0.6-1.3; 1.3-2), and 5 epoch intervals (0-0.4; 0.4-0.8; 0.8-1.2; 1.2-1.6; 1.6-2.0) that are not considered physiological components. And we validated the p-value by t-test for the statistical verification.

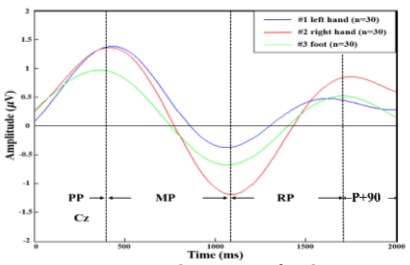

***Figure 1**. MRCP temporal patterns of subject D in Cz channel*

***Table 1**. Classification results of cross-validation and t-test*

Subject	2 epoch intervals	3 epoch intervals	4 epoch intervals	5 epoch intervals	20 epoch intervals
A	77.8	84.4	90.0	84.4	84.4
B	50.7	52.0	53.3	52.0	44.0
C	53.3	58.9	68.9	57.8	41.1
D	55.6	50.0	64.4	55.6	62.2
E	37.8	47.8	52.2	50.0	42.2
Average	55.1±14	58.7±14	65.8±15	60.0±13	50.8±23
P-value	0.0101	0.0356	-	0.0365	0.0684

Figure 1 shows the patterns of MRCP in Cz channel of subject D. The lines (blue, red, and green) show the each temporal patterns of multi-class MI. The vertical dotted lines are the interval of each component (PP, MR, RP, and P+90). The amplitude of each component was shown significant difference during 2 s. Table 1 represents the cross-validation results and p-values in all subjects. The proposed 4 epoch intervals-based feature extraction method had the highest classification accuracy (65.8±15) than the other intervals. The t-test also showed that proposed method has statistically significant (p<0.05) between the different methods except the 20 epoch intervals.

Discussion: The experimental results showed the possibility of classification using MRCP during multi-class MI tasks. The epoch intervals, which were not considered physiological components, showed a low accuracy. As a result, the proposed physiological 4 component based feature extraction method could enhance classification accuracy in multi-class MI.

Significance: The physiological 4 components of MRCP based feature extraction can classify the multi-class MI tasks by high classification accuracy (65.8±15 %), which is larger than the chance level of 33.3%.

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New approach based on frequency features of EEG signals when obstacles suddenly appear during walking

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Introduction: The study of cerebral activity allows a better understanding of the cognitive processes and control external devices for disabled people. In this regard, the use of BCI is actively investigated in rehabilitation tasks of lower limbs through exoskeletons [1]. Several studies have worked on this aspect by detecting the start/stop of gait or attention levels while walking [2]. In [3] it was found out that an EEG potential is generated after the visualization of the obstacle and before the user physically reacts. The goal of this work is to evaluate the frequency domain features of this potential to know if the previous results can be improved.

Material, Methods and Results: In order to register suitable data, a treadmill has been used to keep a constant velocity. The obstacle is presented as a background color change in a screen placed in front of the user. Even though the obstacles are presented visually, this work studies the reaction of the users after the obstacle appearance and before their physical reaction. Therefore, electrodes on the visual cortex are not included in the study. The user is asked to suddenly stop the gait when the obstacle appear and then, after a few seconds continue walking. Inertial Measurement Units placed on the lower limb have been used to know when the user stopped the gait. To register the EEG signals, the ActiCHamp equipment at a frequency sample of 500 Hz has been used. 21 active electrodes distributed over the scalp following the 10/10 International System have been used.
Six healthy users and two i-SCI performed these experiments (users 4 and 6 also participated in the previous study). Each user performs 8 repetitions where 7-8 obstacles appear randomly. The first five repetitions have been used to create a specific model for the user. Windows from 150 to 650 ms after the obstacle appears are selected as *reaction* class and the same number of windows of periods where the users were walking normally are selected as *no reaction* class. A CAR spatial filter is applied to all the windows. Then, 7 electrodes are selected (Fz, FC1, FCz, FC2, C1, Cz, C2) following the study performed in the previous work [3]. Afterwards, the frequency features through the FFT of the 7 electrodes is obtained. A study of several combinations of these frequencies is performed. The best results are obtained with the sum of three frequency bands (from 10 to 20, from 20 to 30 and from 30 to 40). This implies the use of 3 features per electrode having a total of 21 features. Finally a Support Vector Machine (SVM) classifier has been used. After creating the model, the last 3 repetitions have been analyzed in pseudo-online to obtain the results. The pseudo-online analysis takes windows of 500 ms each 200 ms. Each window is processed and classified as commented before. The output corresponds to *reaction* or *no reaction* class. This analysis emulates real time. In order to improve the results, a reaction is detected only when 2 consecutive windows are classified in this class. This way, the false positives are widely reduced. Results from Table 1 show an average of 51.6% of true positives and 22.6 false positives per minute.

Table 1. *Results of the pseudo-online test. TP: True Positives, FP/min: False Positive per minute.*

	Healthy users						i-SCI patients			
	1	2	3	4	5	6	7	8	**Average**	**Previous work**
TP	60%	55%	45%	53%	58%	50%	41%	51%	**51,6%**	**61,5%**
FP/min	21,0	24,0	22,8	12,0	19,2	24,6	27,0	30,0	**22,6**	**11,5**

Discussion: The results regarding the TP are similar to the ones obtained with the previous work, but the FP/min are higher. This implies that extracting temporal features on this kind of signals improve versus frequency features. Therefore, new technics and features should be explored to improve the results, mostly in terms of false positive reduction during real time conditions.

Significance: In this paper the evaluation of EEG signals when a user reacts to an unexpected obstacle has been addressed. The signals have been analyzed using frequency features in order to compare with previous works where temporal features were used. Although TP results are similar, the FP/min increases, and as a consequence the temporal features have more useful information that the frequency features.

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Online classification of visual perception

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Introduction: While motor output is a major focus for rehabilitative BCIs, examining the possibilities of other modalities may also be useful for basic neuroscience research. Here, we examine online classification of visual perception and attention, using Support Vector Machines (SVM) trained on EEG data from earlier visual presentation trials.

Material, Methods and Results: EEG data was recorded from 8 participants in a visual presentation environment, as in [1]. Lab Steaming Layer [2] – similar to BCILAB – was used to capture data from a Biosemi ActiveTwo with 32-70 active recording electrodes at low latency. Data was processed in real time, with minimal filtering, and very noisy channels identified and rejected.

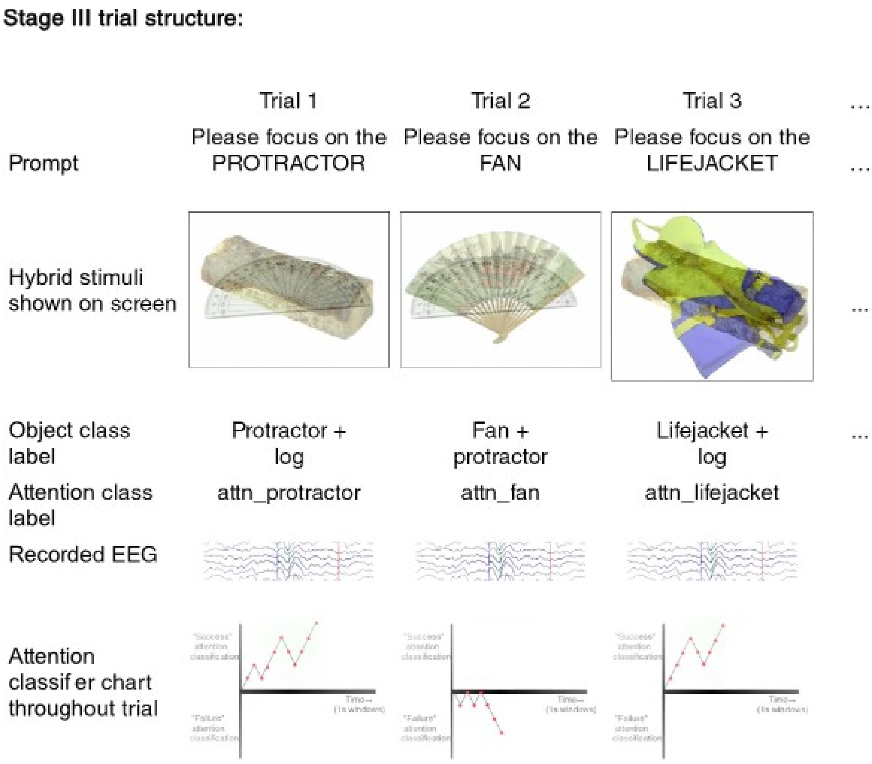

Fig 1 - trial structure and training label

Independent Component Analysis was used to transform the EEG channel activity, to identify and focus on possible sources. We first trained a series of SVM classifier models using data from each EEG channel and IC in turn, with the classification task to distinguish data from one object presentation from another. Peak accuracy was found using a selected IC datasource, as in [1].

We find object-identifying accuracy of around 85% (0.9 AUC) in online object determination from EEG data. This was mostly from occipital alpha components.

In further tests, we attempted to classify not only currently-observed object identity, but also which of two on-screen objects the subject was focussing their attention on. While classification accuracy dropped greatly in response to this harder task, we could still identify attention targets at 0.73 AUC, whereas the attentional distractor was identified at 0.58 AUC. Through an extended online trial feedback experiment, as in [3], we could examine persistence and conscious control of this target-attention-specific classifier activity. With this, we find tentative evidence that subjects can consciously control the activity of a minority of ICs by choosing to attend to specific visual objects.

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Online Optimization of Visual Stimuli for Reducing Fatigue in SSVEP-based BCIs

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Introduction: Visual fatigue induced by flickering stimuli has always been a problem to steady state visual evoked potential (SSVEP)-based brain-computer interfaces (BCIs). Some previous studies revealed that different stimulation properties such as frequencies, duty cycles and colors have impact on user's fatigue and performance. Importantly, the stimulation inducing less fatigue usually causes a reduction of system performance [1], and thus to design an optimal visual stimulator for SSVEP-based BCIs, there is a tradeoff between the user's fatigue and performance. Unfortunately, so far most of the visual fatigue evaluation methods relied on subjective self-assessment, which cannot provide real time feedback for the online optimization of visual stimulator. This paper adopted an objective evaluation method based on the electroencephalography (EEG) spectral analysis proposed in [2] in order to reduce the fatigue.

Material, Methods and Results: Five subjects performed a standard SSVEP-based BCI test. During the experiment, three groups of stimuli with different properties were presented as shown in Fig. 1. The stimuli in the group one have different frequencies, the same duty cycle and color. Five indices for fatigue from our previous research [2] and two indices (i.e. SNR and amplitude) for system performance evaluation were calculated in this experiment. The stimuli were valued with scores based on these indices. The stimuli with different frequencies were sorted according to the scores, which determined the optimal frequency of the visual stimuli for the current subject. The same procedure were carried out for group two and group three, so that the optimal duty cycle and color were selected for the subject.
The selected optimal features built optimal stimuli. This optimal stimulus was then displayed, and the indices of which were compared to the indices of the stimuli in three groups. The result showed that the selected optimal stimuli reduced fatigue with system performance preserved for four out of five subjects.

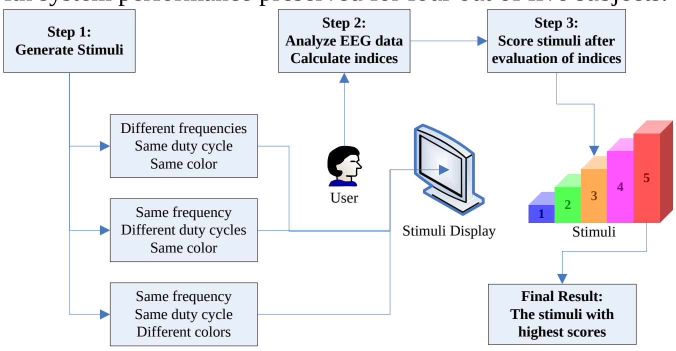

Figure 1. *The procedure of the online optimal SSVEP stimuli design.*

Discussion: One subject out of five did not achieve an improvement of optimal stimuli design. This problem maybe caused by artifacts or it could be a phenomenon such as BCI illiteracy.

Significance: This research proposed an online and automatic tuning for visual stimuli to reduce the fatigue and preserve the performance in using SSVEP-based BCIs. This could be helpful when applying SSVEP-based BCIs to real-life applications.

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Oscillatory modulations during human verbal interaction – A simultaneous EEG/MEG study

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Introduction: Social interactions in daily life play an important role in establishing human social relationships. Using hyper-scanning techniques, many studies have revealed that neural synchronization takes place during social interaction [1]. One EEG study attempted to address inter-brain synchronization when two subjects engaged in verbal communication, and oscillatory modulations in the theta and alpha bands during human-machine interactions were reported [2]. In this work, we investigated reciprocal live verbal interactions between humans, and collected EEG and MEG data simultaneously to seek oscillatory changes in these interactions.

Materials, Methods and Results: Two multimodal EEG/MEG systems (19-ch EEG and 152-ch MEG) located 100 miles apart were introduced to conduct hyper-scanning with two humans (Figure 1(A)). Reciprocal live verbal interaction was performed using condenser microphones and magnetic-compatible earphones. Ten naïve subjects (five pairs, aged 23.9±3.3 years) participated in the experiment and they were strangers to each other. Subjects were instructed to interact verbally with their partners by counting from 1 until the end period. This consisted of five runs in which each run contained six trials for each task period. After 5 seconds of instruction, a task period began with the presentation of a blank, black screen for 30 seconds. Thereafter, three different tasks (interaction, speaking, and listening) were conducted. In the interaction task, one participant began by saying one number, after which the partner said the consecutive number. In the speaking task, each participant spoke numbers beginning with ‘1’ until the given time limit. In the listening task, the participant simply listened to the partner’s voice while s/he counted from 1 to time limit. As a result, we found the oscillatory changes between interaction and speaking conditions (Figure 1(B)); MEG gamma increase and EEG alpha decrease were observed in the left temporal lobe, which was statistically significant (with FDR correction).

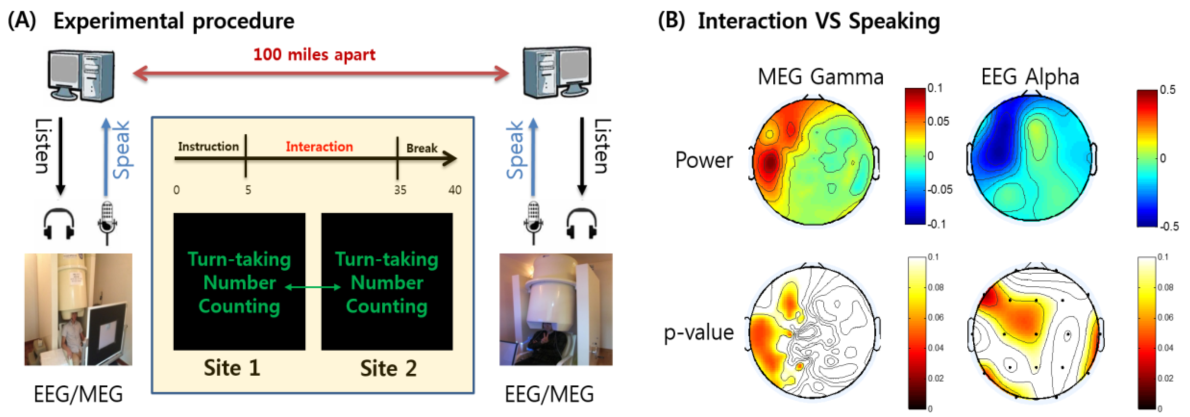

Figure 1. *(A) Simultaneous EEG/MEG experimental procedure of live verbal interaction. (B) MEG gamma and EEG alpha differences between interaction and speaking conditions. Power differences under each condition (top) and significant p-value distributions (FDR corrected) over all subjects (bottom).*

Discussion: We found the significant differences (MEG gamma increase and EEG alpha decrease) in the left temporal lobe; this is closely related to speech perception and production [3]. Therefore, these results may give us to understand neural mechanism in verbal interaction between humans and oscillatory modulations, which may be useful in developing interactive brain-to-brain or brain-to-machine communication techniques.

Significance: Simultaneous MEG/EEG recording for human verbal interaction was conducted at two distant sites.
Acknowledgements: This work was supported by NRF of Korea (2013R1A1A2009029) and MCST/KOCCA in the CT Research & Development Program 2015.

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Potential Use of Electrical Somatosensory Modality for Brain Computer Interface

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Introduction: P300 is commonly used in noninvasive brain computer interface (BCI). Most P300 based BCIs were focus on visual and auditory stimulation [1]. Several previous reports present the potential use of vibrotactile stimulus for P300 BCI [2,3]. As an alternative, electrical somatosensory stimuli can be used for BCI purpose [4]. This paper is to propose a P300 based BCI by using electrical somatosensory stimulation.

Material, Methods and Results: Ten healthy subjects (5 males and 5 females, age ranged from 20 to 28 years old) were recruited with written informed consents. P300 were recorded from each subject by 3 sensory modalities (visual, auditory or electrical-somatosensory) respectively. Each modality has two kinds of stimuli 'Go' and 'No-Go', i.e. Visual stimuli: red solid circle (No-go) and green solid circle (Go), auditory stimuli: low frequency (1kHz) monotone (No-go) and high frequency (2kHz) monotone (Go), somatosensory stimuli to the left index finger: lower intensity (No-go: two times of sensory threshold) and higher intensity (Go: three times of sensory threshold). Go and No-go stimuli were randomly present in 1 to 2 ratio, i.e. 60 Go stimuli and 120 No-go stimuli in each modality. P300 was recorded with a sampling frequency of 1000 Hz and band-pass filtered between 0.1-30 Hz. The linear discriminate analysis method (LDA) was selected to perform classification analysis [4]. Fig. 1 demonstrated P300 of the 'Go' and 'No-Go' at channel 'CPz'.

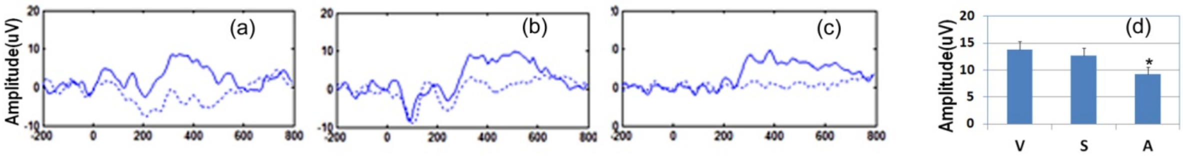

Figure 1. *Sample waveforms of P300 responding to (a) visual (b) electrical, and (c)auditory stimuli, while the solid line is in response to Go stimulation and dot line is in response to No-go stimulation. Comparison of Go P300 amplitudes in 3 modalities (d) shwed that auditory P300 has significant lower amplitude than visual and electrical P300 ($P<0.01$ by one-way ANOVA), while there is no significant difference between amplitudes of visual and electrical P300 ($P>0.05$ post-test by Tukey after one-way ANOVA).*

Comparison of performance among 3 modalities, accuracy ranged from 52% to 79% in electrical condition, with a mean accuracy of 66.99%; 63% to 77% in visual condition, with a mean accuracy of 70.93%; 51% to 69% in auditory condition, with an average at 59.40%. The visual modality had better performance than other two modalities. Electrical modality had higher classification accuracy than auditory modality for each participant.

Discussion: The present study is to prove that electrical stimuli can elicit reliable P300s in rough comparison to visual and auditory stimuli, which can be an input of P300 based BCI. Results showed that electrical stimuli can produce significantly larger amplitudes than for the auditory stimuli and as large as for the visual stimuli. The results are in agreement with previous somatosensory BCI [3], which presented 5 subjects with accuracy ranged from 50% to 100% with mean of 70%. The performance results presented a higher accuracy in electrical modality than that in auditory modality, and an equivalent accuracy as visual modality.

Significance: This study has demonstrated the usefulness of electrical somatosensory P300 based BCI as good as visual stimuli and auditory stimuli.

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Single Channel Hybrid BCI System using Motor Imagery and SSVEP

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Introduction: A user friendly device with few channels/electrodes is important for practical EEG based Brain Computer Interface (BCI) applications of everyday life. However, with few channels (especially a single channel) system, the acquired EEG information limits the classification accuracy or the performance of BCI system. In this paper, we propose a single channel hybrid BCI system using both Motor Imagery (MI) and Steady state visually evoked potential (SSVEP) to show the possibility of a single channel BCI system having higher performance. Since, the SSVEP feature can also be acquired from C3 and C4 channel according to [1], for developing a single channel system either C3 or C4 channel can be used for extracting SSVEP features. Recently, a study has shown that MI features can also be extracted through a single channel using Short-time Fourier transform (STFT) and Common Spatial Pattern (CSP) [2]. As both MI and SSVEP features can be extracted from C3 or C4 channel, it provides the possibility of developing a single channel Hybrid BCI system using MI and SSVEP.

Material, Methods and Results: A 32 channel Neuroscan EEG equipment was used to acquire offline data for a two class hybrid BCI system. These classes include Right hand MI with 15Hz SSVEP and Left hand MI with 20Hz SSVEP stimulus. After artifact removal and epoch extraction of this offline data, STFT was applied on each trial (of 4 seconds duration) of EEG data acquired from C3 and C4 channels. The time-frequency data will be the input for a feature extraction method called Common Frequency Pattern (CFP) as shown in fig. 1A. The features obtained from CFP then were classified using Support Vector Machine (SVM).

A **B**

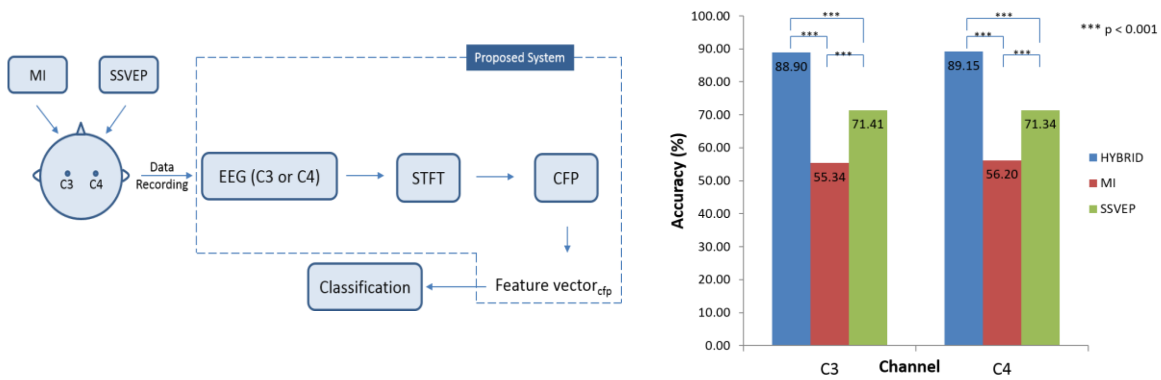

Figure 1. *A)Framework of proposed single channel Hybrid BCI system B) Classification accuracy at C3/C4 channel for time window of 4 seconds*

Considering a trial length of 4 seconds, the highest classification accuracy of 89.15% is achieved through hybrid BCI system, whereas the accuracy is less for MI or SSVEP based system (see Fig.1B). A significance test has shown that there is significant difference in the performance of Hybrid BCI system to that of MI or SSVEP based BCI system.

Discussion and Conclusion: It is observed that both the channels C3 and C4 channels has similar performance. Therefore, use of any of these channels in practical applications will not have significant difference in its performance. Also, it is very common for the performance to drop as the trial length gets shorter. This variation of performance with trial length has to be studied.

Significance: The possibility of a single channel Hybrid BCI with good classification accuracy is shown through this work.

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Soft Drink Effects on Brain Computer Interface Online Performance and Resting-State Arousal

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Introduction: Studies show that mind-body awareness, motivations, and other factors can affect online BCI performance [1, 2]. Since caffeine is the most commonly consumed stimulant and soft drinks represent a substantial portion of caffeine intake, this work studied the effect of soft drinks on BCI performance and resting state brain signals used in BCI. Relative to a control soft drink, the sugary soft drink caused negligible difference in resting state alpha power and BCI performance. A caffeine soft drink decreased resting state alpha power, but maintained BCI performance.

Material, Methods and Results: Noninvasive electroencephalography (EEG) data were recorded for six subjects via a 64 channel Neuroscan cap. Electrodes over left (C3) and right (C4) motor cortex recorded control signals for online BCI. Each subject came in for three sessions. All sessions started with two runs of left or right (LR) virtual cursor control with 30 trials in each run. Then the subject drank a Coca-Cola variant with either caffeine, sugar, or neither substance (considered control). The drink selected for each session was randomized across subjects to use all six drink order permutations. The subjects were blinded to the Coca-Cola variant and consumed the 12 oz. drink in five minutes. Then 32 minutes of resting state data were collected by alternating between eyes open and eyes closed for two minutes segments. Finally, subjects performed two more runs of LR cursor control. The power activities in the upper mu frequency band over left and right hemisphere were linearly mapped to the position of the virtual cursor. To minimize the residual effects, subjects did not consume sugar nor caffeine at least four hours before the experiments. We performed experiments between 1:00 PM and 6:00 PM.

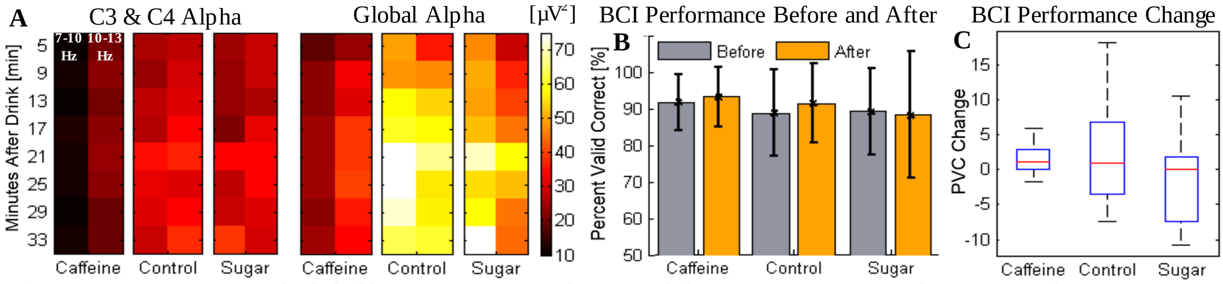

Figure 1. *(a) C3 & C4 and Global lower (7-10Hz) and upper alpha (10-13Hz) power during rest. (b) LR BCI PVC before and after each drink, error bars are standard deviation. (c) PVC change after consumption of each drink.*

The global power of lower and upper alpha frequency bands for three conditions and channels C3 and C4 throughout resting state is shown in **Fig. 1a**. For both C3 & C4 and global, note the similarity between control and sugar consumption in the power of alpha band. Caffeine consumption causes alpha power to decrease substantially from control. Group average percent valid correct (PVC) of all subjects is shown before and after each type of drink in **Fig. 1b**. BCI performance increases slightly after caffeine and control drinks. Sugary drinks cause average PVC to decrease and cause the largest standard deviation of performance. The change of PVC after consumption of each drink is displayed in **Fig. 1c**. Caffeine consumption shows slightly higher improvement of PVC than the control, while the sugar consumption leads to a decrease of PVC. Caffeine consumption also causes the smallest deviation among drinks, while the sugary drink mostly decreases the PVC.

Discussion: The sugary drink seems to have no effect on C3 and C4 alpha power relative to the control. For caffeine, both upper and lower alpha power decreased in C3 and C4, which is consistent with previous literature and global results, where caffeine caused a decrease in global alpha power [3]. Since upper alpha power of C3 and C4 are directly utilized to control virtual cursor movement, this alpha power decrease at rest due to caffeine might lead to a weaker control signal with smaller dynamic range. However, caffeine is also known to increase attention and reduce fatigue [4], which may reduce performance deviation and improve BCI performance. The results show caffeine consumption does not improve BCI performance relative to the control drink. The BCI performance effects due to resting state alpha power decrease, increased attention, and reduced fatigue seem to cancel out one another. Sugar consumption caused a slight decrease in average BCI performance. All postulations should be confirmed with a larger sample size.

Significance: With the prevalence of soft drinks and caffeine, their effects on BCI performance are worth investigating. Caffeine seems to have negative frequency effects and positive attention effects that combine to cause negligible changes in BCI performance, while sugary drinks may decrease BCI performance relative to the control condition. As researchers push the boundaries of non-invasive BCI with quadcopters, robotic arms, and cars, these results shed light on how the world's most popular stimulant, caffeine, affects BCI performance.

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Spatial Abilities Play a Major Role in BCI Performance

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Introduction: Despite their promising potential impact for many applications, Mental-Imagery based BCIs (MI-BCIs) remain barely used outside laboratories. One reason is that 15% to 30% of naïve users seem unable to control them [1] and only a few reach high control abilities. Although different predictors of BCI performance (i.e., command classification accuracy) have been investigated to explain this huge inter-user variability [2, 3], no strong predictive model has yet been determined. This could be due to (a) the often small samples used (N=5 or 6) and (b) the fact that these predictors have been mostly determined based on one-session experiments. Yet there is no evidence that performance obtained at the first session is predictive of users' MI-BCI control ability.

Material, Methods and Results: In [4], we investigated the impact of the user's personality and cognitive profile on MI-BCI performance based on a 6-session experiment. Averaging performances over these sessions reduced the intra-subject variability (e.g., due to fatigue or external factors), and thus led to a better estimation of participants' MI-BCI control ability. Each session comprised 5 runs during which the participants (N=18) had to learn to perform 3 MI tasks: left-hand motor imagery, mental rotation and mental calculation. The results stressed the impact of mental rotation scores (measured using questionnaires), and which reflect Spatial Abilities (SA), on mean MI-BCI performance [$r=0.696$, $p<0.05$] (see Fig. 1[A]). SA are the mental capacities which enable the construction, transformation and interpretation of mental images. In a more recent study (to be published), we trained 20 participants to control a 2-class MI-BCI by performing motor-imagery of their left- and right-hands, within 1 session of 5 runs. Results confirmed the role of SA: mental rotation scores were correlated with peak MI-BCI performance [$r=0.464$, $p<0.05$]. This suggests that SA are a generic predictor of MI-BCI performances.

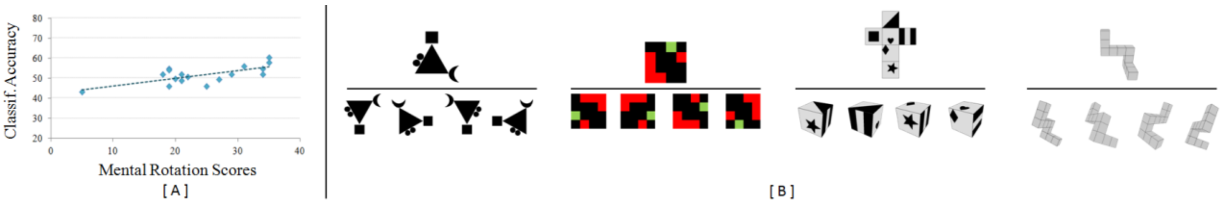

Figure 1. *[A] Diagram representing the mean classification accuracy for the different subjects as a function of their mental rotation score; [B] One item per exercise included in the Spatial Ability training:the shape on top is the target, and the participant must identify the two shapes that are identical to the target among the four below.*

Spatial Ability Training: The strong correlation between SA and MI-BCI performance raised a new research question: Is there a causal effect between SA and MI-BCI performance? In other words: Would an improvement of users' SA result in an increase of their MI-BCI control abilities? We implemented an SA training protocol (see Fig. 1[B]) including different exercise types and difficulties. In the coming weeks, we will test this protocol efficiency in terms of MI-BCI performance improvement by comparing it to a standard MI-BCI training approach. We will also investigate the neurophysiological correlates of the SA training (notably the implication of the motor cortex) to improve the understanding of the relationship between SA and MI-BCI performance.

Perspectives for Stroke Rehabilitation: If a causal link between SA and MI-BCI performance is confirmed, this would be a promising way to improve MI-BCI performance and thus MI-BCI-based applications such as stroke rehabilitation [5]. Also, current MI-BCI based stroke rehabilitation procedures [5] require the execution of MI tasks which can induce (or increase) a depressed state in patients by reminding them of the loss of movement in their limb. Since SA training and mental rotation tasks activate the motor cortex [6], they might also be used as a more transparent way to indirectly induce synaptic plasticity in the motor cortex during rehabilitation.

Significance: Through SA, we propose a new approach for MI-BCI training that could offer promising perspectives for MI-BCI and stroke rehabilitation. We are currently evaluating and validating this approach.

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Spatial Frequency Characterization and Optimization of SSVEP Stimuli

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Introduction: Most traditional SSVEP systems utilize rectangular stimuli that flash by alternating between two solid colors (typically white and black) at different temporal frequencies. However, it is also common for SSVEP systems to use spatial checkerboard patterns as visual stimuli, for which the checkerboards are pattern-reversed for the flashes. Several SSVEP BCI studies have examined the difference between using solid vs. a checkerboard stimulus and have reported conflicting results as to which is superior [1,2]. These studies did not examine the effects of SSVEP stimuli with respect to spatial frequency (i.e. size of the individual checks). Although spatial frequency has been studied in the clinical field by analyzing the morphology of elicited pattern VEPs, the effect of the spatial frequency of checkerboard stimuli on SSVEP performance has not been studied in the context of BCIs where multiple stimuli are presented simultaneously.

Material, Methods and Results: Data were collected from 11 healthy subjects with 16 active electrodes over the parietal-occipital regions. Subjects participated in two online SSVEP experiments in which nine different spatial frequency stimulus conditions were tested (0, 0.15, 0.3, 0.6, 1.2, 2.4, 4.8, 9.6, and 19.2 cycles/deg). In the first experiment, subjects controlled a traditional 4-class SSVEP BCI where each of the four stimuli was presented simultaneously on the top, bottom, left and right portions of the screen flashing with temporal frequencies of 6, 6.66, 7.5 and 8.57 Hz, respectively. During the start of the trail, subjects were cued to attend to a single stimulus, followed by a 6 second stimulation period, and ending with a 2 second feedback period where the predicted target from the BCI was shown. In the second experiment, subjects used the 4-class BCI for continuous control in a simple 2d path-navigation task. The goal was use the four-class BCI (move up, down, left or right) to traverse simple paths as rapidly as possible. To test the effect that spatial frequency has on the elicited SSVEP signal, both experiments were repeated with the nine different spatial frequency conditions in a random fashion. For all trials, the SSVEP signals were classified using standard canonical correlation analysis (CCA). Figure 1 shows the average accuracy and ITR across subjects for the nine different spatial frequency stimulus conditions as well as for varying time window lengths (i.e. observation length used for classification). The SSVEP BCI accuracy (left panel) shows a bimodal distribution with a primary peak at the 0 c/deg (solid stimulus) condition and a secondary peak at the 2.4 c/deg condition. The SSVEP ITR (right panel) shows that the 2.4 c/deg condition achieves the highest transfer-rate amongst all spatial frequency conditions tested.

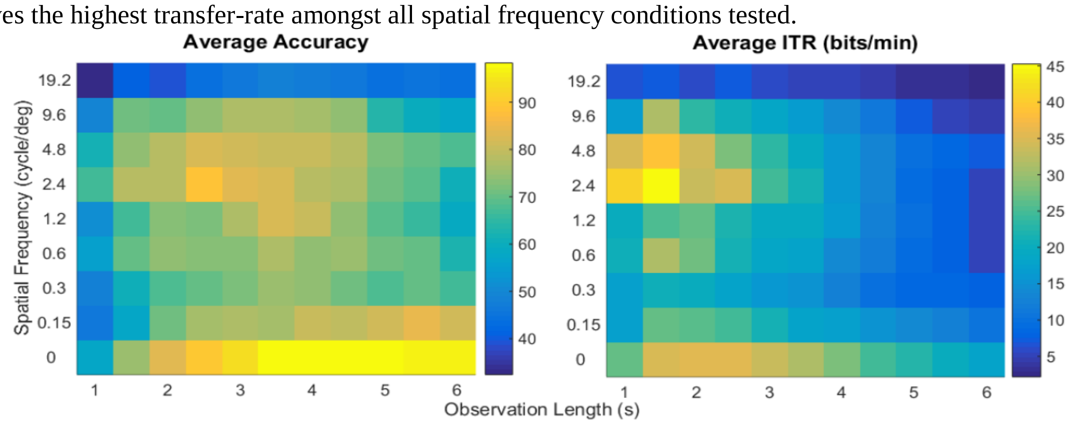

Figure 1. *Average SSVEP accuracy and ITR of the four-class SSVEP BCI from experiement 1. The accuracies and ITRs are shown for the nine differnent spatial-frequency conditions as well as for varying time-window lenghts used in the CCA based classification.*

Discussion: The 0 c/deg stimulus condition achieves the highest accuracy, which increases with increasing observation length. The 2.4 c/deg, is able to achieve a modest accuracy (~85%) in a very short time-window leading to an ITR that outperforms that of the 0 c/deg condition. Interestingly, the accuracy of the 2.4 c/deg condition (along with most of the other checkerboard conditions) decreases with observation length, supporting a potential mechanism of spatial frequency adaptation in the retina using checkerboard stimuli.

Significance: This is the first study to test the effect of different spatial frequency conditions on SSVEP BCI performance. This information can be used to determine the spatial frequency of checkerboard stimuli to optimize BCI performance, with potential improvement over solid flashing stimuli.

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Tactile BCI performance of sensory experts

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Introduction: In direct comparison visual BCI have been shown to outperform tactile BCI [1]. However, it has been shown that extensive sensory training in the tactile modality can lead to cross modal activation of the primary visual cortex in blind [2] as well as in sighted [3] subjects. Within this study we intend to examine whether this effect translates into increased tactile BCI performance.

Methods: Healthy (control participants, n=9) and visually impaired (sensory experts, n=9) participants were recruited. Control participants reported no regular activities related to sensory expertise, all sensory experts were able to read braille. Tactile stimulators (C2 tactors; Engineering Acoustic Inc., Casselberry, USA) were used to stimulate fingers commonly used for braille reading, i.e. index and middle finger of both hands. Stimulus duration was 220 ms, inter-stimulus interval 400 ms, stimulation frequency 250 Hz. Control participants also took part in visual stimulation. EEG was acquired with 12 passive Ag/AgCL electrodes at positions Fz, FC1, FC2, C3, Cz, C4, P3, Pz, P4, O1, Oz, and O2. Ground and reference were at the right and left mastoid. Impedance was kept below 5 kOhm. Signals were amplified using a g.USBamp (g.tec Engineering GmbH, Graz, Austria) and recorded at a sampling rate of 512 Hz. Participants performed three calibration runs (10 sequences) and four copy tasks using seven, five, three and one sequence for tactile and visual (control participants only) modality. Here we report results for three and one sequence(s) only, as for five and seven we faced a ceiling effect.
Statistical analysis: To compare tactile BCI performance between the groups we calculated a repeated measures ANOVA with sequences (2) as within and group (2) as between subject factors, and performance as dependent variables. The same analysis was conducted to compare tactile performance of sensory experts and visual performance of control participants. Amplitude and area between curves were compared using t-tests.

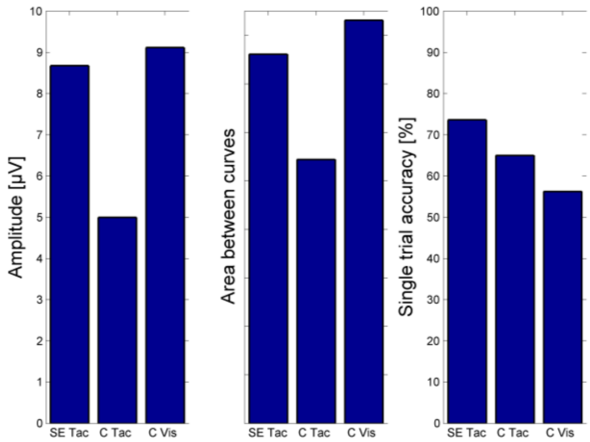

Figure 1 Amplitude, area between curves and single trial accuracy for sensory experts (SE) and control participants (C) for tactile and visual modality.

Results: In the tactile modality, performance of sensory experts was higher than that of control participants for three ($F(15) = 4.826$, $p < .05$) and one sequence ($F(15) = 4,924$, $p < .05$). Area between curves was higher for sensory experts as compared to control participants ($t(15) = 1.866$, $p < .05$, $r = 0.434$), P300-amplitude, however, was not significantly different. Visual P300-amplitude was significantly higher than tactile P300-amplitude of sensory experts ($t(14) = 2.074$, $p < .05$, $r = 0.485$), area between curves, however, showed no significant differences. In line with this, we found no significant differences between visual performance of control participants and tactile performance of sensory experts.

Discussion: Within this study we demonstrated the effect of sensory expertise gained by non BCI-related tasks on tactile BCI performance. Sensory experts outperformed control participants in the tactile modality. Additionally sensory experts were able to achieve tactile performance on the level of visual performance of control participants.

Significance: The results demonstrate the effect of expertise on performance with a tactile BCI. Thus, the lower performance with tactile BCIs is likely to be overcome with training.

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Tactile BCI training for elderly people

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Introduction: Tactile BCI have been demonstrated to perform lower than visual and auditory BCI [1]. In our previous study we were able to achieve mean accuracies as high as 85.8% but did so at the price of low ITRs [2]. Recently the beneficial effect of training on auditory BCI performance has been demonstrated[3], [4]. Whether this effect can also be utilized for tactile BCI performance has not been examined.

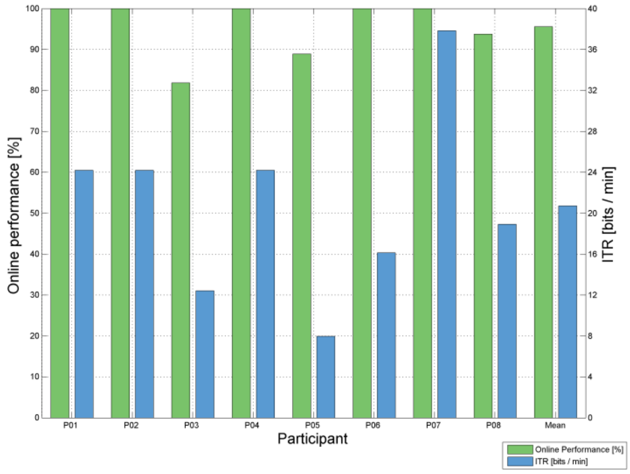

Figure 1 Individual and average post-training Accuracies and ITRs

Methods: N=8 healthy elderly participants aged 50-73 (mean = 60, SD = 6.7) participated in a five-session training. All participants were naïve with regards to BCI. Tactile stimulators (C2 tactors; Engineering Acoustic Inc., Casselberry, USA) were used to stimulate participants left thigh (above knee), right thigh (above knee), abdomen (above navel) and lower neck (at the height of C4 to C8). Stimulus duration was 220 ms, inter-stimulus interval 400 ms, stimulation frequency 250 Hz. EEG was acquired with 12 passive Ag/AgCL electrodes at positions Fz, FC1, FC2, C3, Cz, C4, P3, Pz, P4, O1, Oz, and O2. Ground and reference were at the right and left mastoid. Impedance was kept below 5 kOhm. Signals were amplified using a g.USBamp (g.tec Engineering GmbH, Graz, Austria) and recorded at a sampling rate of 512 Hz. Participants attended five training session each starting with three calibration runs, each lasting approximately 3 minutes. Afterwards, participants navigated a virtual wheelchair trough two virtual courses. Each course required 14 correct movement commands, deviating commands had to be corrected and the maximum number of commands was restricted to 22. During training, number of sequences was fixed to 8 sequences to facilitate high accuracy and prevent frustration. After the last training session participants navigated the courses with an individually adapted and therefore, reduced number of sequences.

Results: All participants achieved above random control in session one with an average accuracy of 89.02%. Accuracy increased to 91.46% during training. We calculated the single trial performance offline and found a significant increase ($X2(4)=11.86$, $p<.05$, $r_{\text{session1 to 5}}= .33$) between session one and session five. During the post-training task participants achieved a mean accuracy of 95.56% and an information-transfer-rate of 20.73 bits / min.

Discussion: Within this study we demonstrated the beneficial effects of training on tactile BCI performance. Furthermore, we were able to achieve high accuracy and information-transfer rates on a level previously unreported for tactile BCI. Notably our results were achieved with participants aged 50-73 years, representing the target population for neurodegenerative diseases or stroke. Taken together, our results demonstrate that high viability can be achieved using tactile BCI.

Significance: We present a previously unreported combination of high accuracy and speed in a tactile BCI. This was achieved by elderly participants after a five-session training and demonstrates the viability of high performing tactile BCI for the target population of BCI aiming at replacing lost function.

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The quantified cook - Physiological responses during cooking food associated with different levels of valence and arousal

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Introduction: Physiological measures could potentially inform us about an individual's emotion in a continuous fashion without requiring distracting questions about currently felt emotions. Considering that positive emotions are critical for the success of foods in the market place, one of the potential application areas is examining emotions during the food cooking process and consumption. The goal of the present study is to explore physiological responses during 'out of the lab' cooking and consumption in a simulated home environment. We compared electrodermal activity (associated with arousal), heart rate and EEG frontal alpha asymmetry (associated with pleasantness, or more specifically, approach or avoidance motivation) during cooking two dishes that were expected to elicit distinct emotions during the cooking and consumption experience.

Material, Methods and Results: 41 participants were asked to cook and taste two stir-fry dishes, following auditorily presented instructions that were equal for both. One of the dishes contained chicken (expected to evoke pleasant emotions/approach and intermediate arousal), the other one mealworms (expected to evoke unpleasant emotions/avoidance and high arousal). The order of dishes was counterbalanced between participants. EEG, skin potential and ECG were recorded using an ambulant system (Mobita, TMSi). EEG electrodes were water based. Physiological variables were extracted relative to a resting baseline from four intervals that followed the following instructions: 1.'remove the lid from the bowl', (either exposing chicken or mealworms); 2.'Add the contents of the bowl to the pan and keep on stir frying'; 3.'Use the spatula to place a scoop of the dish on the plate'; 4.'Take a bite'. After cooking each dish, participants were asked to rate arousal and valence scores during these intervals. Dependent variables were evaluated using ANOVAs with condition (chicken versus mealworm) as a within participants independent variable, and order (chicken versus mealworm first) as a between participants independent variable. Subjective ratings confirmed that participants experienced high arousal and low valence in the mealworm condition compared to chicken, especially at the first (exposure) interval. As expected, skin potentials were larger for mealworms than for chicken at the exposure interval. For heart rate, there were interactions between condition and condition in all intervals, such that heart rate was much lower in the mealworm compared to the chicken condition when chicken was presented first, while it tended to be the other way around when mealworms were presented first. For the exposure interval, first EEG results show a close to significant effect of condition on prefrontal alpha asymmetry in the expected direction (relatively low alpha in the right hemisphere which is consistent with an avoidance motivation). Using SVM classification analysis (10-fold cross-validation across subjects) we could distinguish with up to 82% accuracy between cooking chicken and mealworms using ECG and skin potential variables.

Discussion and significance: In our first analyses, we found the expected effects in skin potentials and a trend for prefrontal alpha asymmetry, as well as reliable classification between the two conditions under relatively difficult experimental circumstances. Firstly, physiological signals were affected by noise from movements and secondly, we could present the participants each condition only once. This study adds to the literature showing that counter to what is often assumed, arousal is not associated with heart rate acceleration under all circumstances. Different studies have found disgust to increase or decrease heart rate, or to not affect heart rate at all. The present study fits in a range where we use physiological responses to distinguish between different emotional conditions in (simulated) 'out of the lab' situations, such as reading arousing and non-arousing sections in a novel [1]. This study also provides new insights into the role of emotions in the cooking and consumption experience and includes a new approach in this area for creating innovative, healthy products and dishes.

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Towards a BCI Based on Vergence Eye Movements

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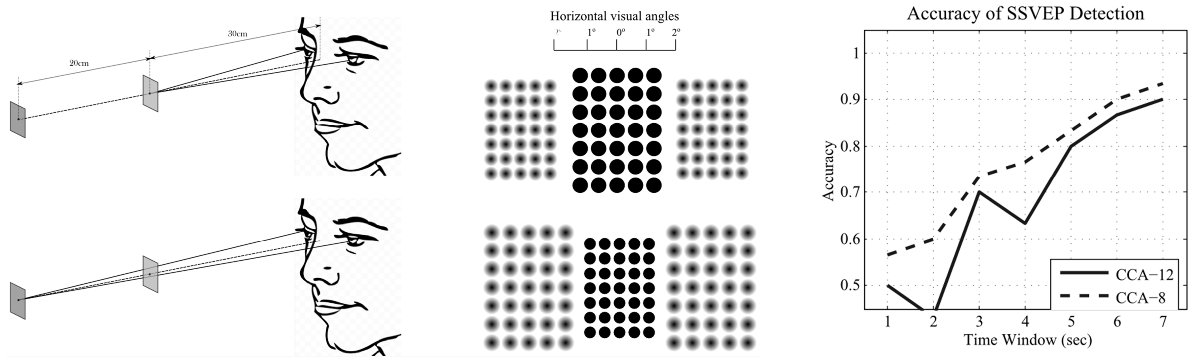
Introduction: Vergence eye movements occur when each eye moves simultaneously in direction opposite that of the other eye, ensuring that the image of an attended object is projected in the fovea of both eyes [1]. Binocular disparity and depth of field play important roles in 3D perception [2]. In the present work, a novel SSVEP-BCI stimulation setup is proposed, which allows users to select the target stimulus by vergence. With this aim, two stimuli are placed collinearly with the midpoint between the eyes (Fig 1a) and properly separated so that if any stimulus is attended, the other one is perceived duplicated and defocused due to the binocularity disparity and depth perception, respectively (Fig.1b). Hence, the elicitation of SSVEP by the attended stimulus is evaluated.



(a) (b) (c)

Figure 1. *(a) Placement of two LED stimuli when the nearest and farthest stimuli are being attended. (b)Subjective perception of stimuli when the nearest one (top) or farthest one (bottom) is being attended. (c) Acccuracy rate of SSVEP pattern detection.*

Material, Methods and Results: Two stimuli based on 7x5 green LED arrangements of dimensions 18x13mm^2 and flickering at 5.6 and 6.4 Hz were used. One of them was placed at 30cm from the center point of the user's eyes and a second stimulus was placed 20 cm behind the first one (Figure 1a). A preliminary experiment was conducted with a healthy subject. EEG signals were recorded from passive electrodes at locations P1, P2, P3, P4, Pz, PO3, PO4, PO7, PO8, POz, O1, O2, and Oz, with bi-auricular reference, grounded at AFz and with a sampling frequency of 200 Hz. Signals were re-referenced at Pz and Canonical Correlation Analysis with eight (CCA-8) and twelve (CCA-12) electrodes were used to evaluate the SSVEP pattern elicited by the attended stimulus. Signals of sixty trials of 9 s were recorded (2 s of rest and 7 s of task). Subject was asked to attend one of them stimulus randomly. Accuracy rates for different time windows (TW) are shown in Fig. 1c. SSVEP pattern was clearly elicited attaining accuracy rates greater than 0.8 for TW > 4 s. The highest accuracy was 0.93 with CCA-8 for TW = 7 s.

Discussion: Results indicate the attended stimulus can elicit a distinguishable SSVEP pattern with high accuracy rate. This is because the amplitude and latency of visual evoked responses are affected by defocusing [3]. Thus, a focused stimulus is able to elicit a SSVEP pattern even if non-focused stimulus is present in the field of view [4]. In addition, Conjugate (horizontal or vertical) eye movements are not required, even if the user is able to do so, to select the target stimulus because both stimuli are placed in same imaginary line (Fig. 1a).

Significance: The stimulation setup here proposed could be evaluated by patients with motor impairment by virtue of the convergence together with the accommodation of the lens (which brings the object into focus) and pupillary constriction (which increases the depth of field and sharpens the image on the retina) are reflexive movements that responses elicited by interest in a near object [1].

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Towards Mobile and Wearable Brain-Computer Interfaces

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Introduction: Brain-Computer Interfaces (BCIs) have not been adopted as a control paradigm for mainstream use because most BCI systems are cumbersome, difficult to set up, and do not generally perform well enough in mobile settings to replace existing input modalities. However, BCIs may have promise as part of multi-modal systems that augment interactions when the user's hands are not free and/or voice commands are not possible, often a requirement in highly mobile application domains. With recent advances in electrode capabilities, and improvements in the processing power of mobile devices and head-worn displays, it is now possible to acquire, send and process EEG signals in real-time on mobile devices. These improvements make it possible to build a wearable mobile BCI, which could provide alternate interaction methods for mainstream users as well as the disabled population. This abstract describes two pilot studies in our ongoing work designing and evaluating wearable-mobile BCI components.

Material, Methods and Results: In our first study, our aim was to design a BCI to detect SSVEP with all wearable components. Google Glass [2], was used to present two flashing visual stimuli to the participant, at 13 Hz and 17 Hz frequency simultaneously. Our EEG amplifier was an OpenBCI board that we clipped to the participant's belt using a custom 3D printed clip. We used three electrodes: occipital (Oz) as signal, mastoid for ground, and the earlobe for reference, to detect the SSVEP signal. We recorded the EEG data for offline analysis. Over 10 sessions, using the apparatus illustrated in Figure 1, we could detect to which of the two stimuli our participant was attending to with 76%-84% accuracy for 13 Hz and 67%-72% accuracy for 17 Hz, for amplitude spectra from PSD as feature for 1 second long sliding window SSVEP using 10 cross-fold validation RF classifier trained on each stimuli individually. We extended the experiment for walk-stop-watch stimuli scenario and found the accuracy to be 93% for single stimuli 1 second long sliding window SSVEP.

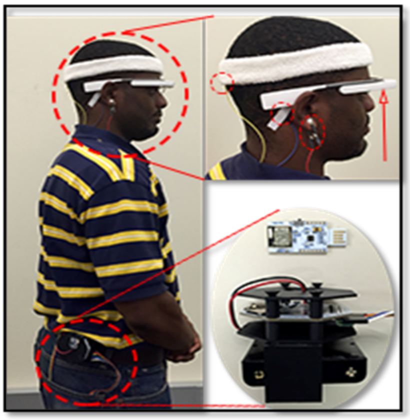

Figure1. *Google glass with SSVEP stimuli and OpenBCI Board*

The aim of our second study was to determine if we could replace the scalp electrodes with easily made customized in-ear electrodes adapted from the ear-electrode design discussed by Looney [1]. We used an eFit scanner to create a model of the participant's left ear. We then 3D printed an earpiece, and placed 3 pre-gelled Ag/AgCl ground plate electrodes covered with silver foil so they would contact the walls of the ear canal in the outer ear. Resulting in-ear electrode and Oz for comparison was attached to the wearable OpenBCI system and a flashing 13Hz LED located 6 cm away from the user. As demonstrated in Fig 2, the peak SSVEP amplitude for the occipital region is higher than ear canal, but SNR increased as well thus resulting in comparable accuracy of detection of 80-90% from ear and scalp using a wearable BCI.

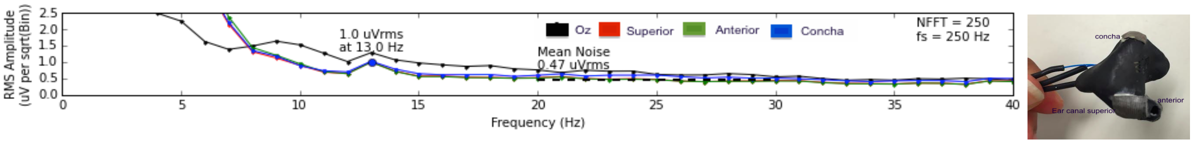

Figure 2. *(above) 13 Hz SSVEP responses from LED with occipital and ear electrodes. (right) Custom made earpiece with labeled electrode placements*

Discussion and Significance: The first prototype demonstrated that SSVEP signals could be collected from a fully mobile and wearable BCI system. Because the display was worn on the face and the bioamplifier was small enough to clip to a belt while still being capable of effectively detecting SSVEP, we conclude that it is now feasible to make a fully wearable BCI system using commercial components.

The second experiment demonstrated that we could substitute in-ear electrodes, making the BCI system smaller and less obtrusive. We have developed a quick, easy, inexpensive way to create custom ear-electrodes, which will enable our ongoing study to test a much wider range of users. Though there is more work to be done before wearable BCIs can be used in everyday life as simple control systems, these studies have shown the feasibility of the mobile and wearable approach.

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Tripolar Concentric Ring Electrode Encephalography Reduces Muscle Artifacts for BCI Applications

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Introduction: Brain-computer interfaces (BCIs) are systems that allow communication between the brain and the external world. Brain signals related to human intention are collected via electroencephalogram (EEG) and translated into control signals. The EEG is sensitive to muscle activity, electromyography (EMG), related artifacts that occur from user movement. Besio developed tripolar concentric ring electrodes (TCREs) that closely approximate the Laplacian using the derivation 16*(M-D) – (O-D) where M, D, and O are the potentials on the middle ring, central disc, and outer ring, respectively [1, 2]. This formula is incorporated into our t-Interface 20. By taking the difference between closely spaced (1.0mm) sensing elements, the common noise to each element is cancelled. This is different than the typical monopolar (disc) EEG signal, which is derived from the difference in potentials between a recording electrode and a reference electrode. Conventional disc electrodes are centimeters apart and sharing less common noise, thus, the noise is not cancelled. In previous research, we found that EEG with TCREs (tEEG) has significantly better signal-to-noise ratio, less mutual information, and higher spatial resolution [1,2]. We also found that the outer ring of the TCRE can be used to emulate the disc electrode [3]. Further, real-time center-out cursor control with tEEG was significantly better than with EEG [4]. The current experiment compares the effectiveness of tEEG and EEG for attenuating muscle artifacts.

Material, Methods and Results: We recorded tEEG and outer ring EEG in 5 healthy participants. The tEEG was preamplified (gain of 187) and the EEG was buffered both with our custom preamplifier the t-Interface 20. We placed 20 TCREs in each location of the 10/20 system, ground on the forehead, and reference as an average of the left and right mastoid processes and the occipital region (near Oz). Data were recorded (400 S/s, 1 to 100 Hz) in each participant using the following protocol: one 30-second segment of rest, ten 30-second segments of right head turn, ten 30-second segments of left head turn, and ten 30-second segments of jaw clench.

Signals from tEEG and EEG were band filtered from 10-100Hz, and a signal to noise ratio (SNR) was calculated by taking the ratio of the average power of the movement segment to that of the rest segment for each electrode location in each movement trial for both the tEEG and EEG signals. We then took the mean of those ratios for tEEG and EEG across all participants for each movement category: right head turn, left head turn, and jaw clench. For right head turn, the mean ratios were 3.3±5.0 and 16.1±14.7 for tEEG and EEG respectively. For left head turn, the mean ratios were 3.9±7.4 and 21.7±23.6 respectively, and for the jaw clench the mean ratios were 11.9±28.9 and 35.9±80.7 respectively. In each movement category, the mean ratio was smaller for the tEEG than the EEG, indicating less movement artifact in the tEEG signal. This difference was found to be statistically significant (Wilcoxon signed rank test, p-value <0.0001).

Discussion: Fig. 1, from Pz, exemplifies that TCREs significantly reduce muscle artifact in tEEG recordings when compared to EEG. Local muscle artifacts from directly under the TCRE are sensed, however distant muscle artifacts are attenuated sharply. In the future we will compare more participants and other artifacts.

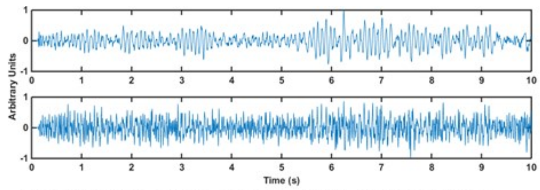

Figure 1. *Top – tEEG, Bottom – EEG. Right head turn with eyes closed. Notice prominent alpha waves in the tEEG while the EEG is contaminated with muscle artifacts.*

Significance: One of the factors negatively influencing BCI performance is the presence of muscle artifacts in EEG signals and being able to reduce these artifacts with a TCRE could prove an efficient tool to improve BCI performance.

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Visual Perceptual-based Spatial Location Discrimination Using Single-trial EEG Analysis

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Introduction: Decoding a person's brain activity to infer the current perceptual state of that person has recently drawn great interest among researchers (see [1] for a review). Despite much recent progress, the spatiotemporal activations that encode perceptual information have not yet been reliably identified. Research on this field is not only important to neuroscience but resulting knowledge could also be used for practical applications, such as reactive brain-computer interface (rBCI). Furthermore, decoding perceptual information for single trials in a cheap, non-invasive way from recorded brain signals is not a trivial task. In this study, the aim is to demonstrate that it is possible to determine different spatial location cues which covertly appear to the left or right visual field using scalp electroencephalography (EEG) signals within milliseconds.

Material Methods: A custom-made visual stimulus presentation device with one central visual reference marker (fixation) LED and four target light LEDs was used to present experimental stimuli, resulting in four stimulus locations (see Fig. 1). EEG data was collected from ten healthy subjects while performing the delayed memory-guided saccade task to visual stimuli located in their straight-ahead visual field, i.e., subjects need to focus on the fixation LED even the stimulus presents. By using SPM12 artifact detection functionality, the artifact-free 30-channel EEG segments of length 400ms were selected. A sliding window of length 200ms and a step size of 20ms is used to search the active window. The proposed method uses best basis-based wavelet packet entropy [2] as feature extraction, fuzzy entropy [3] as feature reduction, and naive Bayes classifier (NBC) as a classifier. To obtain an idea of the distribution of the attainable accuracies, 10-fold cross-validation was performed on a four-class classifier and two-class classifiers for reliable estimation.

Results: Average cross-validation results are summarized in Table 1. It shows that (1) the four-class classifier dividing the target into four different locations is with well above chance (2-class is 50% and 4-class is 25%); (2) comparison pair <L2 vs. R2> yields the higher discrimination accuracy than pair <L1 vs. R1>. Subject S3 and S9 showed the higher discrimination accuracy in pair <L1 vs. R1> than pair <L2 vs. R2> due to using different active windows and different channel sets.

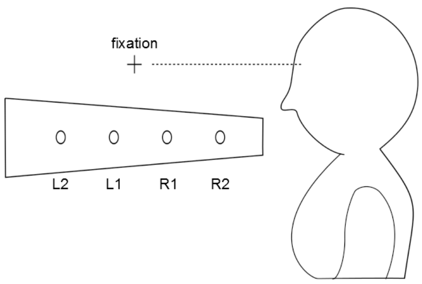

Figure 1. *Schematic of visual perceptual light stimuli. The fixation LED was positioned 5 cm above the center of the stimuli. Four visual targets were at 60cm viewing distance and were at 2.5 and 7.5 degree visual angle to the left and right of body midline / straight ahead.*

Table 1. Discrimination accuracy for each subject (%).

Subject	4-class	2-class	
	L2 vs. L1 vs. R1 vs. R2	L1 vs. R1	L2 vs. R2
S1	45.561	80.832	82.538
S2	42.085	75.743	77.455
S3	40.886	78.898	75.735
S4	44.655	76.467	80.154
S5	49.058	77.833	83.320
S6	41.657	76.379	76.561
S7	45.375	80.359	84.091
S8	47.011	76.055	82.267
S9	44.702	81.576	80.806
S10	43.994	79.554	81.847
Ave	44.498	78.370	80.477

Significance: The result demonstrates that a short time segment EEG activity pattern before eye movement is a useful tool for covert visual perception location discrimination. The proposed method can help design an actual reactive BCI system for detecting perceptual-spatial location.

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Comparisons and Calculations in the Human Posterior Parietal Cortex

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Introduction: The parietal cortex is centrally involved in sensorimotor transformations for motor outputs such as reaches, saccades, and grasps [1]. These actions require computations on quantifiable variables such as distance and size. This fundamental link between sensorimotor planning and execution and numerical processing may explain why, in both animal electrophysiology and human neural imaging studies, the parietal cortex has been implicated in quantity representation during arithmetic, comparison, and other number manipulations [2, 3].

Material, Methods and Results: We investigated numerical representation in the posterior parietal cortex (PPC) using intracortical recordings from a human with tetraplegia [4]. From two 96-channel microelectrode arrays, we identified neurons in the anterior intraparietal area and Brodmann's area 5 whose firing rates modulated during mental arithmetic calculations and quantity comparisons. These neural activities reflected numerical value, arithmetic and comparison operators (i.e. plus or minus, greater than or less than), and spatial location of answers.

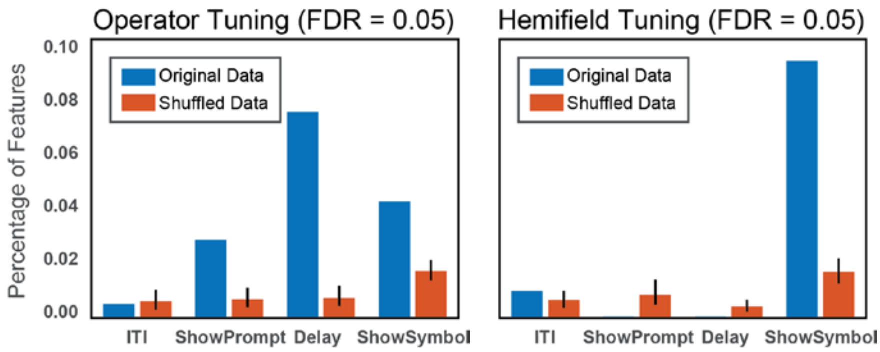

Figure 1. *Percentage of neurons tuned to arithmetic operator (i.e. plus vs. minus) and answer hemifield (i.e. left vs. right) in an arithmetic calculation task. Tuning percentages were compared to shuffled data at a false discovery rate of 0.05.*

In an arithmetic calculation task, about 11% of the neuronal population (25/218) exhibited tuning with respect to the arithmetic operator (i.e. plus or minus), and about 10% of the population (21/218) modulated with respect to the answer hemifield (i.e. left or right) (Fig. 1). Similar trends were observed in a quantity comparison task, where 45% of neurons (45/97) could distinguish the answer hemifield and 12% of neurons (12/97) represented the comparison operator (i.e. less than or greater than) when comparing the size of two circles.

Discussion: Although arithmetic and comparison operations are distinct from movement, the neural circuitry required to perform movement-related sensorimotor transformations is likely well suited to involvement in the processing required to compare and calculate quantities. This aspect of the parietal cortex could provide insights into how to best use PPC for neural interfaces, both to avoid interference as well as to optimize control.

Significance: These data provide the first evidence from intracortical electrophysiological recordings made in human for the involvement of PPC in quantity comparisons and calculations. The involvement of the parietal cortex in numerical processing confirms an important function of this versatile brain area, and points toward potential applications in neural prosthetics.

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Demonstration of a Chronic Brain-Computer Interface using a Deep Brain Stimulator

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Introduction: Prior brain-computer interface (BCI) research in human subjects has been limited in its ability to test systems over large time scales. Implanted BCI systems often use externalized electrocorticography (ECoG) electrodes as a signal source and are not safe for long term use (greater than a few weeks) in humans. Non-invasive systems using electroencephalography (EEG) electrodes on the scalp are not practical outside a laboratory setting because of required recalibration and inconvenient wearables such as head caps. Our approach to chronic BCI uses an FDA-IDE approved BCI platform comprised of a strip of cortical electrodes and a deep brain stimulator (DBS) currently approved to treat movement disorders. This DBS system allows sensing of brain activity through the same channels used for stimulation, providing a signal source usable over periods of months to years. We supplement this device with external hardware and software [1] to provide a chronic implanted BCI signal source, thus bypassing the extensive animal and human trials needed to develop new devices for chronic experiments.

Material, Methods and Results: One patient was implanted with a Medtronic Activa PC+S DBS for treatment of Essential Tremor (ET) in his right hand. The DBS electrode was implanted in the left ventral intermediate nucleus of the thalamus. Additionally, a Medtronic Resume II (Model 3587) 4 electrode strip was implanted over the left hand motor and somatosensory cortex (M1 and S1). One week and one month after surgery, recordings were taken from one electrode on M1 referenced to one electrode on S1 while the patient (1) moved and (2) imagined moving their right hand and right arm. The imagined movement recordings were used to generate thresholds for a BCI decoder using beta band power (16-32 Hz), which was mapped to the velocity of a cursor in a visual BCI task (a method used in many cases of sensorimotor activity based BCI as described in [2]). A screenshot of the BCI task is shown in Figure 1, and a trajectory generated by the patient to hit successive targets during an experimental trial is shown in Figure 2.

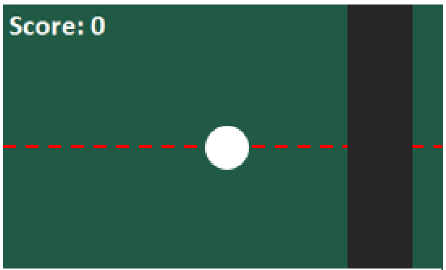

Figure 2. *Screenshot of BCI task (axis of motion denoted with dashed red line). Patient is asked to attempt to move the cursor into the dynamic rectangular targets.*

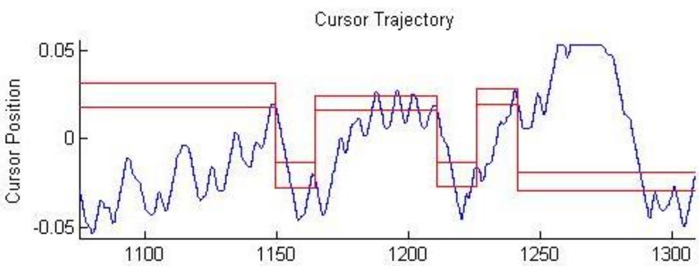

Figure 1. *Cursor trajectory (blue) generated by subject to hit task targets (red). Cursor position units relative to in-game dimensions.*

Discussion: Our preliminary results demonstrate that DBS devices are a promising platform for chronic ECoG BCI experiments. We are conducting ongoing experiments with our current subject and are approved to enroll up to five subjects. This BCI platform will allow for new long-term investigations into many areas, including how well BCI training is retained, how the ability to use a BCI may change during disease progression, and how non-naive BCI users adapt to novel decoders.

Significance: Our platform for chronic BCI enables experiments of unprecedented length to investigate how human subjects learn to use ECoG based BCI systems.

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Detecting P300 ERPs with Convolutional Networks

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Introduction: It is well known that there is considerable variability in P300 Event-Related Potential (ERP) detection accuracy across individuals and even day-to-day for one individual. The location in time and the shape of the P300 can even vary from trial to trial. Convolutional Neural Networks (CNNs) have been shown to learn small patches of pixel intensities that occur at varying locations in order to identify objects in images. Similarly, CNNs can learn small sequences of EEG that occur at varying times to support the detection of P300s [1]. Here we present initial results of CNN classification of EEG recorded during brief visual presentations of single letters as the subject is counting the occurrences of target letters in order to elicit P300s. The CNN is found to perform better than linear discriminant analysis and fully-connected neural networks.

Material, Methods and Results: EEG data were collected at 1024Hz using the Biosemi ActiveTwo system. Sixteen participants volunteered including nine participants with no impairments in a laboratory environment and seven participants with severe motor impairments in the participants' homes. A total of 120 target trials and 360 non-target trials were collected from each participant. Eight channels were selected and the EEG signals were preprocessed using a linked-earlobe reference and a zero-phase bandpass filter from 0.5-20Hz followed by downsampling to 64Hz. Classifier hyper-parameters were tuned using 10 repetitions of 80% random subsampling validation over the first 2/3 of the data while the final 1/3 was reserved for testing generalization performance. Three classification methods were compared: 1) Regularized Linear Discriminant Analysis (LDA). 2) A Neural Network (NN) with 30 hidden units and softmax visible layer. 3) A CNN with two convolutional layers each consisting of 10 hidden units with a width of 10 along the time axis and 2:1 decimation. The convolutional layers are followed by a fully connected layer with 10 hidden units and a softmax readout layer. The NN and CNN were regularized using early stopping. The test single-trial balanced classification accuracy (balanced accuracy = average of target percent correct and non-target percent correct) averaged across all participants was 71.52% for LDA, 71.77% for NN and 75.22% for CNN.

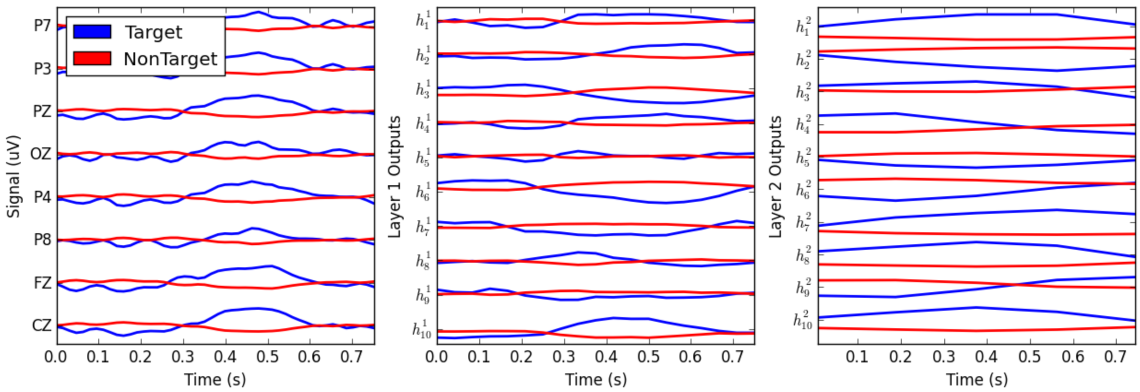

Figure 1. Left) *The mean target vs non-target signal values for each channel.* ***Center)*** *The mean response for each hidden unit in the first convolutional layer.* ***Right)*** *The mean response for each hidden unit in the second convolutional layer.*

Discussion: Fig. 1 shows the mean target and non-target signals and the mean response of each hidden unit in each convolutional layer for a single participant. In the first layer, it appears that each hidden unit isolates various components of the ERP, highlighting some early and mid-course components. As the signal progresses to the second layer, considerable separation is seen between target and non-target, especially near the center of the segments where the P300 waveform is typically observed.

Significance: Initial results suggest that CNNs perform slightly better than standard approaches. More sophisticated regularization methods, such as L2 or L1-norm penalties or dropout, as well as further exploration of network architecture may lead to additional performance improvements.

Acknowledgements: This work was supported in part by the National Science Foundation through grant numbers 0208958 and 1065513.

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Development of an SSVEP Brain Computer Interface Robust to Data Nonstationarity

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Introduction: This paper seeks to demonstrate methods to design SSVEP Brain Computer Interfaces (BCI) that are robust to nonstationarities in EEG data. EEG signals are generated by nonstationary random processes for multiple reasons including but not limited to outside noise and user fatigue. Traditional data collection using stationary distribution assumptions needs to be done frequently to compensate. However, a high volume of data is needed to ensure classification accuracy, and these goals often conflict when factors such as user fatigue introduce nonstationarity to the data distributions. One solution to this problem is to intelligently incorporate incrementally available data alongside past data to adjust for changes in the EEG's statistical information. In this paper, the use of the Learn++.NSE [1] algorithm is proposed as the foundation of a BCI system that is robust to nonstationarities in EEG data.

Material, Methods and Results: Single channel EEG data (OZ on the international 10-20 system) was collected from ten end users who completed a binary communication task using checkerboards flickering at six and twenty Hz (University of Pittsburgh IRB No. PRO15060140). The data was filtered using a 2-45 Hz FIR bandpass filter. Four dimensional feature vectors were constructed by measuring the power spectral density at the first two stimuli frequency harmonics for each checkerboard, and four usage sessions occurred to generate one hundred feature vectors each. The features were chosen due to the fact SSVEP stimuli frequency harmonics are often present in the power spectral density estimation. The first through third sessions were separated by at least three days while the third and fourth sessions happened consecutively. Several classification schemes were selected to test performance with incrementally available data. Among these were an ensemble learning algorithm where LDA was the base learner, an LDA classifier that adds new data with no consideration between previous and incoming data, and an LDA classifier considering only the most recent data. The Learn++.NSE algorithm was chosen for the ensemble due to its ability to incorporate new incremental data from possibly nonstationary sources.

The first two hundred vectors were defined as a base training set and were made available to all classifiers besides the recent LDA classifier. The one hundred vectors from the third session were divided into increments of ten. The last hundred vectors from the fourth session were used for testing. Each classifier was tested using each combination of $k = 1\text{-}9$ increments in addition to the base set as training data. The area under the curve (AUC) of the receiver operating characteristic curve was calculated on the test data set and averaged to obtain a performance estimate for the amount of data.

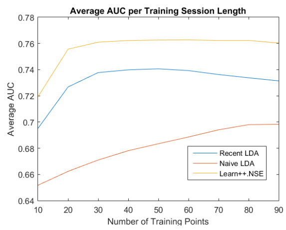

Figure 1- Comparison of the methods' AUC as a function of available training data. Results were averaged over ten participants.

Discussion: Figure 1 shows the AUC as a function of data availability averaged over ten participants. In general the Learn++.NSE algorithm exhibited faster learning capability over the naïve LDA classifier. The figure demonstrates this capability as the accuracy increase per calibration segment was higher in the Learn++.NSE case compared to the naïve LDA classifier. The Learn++.NSE ensemble also had a positive AUC offset over the recent LDA classifier. These results indicate that the Learn++.NSE algorithm may offer responsiveness to nonstationarity while being able to utilize a previous knowledge base.

Significance: The findings from this offline study outline the foundation from which a robust BCI can be built. Learn++.NSE's ability to form classifier weights based on nonstationarity information contained in each member classifier results in the system's capability to respond to those nonstationarities. As Figure 1 shows, the AUC based on past and incoming information increases more quickly than blind consideration of all data received. Training data from past sessions also immediately increases performance over using only the most recent data. These combined results indicate that less calibration is needed to achieve a given performance level using Learn++.NSE over static classifiers. Assuming a nonstationarity due to user fatigue is induced at a fixed time, the system can be operated longer before that time is reached due to the lower calibration requirements. Lastly, the work shown here will also form the basis of an online learner that utilizes fuzzy labels to adjust to changes in EEG data.

Acknowledgements: Funding and support provided by the University Of Pittsburgh Swanson School Of Engineering, the Office of the Provost, and the University of Pittsburgh Central Research Development Fund.

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Electrophysiological recording stability in human intracortical brain-computer interface users

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Introduction: The reliability of clinical intracortical brain-computer interfaces (BCIs) will depend on the stability of the neural recordings. Neural decoders will become less effective if a significant portion of the recorded population changes. In order for the BCI user to have satisfactory performance, the decoders will need to either be adjusted or completely retrained to compensate for changes in neural recordings. Here we look at recordings within and between days to determine the rate at which the units that are recorded are lost or changed, providing guidelines for how often decoders will need to be adjusted or retrained.

Material, Methods and Results: Two subjects with tetraplegia were implanted with Utah arrays and completed 2-3 BCI test sessions per week for 31 (Subject 1) and 6 (Subject 2) months. Recordings made during decoder training were used to identify units that were identically recorded in different sessions (stable units) using an algorithm that compares unit waveform shapes, firing rates, auto- and cross-correlation [1]. Additionally, within day comparisons for each subject were done based on 5 (Subject 1) and 4 (Subject 2) 7-hour recording sessions during which 8 evenly spaced recordings were made to study stability on the time scale of hours. On the time-scale of hours to days it can be assumed that an equal number of new units replace any lost units, resulting in a constant number of recorded units even as stable units disappear.

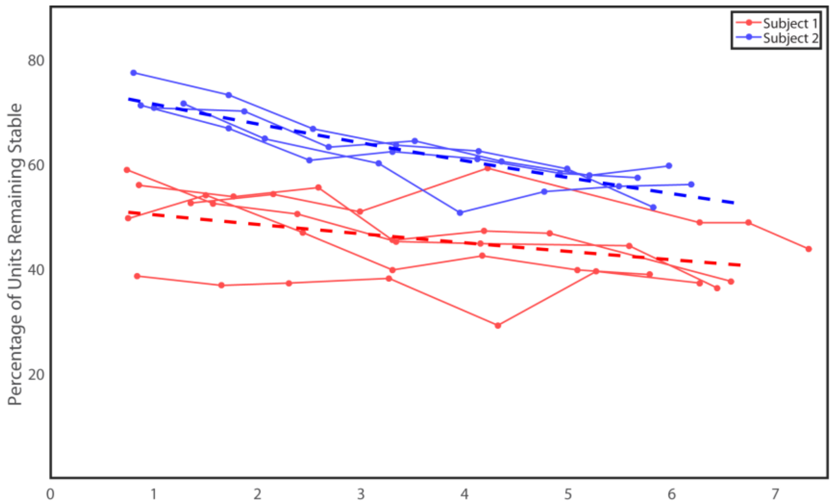

Figure 1. *The percentage of total units that remain stable across 7 hours. All 9 sessions are shown in solid lines. The dashed lines show the exponential fit for each subject. The decay rates were calculated after the large initial unit loss of primarily noisy units.*

Subject 1's recordings had an average of 29 out of 191 units remain stable for one week (33 out of 315 for Subject 2). During the 7-hour recording sessions 3.7% of Subject 1's units were lost from the recorded population every hour (5.3% for Subject 2, see Figure 1).

Discussion: These results provide a timeline for expected decoder performance decline. If a decoder only needs a small number of neurons, like the 15-unit 2D decoder from Ganguly & Carmena [2], then it could be expected to last at least a week if the BCI user has two-arrays with a similar recording quality to our subjects' and stable units can be identified in the recorded population. Identification could occur before decoder training allowing only stable units to be used. Alternatively, one could identify and exclude lost units as they drop out of the recorded population. The required number of stable units will depend on the quality of information the population provides and the necessary amount of information for the BCI tasks to be performed. These stability rates provide insight into the rate that decoders need to be updated to maintain performance.

Significance: This study provides quantification of the stability of both long and short-term intracortical recordings in 2 subjects. This data provides guidance for how often recalibration will need to be performed, which may be particularly useful as we work towards self-updating BCIs.

Acknowledgements: We would like to thank the subjects for their dedication to the study. This project was funded by DARPA contract number N66001-10-C-4056.

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Frontal-Temporal Connectivity Dysfunction in a Mouse Model of Schizophrenia

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Introduction: Development of an appropriate neuro-psychopharmacology model of schizophrenia remains a challenge. Hallucination in schizophrenia patients is representative of perceptual and sensory processing malfunction and the auditory steady state response (ASSR) is a common approach for evaluating the auditory and sensory deficits in the brains of these patients. In this study we investigate the frontal-temporal connectivity pattern in mice models with lack of the PLC-β1 enzyme as schizophrenia-like endophenotypes through their brain functional analysis using quantifying dynamic neural interactions of cortico-subcortical connections. The results show altered brain connectivity to the left auditory cortex in these mutant types. The multidisciplinary goal of this study can aid to differential diagnosis of schizophrenia, validating of novel medications via histology on this animal model, and eventually facilitating the development of a closed-loop BCI system as a neurofeedback therapy for the disease.

Material, Methods and Results: Chronic surgery was performed on 6 histologically confirmed PLC-β1 heterozygous mice and 7 controls for electrode implantation on frontal and auditory cortex (2 frontal EEG and 2 auditory LFP recording). The animals were passively stimulated using frequency-modulated (FM) auditory steady state stimulation (ASSS) with four different frequencies of 20, 30, 40 and 50 Hz while EEG was recorded. An adaptive directed transfer function (ADTF) was built to quantify the neural dynamic interactions between each pair of electrodes. Significant ADTF values were determined based on 200 surrogate data constructed from random phase shuffling. Using a significance level of 0.05, significant and non-significant ADTF values were set to 1 and 0, respectively, to show the percentage of animals with significant connectivity values for each connection, frequency, and time point. Figure 1 shows the percentage of animals with significant connectivity between each pair of connections at stimulus frequency of 40 Hz. The results show an obvious decrease of connectivity from both hemispheric frontal channels to the left auditory cortex for the mutants.

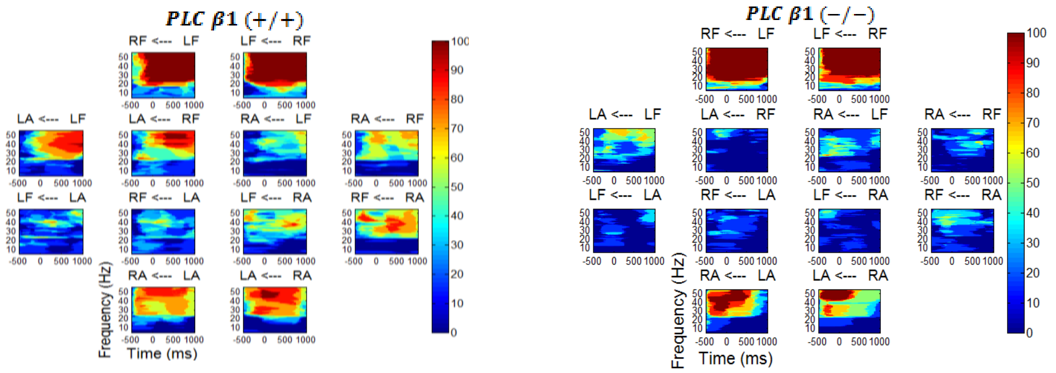

Figure 1. *The percentage of significant ADTF values for the control (left panel) and PLC- β1 (-/-) (right panel) groups at the 40 Hz stimulus frequency*. The *direction of information flow is indicated above each subplot*..

Discussion: The connectivity analysis showed considerable deficits in the long range connections to the left auditory cortex in the mutants compared to the control group. This can be representative of frontal-temporal connectivity dysfunction that affects the long range connections and supports the the existing schizophrenic dysconnection hypothesis in the mice models with lack of the PLC-β1 gene [1]. Moreover, these results corroborate prior studies that showed disruption of left hemisphere neurophysiology and neuroanatomy in humans with schizophrenia [2-3].

Significance: Characterization of the connectivity deficits in animal models of schizophrenia represents the first step toward the design of therapeutic BCI systems for humans with schizophrenia. These systems will provide neurofeedback of connectivity measures in EEG to stimulate normal or alternate connectivity patterns with the objective of improving undesirable symptoms or associated behaviors of schizophrenia.

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Intelligence and Brain Dynamics in Children with Cerebral Palsy

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Introduction: Functional connectivity studies in children with cerebral palsy (CP) show tend to recruit more cortical regions, have longer global network path lengths, smaller P300 amplitude, decreased alpha power and decreased functional connectivity in the frontal lobe alpha band than typically developing (TD) children. These differences also are shown in children with lower cognitive function. However, only 50% of children with CP exhibit intellectual disability. This suggests different functional connectivity patterns may be associated with the neural substrate of cognitive ability of people with different neuropathology[1, 2].

Material, Methods and Results: Using our P300 BCI-adapted Pearson Peabody Picture Vocabulary Test (PPVT-IV) on 5 TD children (16 ± 3.6) and 5 age-matched children with CP (16 ± 4.6) [3], we collected electroencephalography (EEG) data and PPVT-IV results. PPVT-IV results were used as a proxy for intelligence and compared to the subject's brain dynamics: P300 amplitude, path lengths, alpha power and functional connectivity.

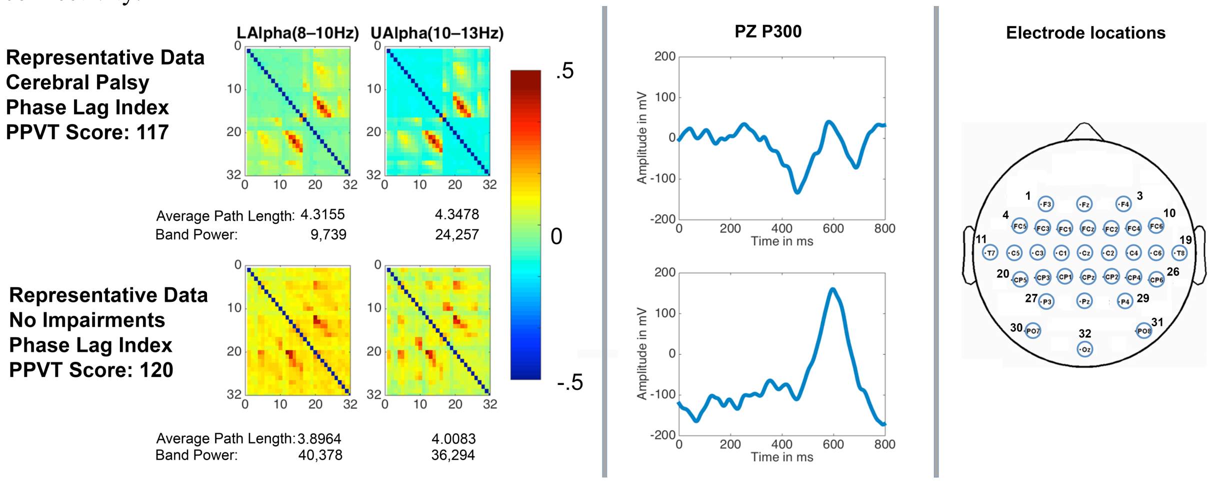

Figure 1. *Representative data of a subject with CP and typically developing counter part. Left: Heat map of funcitonal connectivity based on electrode connectivity. Center: Grand average P300 of Pz electrode. Right: Electrode montage used.*

All CP subjects had lower connectivity in the frontal lobe alpha bands compared to age matched TD peers. We found no significant difference ($p = 0.26$) in path length (4.64 ± 0.18 for CP compared to 4.58 ± 0.40 for TD) or in PPVT test scores. The P300 amplitude at Pz was smaller for the CP group with a grand average of 109 ± 58 µv compared to 132± 65 µv. Using a spearman correlation PPVT-IV scores were not significantly correlated. However, both TD ($r = -0.47$) and CP ($r = -0.41$) lower alpha trended negatively.

Discussion: Our results suggest that previous finding relating functional connectivity to intelligence does not directly apply to children with cerebral palsy. Subjects with CP had lower connectivity in the frontal lobe alpha bands, alpha band power and P300 amplitude than typically developing children. However, they scored similarly to typically developing children on the PPVT, demonstrating that typical brain dynamics associated with intelligence do not apply. We believe this is due to the neural compensation resulting from the subject's pathology.

Conclusion and Significance: Our work demonstrates that further research is needed to understand the relationship in brain dynamics and intelligence in people with brain insults.

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Motivation matters: Psychological models in brain-computer interfacing

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Introduction and Methods: To date, no theoretical models on the effect of motivation in brain-computer interfacing (BCI) do exist. Therefore, it is necessary to apply existing motivation theories to a BCI context. Within this theory transfer specifics need to be taken into account not only concerning the BCI user population (severely motor impaired individuals or healthy volunteers) and the BCI measurement situation (BCI study in the laboratory or a patient's home) but also the input signal which could be autonomously elicited like the P300 or controlled as a result of self-regulated learning (sensorimotor rhythm=SMR BCI). Thus, motivation models of self-regulated learning, like the adapted *Cognitive Model of Motivation* [1] seem applicable to the SMR BCI context, while Johnson's model of the P300 amplitude [2] might be useful in P300 BCI studies. Both could be influenced by the *Self-Determination Theory* [3] specifying the effect of motivation caused by reward (extrinsic motivation) and very likely playing a role in healthy volunteers. For motor impaired BCI users, on the other hand, motivation caused by performing a task per se (intrinsic motivation) and the need for competence and autonomy seem most applicable as presented in the *Cognitive Evaluation Theory* [4]. As a common basis for all BCI study participants there must be some valence of the outcome of BCI control, may it be intrinsic or extrinsic that together with expectancy of being able to control the system and the ability to do so might determine BCI performance. Therefore, Vroom's *Performance Model* [5] was chosen here as a basis of motivation influencing BCI performance while it was well acknowledged that other theories have an impact as well.

Results: As a first attempt to present a theoretical approach of the influence of motivation on BCI performance we present the motivation models including valence and expectancy for a P300 (MOTIVE-P300, see figure 1) and a SMR context (MOTIVE-SMR, see figure 2).

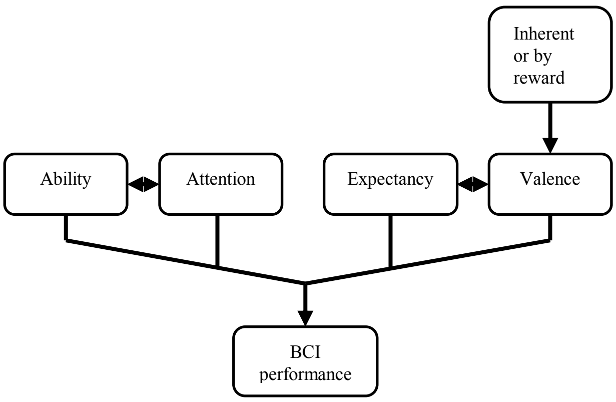

Figure 1. *MOTIVE –P300 model.*

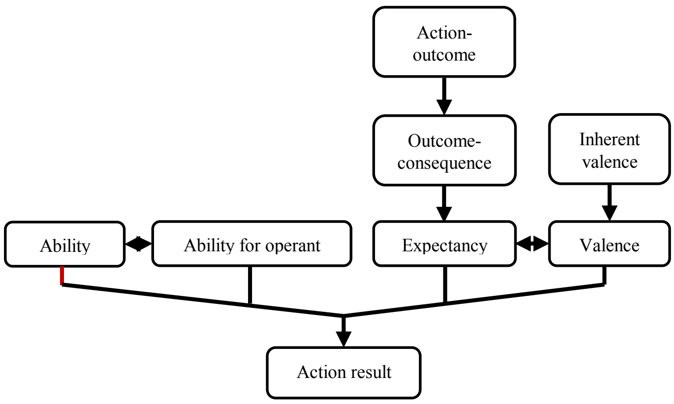

Figure 2. *MOTIVE –SMR model.*

Discussion: The here presented motivation models are based on existing BCI research results on the effect of motivation and on motivation theory. They need to be experimentally evaluated and their possible usefulness can only be judged thereafter.

Significance: If these models allow for variance explanation in BCI performance by identifying the role of motivation, they might bridge a gap between Psychology and BCI research and present a basis for further hypothesis testing.

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Music rhythm reconstruction from ECoG

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Introduction: Imagine being able to record the music you're humming in your head and play it back to others. Prior neuroscientific studies have highlighted auditory processing in the brain in relation to speech [1,2,3] and demonstrated that envelope and spectral properties of perceived speech could be reliably reconstructed. Other studies showed successful reconstruction of acoustic properties from speech production [4] and automatic speech recognition of entire phrases [5]. Perception of melodies and rhythm is generally ubiquitous in humans across age and culture and should also lead to robust representations in neural data. However, only a few studies have investigated neural responses to complex musical stimuli in electrocorticography (ECoG) [6] and have not investigated rhythms and melodies indepentently. Numerous studies exist investigating different aspects of music perception using functional Magnetic Resonance Imaging (fMRI) or the scalp electroencephalogram (EEG), but both of these technologies have limitations in either spatial or spectral resolution, which are necessary for the investigation of the fast processes underlying music perception and production. ECoG, on the other hand, measures high spatial and temporal resolution electrical potentials unfiltered by the skull and scalp, which is more ideal for the investigation of music. Here we investigate cortical responses to perceived drum rhythms and demonstrate reconstruction of the perceived rhythm sound intensities. The investigated drum rhythms lack the rich melodic and harmonic information present in previous studies. Reconstruction of this very simple musical stimuli therefore illustrate basic rhythm perception.

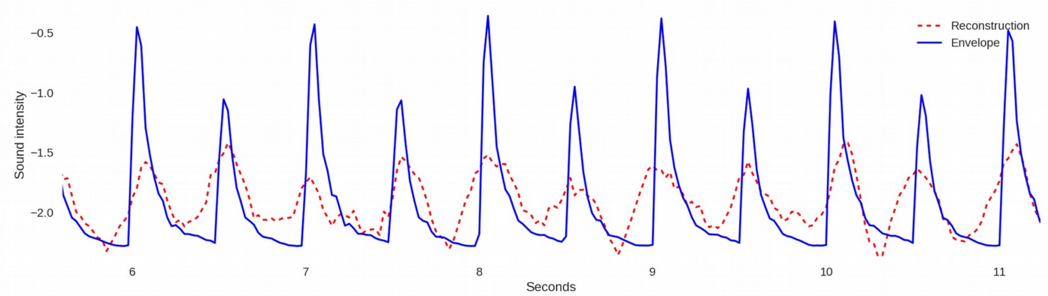

Figure 1. *Drum envelope (blue) and reconstructed (red-dotted) envelope based on high-gamma activity in ECoG electrodes.*

Material and Methods: We presented a simple drum rhythm to seven participants undergoing surgery for intractable epilepsy. Subjects had between 34 and 96 subdural ECoG electrodes implanted (3 left, 4 right hemisphere, frontal; parietal and/or temporal areas covered), based on the clinical need. The sound envelope was extracted using the Hilbert transform in 50 ms windows. We extracted broadband-gamma (70-170 Hz) power in 50 ms windows and time-aligned the ECoG activity to the presented sound stimuli.

Results: We evaluated the possibility to reconstruct perceived sound intensity from the gamma power features across spatial channels using Lasso regression, and evaluated the correlation coefficients (Spearman's r) between actual sound intensity and reconstructed envelope. Statistically significant ($p<0.01$) correlations could be achieved for all subjects with correlations coefficients up to *0.45* (mean *0.15*). Figure 1 illustrates the drum envelope (blue) and the reconstruction (red) from ECoG signals.

Discussion: We show that neural data measured directly from the cortex using ECoG can be used to accurately reconstruct the intensity of a repetitive drum stimulus.

Significance: This is a first step towards synthesizing musical rhythms from mental imagery using intracranial signals by reconstruction very basic musical phenomenon.

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Neural Signature of Selective Sensation based Tactile BCI in the Context of ECoG Investigation

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Introduction*:* Tactile BCI, independent of the visual and gaze participation, has recently received much interest. The first prototype of tactile BCI has been proposed by Mueller-Putz in 2006 and was based on steady-state somatosensory evoked potentials (SSSEP) [1]. Experiments on five subjects have shown that the classification accuracy for this BCI modality ranged from 64% to 84%, with average accuracy of 70.4%. Later, similar to the visual P300 BCI, a tactile P300 system, based on the oddball paradigm, has been proposed by Brouwer in 2010 then [2]. This system achieved a mean accuracy of approximately 72% in 11 subjects for two targets selection. Recently, we have proposed a tactile BCI based on oscillatory dynamics from the somatosensory area of the brain and we termed this approach as selective sensation BCI [3,4]. Up to now, 43 subjects have been recruited so far, with a mean accuracy of 79.2% and BCI-illiteracy rate of 16.3% (7 out of 43 below 70%). In this study, the neural signature of SSSEP-based and ERD/ERS-based (selective sensation) tactile BCI will be examined in the context of ECoG signal modality.

Material, Methods and Results*:*

One subject (female, 18 years old) suffered from intractable epilepsy, and underwent temporary placement of a subdural electrode. This Study was approved by the Ethics Committee of Huashan Hospital. Participant signed the informed consent forms by themselves or legal guardians before participating in the experiment.

Mechanical stimulation was applied to the index finger. The stimulation device produced 27-Hz sine wave, which was modulated with a 175-Hz sine carrier wave. Linear resonant actuators (10 mm, C10-100, Microdrives Ltd.) were used. ECoG signals were recorded using a SynAmps2 system (Neuroscan). The reference electrode was located on the right mastoid, and the ground electrode on the left mastoid. The signals were recorded from DC to 500 Hz, digitally sampled at 2000 Hz.

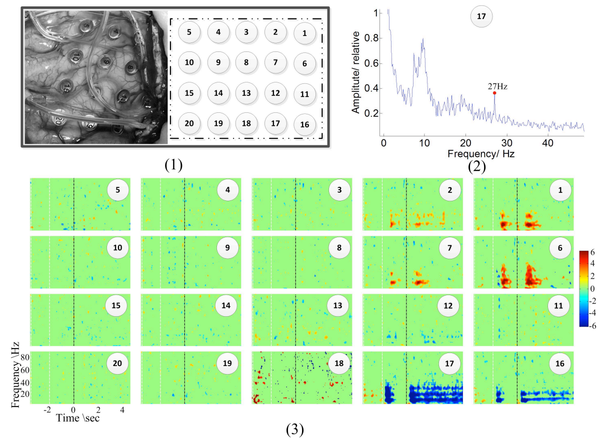

Figure 1. Neural Correlate of tactile sensation. (1) Electrode array on the cortex and number order. (2) Power spectrogram at channel No. 17 with respect to 27 Hz tactile stimulation. (3) Event related spectrum perturbation across all channels, non-significant parts were wiped out under bootstrap significance level of P = 0.01. Time zero corresponds to the start of sustained tactile stimulation.

The ECoG electrode array was placed on the left frontal lobe, see in the Fig. 1(1). Subject was required to close her eyes and rested. When the index finger was tactile stimulated, the subject was required to focus attention on the sensation. 40 trials were recorded, which lasted for 6~7min. Within each trial, after 2s a vibration burst, lasting 200 ms, was applied to alert the subject to be ready for the subsequent task. Then 2 second later, sustained stimulation was applied, which lasted for 5s. After 2~4 second random time interval, next trial started. Power spectrum in Channel 17 (localized on sensory cortex) with respect to 27Hz sustained stimulation was shown in Fig. 1(2). Event related (De)synchronization (ERD/ERS) across all channels was shown in Fig. 1(3).

Discussion: The stimulation evoked SSSEP response has a frequency specific feature, complementarily the induced ERD/ERS oscillatory dynamics, which also reflects somatosensory processing, has a non-stimulation frequency specific feature. In the context of ECoG investigation, we have found the coexistence of both frequency responses and also much stronger ERD responses, which lays the mechanism for tactile BCI construction. Interestingly, we have found that there is an ERS response on the motor cortical area (Channel 6), indicating motor cortex suppressing or in idle state during sensation tasks for better stimulation processing.

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Temporal dynamics of mouth motor cortex activity during speech

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Introduction: In order to restore communication with severely paralyzed patients by using a BCI, attempts have been made to classify speech units [1,2]. Although classification of these units from the mouth motor cortex seems possible, accuracy levels are usually not sufficient for an assistive speech BCI. Understanding the source of the variability in mouth motor related brain signals might improve feature selection and classification. Here, we investigate the relationship between word duration and the temporal dynamics of the brain signals in the mouth motor cortex.

Material & Methods: Two epilepsy patients who were implanted with electrocorticography (ECoG) electrodes for clinical reasons at the UMC Utrecht hospital participated in this study. Both subjects had grid coverage over the right central hemisphere, including the mouth motor area (for subject 1 only the upper part). Subjects were asked to read out loud words presented on a screen that was positioned at a distance of about 1 m. Recorded signals were filtered for line noise and common average re-referenced, after which power in the high frequency band (HFB) range (65-135Hz) was extracted. Electrodes showing a significant response to the task were identified by computing the correlation with the task. The HFB power signals from these electrodes were normalized over time and averaged to create one motor mouth response signal per subject. Averaged signals were smoothed and epoched in 3-sec trials around voice onset. Trials were subsequently grouped into three groups based on speech duration (short, middle & long words). A one-way ANOVA was performed per time point to identify time periods with significant differences between groups. Additionally, for every trial, the HFB response duration was calculated as the width of the peak above a threshold (baseline mean + 2*sd). Differences in the total HFB response duration between short, middle and long words were tested for significance using t-tests.

Results: Electrodes showing a significant HFB power change to the task were located on the middle or inferior pre- and postcentral gyrus. Signals from these electrodes showed a clear speech-related HFB peak, followed by a period with significant differences in the HFB response between word durations (Figure 1). Total HFB response duration was significantly different between word durations for subject 2 (Figure 2).

Discussion: The results suggest that the duration of words influences the temporal dynamics of the brain signal in the mouth motor cortex. For all subjects, longer words tend to have a period after the HFB peak with higher activity than short words. Furthermore, subject 2 showed a positive linear trend in peak width. For subject 1, this effect was not statistically significant, which may be explained by the low number of trials and a suboptimal grid position. It may be possible that the temporal neural differences for short and long words are most obvious in the more inferior parts of the motor cortex. Whether or not the HFB response duration is related to the number of movements one makes during the articulation of a word should be further investigated.

Significance: The current results suggest that word length may be a strong but limiting feature for BCI classification. Research on decodability of patterns associated with specific words would benefit from using equal-length words to avoid the word length confound.

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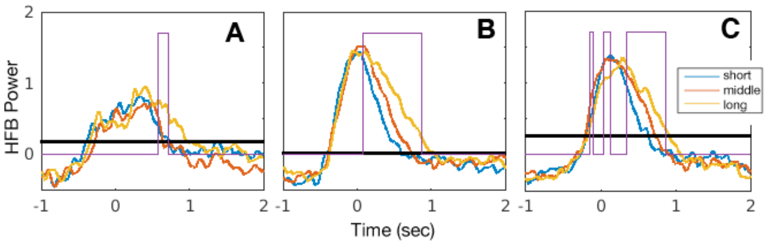

Figure 1. *Mean HBF response traces for short (blue), middle long (red) and long (yellow) words, for (a) subject 1, (b) subject 2 run 1 and (c) subject 2 run 2. On the x-axis, time is depicted with 0 being voice onset. On the y-axis the HFB power is shown. The black horizontal line is the threshold above which activity was assumed to be task related. The purple block function shows the periods with a significant difference in response between the three groups, indicated by a one-way ANOVA (FDR corrected).*

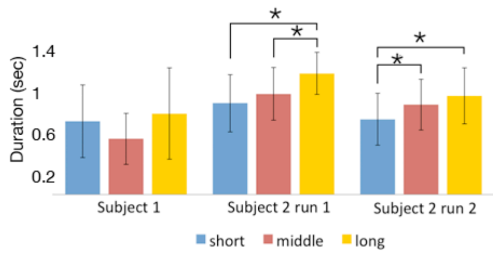

Figure 2. *Mean and standard deviation of the HBF peak duration (in sec) per dataset, for short, middle & long words. Significant differences are indicated with an astrix (α=0.05/3, bonferroni corrected).*

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Visual and auditory P300-BCI: influence of daytime on P300 amplitude in patients with ALS

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Introduction: The P300 event-related potential is often used as input signal for BCI. In many studies it has been shown that healthy subjects and also patients with neurodegenerative disease can control such a BCI with an accuracy above 90% correct responses [e.g., 1]. Also, BCI relying on auditory stimulation are increasingly investigated, but yield considerably lower information transfer rates [e.g., 2]. Further, patients often present with lower amplitudes. When considering BCI for use in daily life of patients, it is important to know whether the brain signal of interest is stable during the day. Thus, we investigated the visual and auditory P300 amplitude in ALS patients and healthy subjects throughout the day.

Material, Methods and Results: 14 ALS patients (ALS-FRS score: (M = 21.79, SD = 10.53; age: M =67.93, SD = 10.46) and 14 age and sex matched healthy subjects (Ethical Approval obtained). Participants were tested at their home at 10 am, 12 am, 2 pm and 4 pm. EEG was recorded at Fp1, Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, CP3, CP4, P3, Pz, P4 and Oz. Auditory stimuli were 160 standard (1000 Hz) and 40 deviant (2000 Hz) tones presented in pseudo-random order with the restriction that any two deviant tones were separated by at least one standard tone. Tone duration was 50 ms. Stimulus onset asynchrony (SOA) was 1200 ms with a random latency jitter of ± 0.15 s to avoid habituation to a certain SOA. Visual stimuli were short (50 ms) presentations of the letters “H” (40 times, deviant) and “S” (160 times, standard) in white font (120 pt) on a black background in the centre of a computer monitor. Stimulus onset asynchrony (SOA) was 1.2 ± 0.15 s. Statistical analysis: rANOVA was conducted with time (4), modality (2) and electrode (3, Fz, Cz, Pz) as within and group (2) as between subject factors. P300 amplitude as dependent variable. Pearson correlation between ALS-FRS and P300 amplitude was calculated to assess the effect of disease severity on the P300 amplitude. Preliminary data analysis was published in [3].

We found significant main effects of modality ($F(1,24) = 7.23$, $p = .013$) and region ($F(2,48) = 17.62$, $p < .001$) (Fig. 1). All other tests were not significant, i.e. no effect of time of the day and group! Disease severity did not affect the P300 amplitude of either modality.

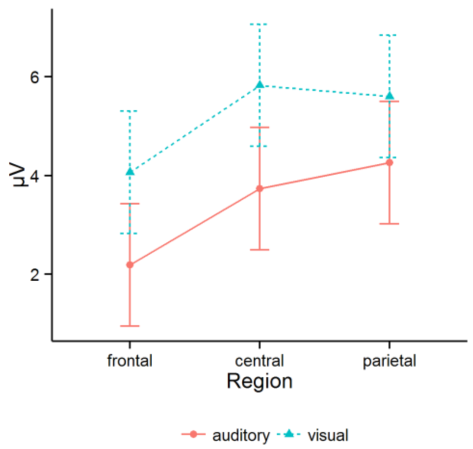

Figure 1. *Main effects of amplitude and region. Visual P300 amplitudes were significantly larger than auditory ones, smaller at Fz and equally high at Cz and Pz. Error bars represent 95% confidence intervals.*

Discussion: The most striking result was the lack of differences in amplitude between healthy subjects and patients with ALS; this may have been due to the large variation of diseases severity. As seen before, P300 amplitudes were lower for the auditory than the visual modality. Time of the day did not affect the P300 amplitude. Whether this would transfer to stable P300-BCI performance, which requires more than paying attention to visual and auditory stimulai remains to be investigated.

Significance: These results are encouraging for P300-BCI use in patients with ALS. They imply that patients may use the BCI at any time of the day and that reductions of the P300 amplitude in comparison to healthy subjects may not occur until the later stages of the disease.

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Why BCI researchers should focus on attempted, not imagined movement

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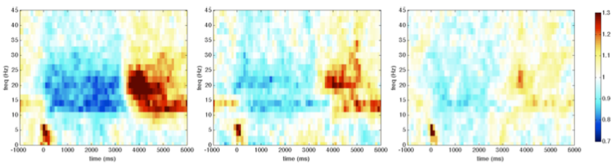
Introduction: For the past decades, developments on non-invasive motor-based Brain-Computer Interfaces (BCIs) have mainly relied on one major assumption: that motor imagery in healthy users is a good model of the strategy a motor-impaired individual would be using for BCI control. Consequently, motor imagery (MI) has been adopted as a meaningful task for both healthy and impaired users. However, the brain response is difficult to detect in some subjects and therefore high accuracy cannot always be achieved. We argue that for more reliable and efficient communication and control, patients should use movement attempt (MA) instead. Moreover, not imagined but movement execution (ME) can be shown to be a better model in healthy users of this end user strategy of attempted movement.

There is considerable evidence that the neural response of MI differs significantly from both ME and movement attempt (MA) in paralysed individuals. Indeed, the ERD produced during MI is generally weaker than for ME. This difference is not surprising, as MI differs from ME in a number of ways; (1) MI requires an active process of inhibiting movement execution, and (2) MI has no proprioceptive feedback about action execution. Whilst the lack of feedback is similar to the situation in paralysed individuals the inhibitory process is a potential difference. Thus it is unclear whether paralysed individuals should use MI or MA to control a movement-based BCI. Further one cannot simply assume that imagined movement in healthy individuals is an effective substitute for attempted movement in paralysed individuals.

Material, Methods and Results: To investigate this question we re-analysed two existing EEG datasets from our lab which compared ME, MA and MI within subjects. In the first study [1] ten tetraplegic patients performed attempted and imagined fingertapping with both hands– allowing us to investigate the effect of output inhibition in paralyzed individuals. In the second [2] dataset 4 healthy individuals performed ME, MI and MA, where a neuromuscular blocking agent was used to prevent prevent muscle activity in the MA condition. This experiment allowed us to again investigate the effect of output inhibition in MI and also the similarity of ME and MA in healthy individuals. A summary of the main results of these analyse is presented in Figure 1.



Dataset	ME	MA	MI
Tetraplegics [1]	-	76	67**
Healthy [2]	84	82	70**

Figure 1. *Left: Grand Average time-frequency responses for Executed (a), Attempted but blocked (b) and imagined (c) finger tapping in healthy participants. Right: Average percentage correct classification for the two studies, **indicates significantly (p<.05) reduced performance.*

Discussion: Our results clearly show that for both paralyzed and healthy individuals MI results in significantly lower BCI performance. Further, the results in healthy individuals indicate that ME generates more similar responses to MA, in terms of both classification rates and spectral components than MI.

Significance: Considering the combined evidence presented here, we conclude that (1) Instructions to BCI end users should focus on attempted, not imagined, movement strategies and (2) Executed movements form a more realistic model of BCI end user strategies. Therefore BCI testing and validation with healthy users should be based on motor execution rather than motor imagery.

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Distinct timescales of cortical reorganization in a long-term learning task using an intracortical brain-computer interface

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Introduction: Skill learning is associated with a functional reorganization of cortical neural activity. Traditionally it is difficult to study the link between changes in neural activity and the concurrent behavioral improvements during skill learning, primarily because in most tasks it is difficult to interpret the direct behavioral impact of particular changes in neural activity. Here we leveraged an intracortical brain-computer interface (BCI) learning paradigm to determine how long-term practice leads to skill acquisition in a BCI movement task. In a BCI, the experimenter provides the subject a definitive mapping between neural activity and the movement of an effector (in our case, a computer cursor). Each new BCI mapping thus provides the subject a new tool that must be mastered through continued practice. One unique advantage of this BCI learning paradigm is that the mappings of individual neurons to cursor movement can be manipulated to test the specificity of adaptive responses.

Materials & Methods: We trained two Rhesus macaques to perform a two-dimensional center-out cursor control task using an intracortical BCI. Each BCI mapped neural activity recorded from a 96-electrode recording “Utah” array placed in primary motor cortex to the velocity of the computer cursor using a population vector algorithm decoder [1]. Once subjects were proficient at the brain-control task with an intuitive mapping, we provided new mappings for them to learn where we rotated the directions in which a randomly selected half of the recorded neurons pushed the cursor. This specific type of perturbation to the BCI system allows us to dissociate whether adaptive changes in neural activity affect all neurons equally, or whether subjects can solve the credit assignment problem, and use global error signals to identify and selectively adapt the individual neurons responsible. We held this perturbed mapping fixed for several weeks by tracking neurons across sessions, to observe the longitudinal changes in activity that occur with practice.

Results & Discussion: Our prior work focused on short-timescale adaptive responses to this type of perturbation, lasting only a few hundred trials. There we identified both a global “re-aiming” response that impacted the activity of all neurons equally, and a local “re-tuning” response specific to the perturbed subset of neurons, indicating subjects were able to solve the credit-assignment problem [2, 3]. However, the global re-aiming response dominated the adaptive response, accounting for ~85% of the overall error reduction, while re-tuning accounted for only 15% of the error reduction. Here we found that the weak local re-tuning response gradually builds up with long-term training, eventually accounting for nearly 50% of the overall error reduction. Interestingly, the angular error, used here as a way to assess the subjects’ movement precision, reached asymptote after only one day of training on the new mapping. However, the local “re-tuning” response continued to build, slowly but consistently, for weeks after the angular error converged, indicating that it was not driven by rotational error. Instead, we found a slight but measurable decrease in the time of target acquisition that correlated with the build-up of the re-tuning response. The distinct timescales of the behavioral improvement and the neural reorganization during long-term practice on our unique BCI task suggests that skill learning is a two-stage process. In the first stage, rapid, coordinated changes in activity across all neurons act to quickly (within one day) reduce behavioral errors during task performance. In the second stage, long-timescale changes in the tuning of individual neurons act to gradually improve the efficiency of the movement over weeks of practice.

Significance: Learning is a fundamental principle of brain operation that impacts many aspects of neural function. The current study expands our understanding of the neural basis of learning at the system level, including its strategies, timescales, and the potential mechanisms involved. This work also has practical implications relating to how subjects learn to control an intracortical BCI, which may one day allow for shorter training times.

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Separable decoding of cue, intention, and movement information from the fronto-parietal grasping-network

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Introduction: Neurons in premotor and parietal cortex are known to represent a broad variety of different cognitive processes including visual, decision, intention, and movement signals. Recent experiments revealed that several cognitive features are mixed-coded within and between individual neurons, and can be studied by analyzing the neuronal population dynamics (Raposo et al., 2014). Furthermore, different cognitive features might be represented in different dimensions in the population code (Kaufman et al., 2014). Such a coding scheme allows a broad variety of information being present simultaneously in the same network as well as selective decoding of specific information with high reliability, provided the code is understood.

Material, Methods and Results: Here we investigated the processing of hand grasping in the fronto-parietal grasping network (areas F5 and AIP) in two macaque monkeys while performing two grip types (power or precision grip) either by visual instruction or by following a decision rule (Michaels et al., 2015). At the level of single trial population dynamics, we could disentangle visual information from intentional and movement information in this task. We estimated linear separation planes in the full neuronal state space of all neurons from each area in order to selectively extract the information (visual, intentional, and movement) of each category (Figure 1).

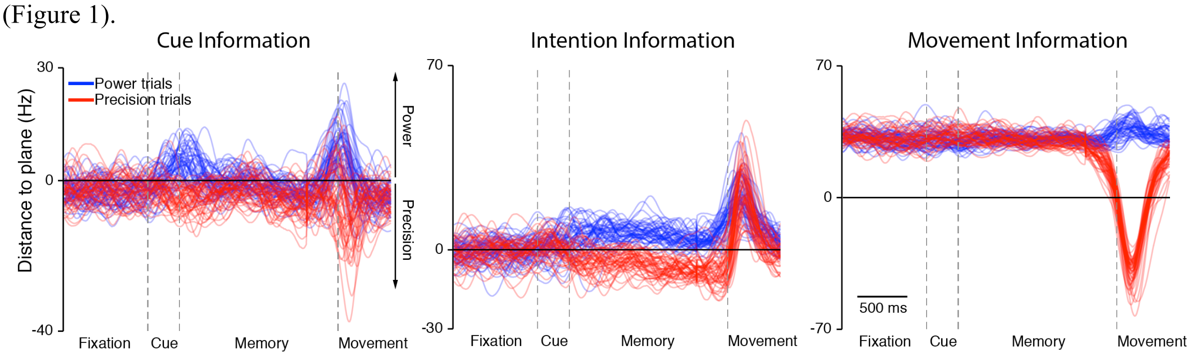

Figure 1. *Visual, intention and movement information of the same neuronal population of one example dataset for area F5. Units are distance (in Hz) to n-dimentional seperation plane, with n = number of units recorded in parallel. Only visual instructed trials are shown. Pannels for cue, intention, and movement information are based on the same neuronal population activity but show the distance to different seperation planes. Each line represents one trial color coded by the performed movement. Positive and negative values correspond to decoded information (visual, intentional, and movement). Note that the presence of offset shift are due to population rate shifts that contain no grip information.*

In both areas, the angles between the separation planes were nearly orthogonal to each other (F5, AIP: visual to intention: 86˚, 81˚; visual to movement: 93˚, 87˚; intention to movement: 77˚, 83˚), confirming the simultaneous presence of independent information in the same neuronal circuit. Both areas also showed a clear presence of all three categories.

Discussion: Instead of analyzing selectivity in the fronto-parietal grasping network separately for individual single units, we extracted information about cue, intention, and movement information from the population dynamics. This approach allowed us to access these different information categories separately, in particular the grasping movement intention, which could lead to better decoding methods for reliable robot hand control.

Significance: The possibility to independently and reliably extract cue-, intentional-, and movement information from single-trial population activity is crucial for future neural interfaces that can function robustly in natural environments, e.g., with sensory disturbances and in varying contexts. To know in advance which movements are possibly intended for execution also allows for more accurate and faster prosthetic control.

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GKT-Enhanced Applications

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Introduction: The Guilty Knowledge Test (GKT) is a method for detecting knowledge, or an associated reaction of the brain, that is relevant to a given task. GKTs have been extensively studied in psychology and are used in laboratory experiments, field studies [1] and court trials [2] to detect concealed information. GKTs are also known as Concealed Information Test (CIT) or the closely related Brain Fingerprinting [3, 1]. The achieved estimations (information present and information absent) vary according to the test subject and the method used for analysis from 80-95% [4, 5] to 100% [1, 6, 3].
We introduce the concept of GKT-enhanced Applications (GKTeA) where general applications and games are improved by combining them with GKTs [7]. In this way we are creating and adding an additional physiological input paradigm to the cognitive state [8] to improve HCI. GKTeA focus on passive BCIs [9, 10, 11] for healthy users. As an example, we present a GKT-enhanced treasure hunt game, where players try to find hidden locations or places by solving riddles and so collecting GKT-relevant clues. The GKT adds new element to the game, opens the door for new challenges and renders cheating nearly impossible.

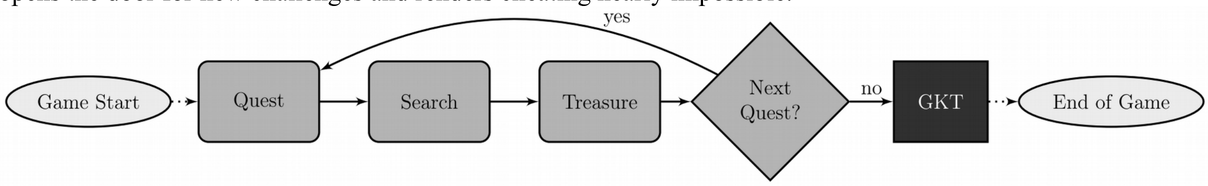

Figure 1. The schematic course of a possible implementation of a GKT-enhanced treasure hunt game executing the GKT after the hunt.

Material, Methods and Results: In combination with GKTs, a non-invasive portable and wireless BCI based on electroencephalography is most practical. To support the idea of a gaming scenario, we use a commercial gaming BCI, the Emotiv Epoc. The Emotiv BCI is not optimal for a variety of reasons, but our previous work [12] showed acceptable results and good usability. The underlying framework to perform the GKT is given by [6, 7, 13, 3]. The basic treasure hunt game performs as normal, but every treasure contains a GKT-relevant Object (GKTrO). While in the game or after the hunt is finished (see Fig. 1), the proof of every solved riddle can be prompted by a GKT asking for the GKTrO without disclosure of information to other competing players. This game can be realized as an online (multiplayer) game or real life (geocaching) experience.

Discussion and Significance: We introduce the novel term GKTeA and utilize the GKT as an additional factor to the cognitive state of the user. We transfer the concept of GKT as a useful benefit into the world of general applications and games for healthy users. Dependant on the game design cheating can be very hard, because of various different ways to select and present the GKTrOs and there meaning. Thus not only reaching the final goal is checked, but each step on the way. A more complex game design may increase the number of elements in the GKT, but the effort stays nearly constant. The example game and our experiments show the validity of the GKTeA assumption and functions at least as a proof of concept.

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Motor Imagery Based BCI Racing: Challenge a Friend with 4 Channel Dry Electrode EEG

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Introduction: Most current BCI applications are realized with EEG systems having a dense net of conductive gel electrodes connected to a non-portable unit. These EEG systems lack mobility and robustness, thus making brain-computer interface applications in daily-life scenarios inconvenient or unfeasible. Recent advancements in terms of miniaturization and wearability have made it possible for measurements to be performed outside the laboratory environment. Here, we investigate a combination of a motor imagery BCI with a relaxation/concentration paradigm to operate remote-controlled cars in a gaming application using IMEC's wearable EEG system with 4 active dry channels. Two players engage in a BCI-controlled racing game, choosing the directions of their cars with motor imagery, while controlling the car's speed by relaxing/concentrating. The application is available as a demonstrator.

Material, Methods and Results: In this work, we facilitate a minimalistic BCI approach that uses two low-power wireless EEG headsets developed at IMEC, which have 4 active dry EEG channels each [1]. EEG headset mounting process requires less than a minute, allowing for easy game setup. The headset comprises 6 reusable silver-silver chloride (Ag/AgCl) electrodes with 12 posts, each 2 mm deep. The 4 active channels are positioned at C_z, C_3, C_4 and P_z of the International 10-20 system, while the reference and patient ground electrodes are positioned at left and right mastoid, respectively. The headsets transfer the acquired data over Bluetooth to a workstation running an in-house developed EEG acquisition and visualization software. BCI commands are actuated through ZenWheels micro cars which are controlled via Bluetooth, implemented in the same software. The data is analyzed in real-time for facilitating

Motor imagery response detection from imagined left and right hand movements by means of pre-trained classifiers. The classification is performed in two steps. Firstly, common spatial filters are applied to extract spatial components that differ maximally for both motor imaginary classes [2]. Secondly, score values from linear discriminant analysis are used to operate the steering axle of the cars. If the score values exceed a predefined threshold, the steering is turned left/right for two seconds and the cars navigate in the direction of the detected motor imagery class.

Relaxation/concentration level detection from the background brain activity. The level is estimated based on the mean spectral power in the theta, alpha, and beta frequency bands over the central and parietal cortex [3]. The relaxation/concentration ranges are calibrated beforehand for each participant.

To prepare the gaming application, we collected the data on two subjects engaged in a motor imagery BCI training sessions. The measurements were performed in a regular office environment, susceptible to external interferences of electrical or physiological nature. Each subject participated in 4 recording sessions distributed over several days. Results from offline analyses shows an average classification accuracy of 92.5% (std=4.5%) for imagined movements between the two participants.

Figure 1. A picture taken during the BCI racing game. The two opponents wearing the wireless headset are in the upper left corner, the white and orange remote controlled cars are driving on a racetrack on the table.

Discussion: These findings indicate that despite using a minimalistic approach in uncontrolled environment, we are able to achieve state-of-the-art classification accuracies that can be successfully utilized in gaming applications such as the one presented here.

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The impact of a BCI for creative expression on the quality of life of two artists in the locked-in state

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Introduction: Brain Painting is an ERP based BCI application that allows for creative expression. Two artists (pseudonyms: HP and JT), diagnosed with amyotrophic lateral sclerosis (ALS) and in the locked-in state, have been using Brain Painting since 2012 (HP) and 2013 (JT) independently of BCI experts in their home environment [1-2], see **figure 1**. They have been using it in several hundred sessions and for several hundred hours duration. In this long-term study it was shown that use of Brain Painting improved quality of life (QoL) of these artists, in particular their self-esteem, self-confidence, well-being, feeling of usefulness, ability to participate and productivity [1-2].

Material, Methods and Results: To obtain a broader and deeper insight *how* Brain Painting influences the life and QoL, qualitative measures (interview) were applied. Interview questions were based on the quantitative results of the psychosocial impact of assistive devices scale [3], for instance, artists were asked *how* Brain Painting impacts the indicated dimensions (e.g., well-being) that were rated as "strongly impacted". Interview took place after 3,5 (HP) and 2 (JT) years of usage of the BCI. Communication was enabled with help of assistive devices (HP) or by translation of an assistant by reading movements of the lips (JT).

Figure 1. *JT in his art studio while painting with the BCI (left). The created painting has the title "Metropolis" (right).*

Regarding *well-being* JT stated „If I couldn't use Brain Painting, I would feel alone". He stated further "I painted before and now I can still create paintings, this contributes to my self-esteem" (*self-esteem*), "Everything that I can do creatively, makes me happy" (*happiness*). "Other artists visit me - they are astonished what is possible with Brain Painting" (*ability to participate*). HP summarized: „I have a stable *self-esteem* and *self-confidence* and I feel mostly well, but of course Brain Painting contributes to my self-confidence and self-esteem by having new challenges. *Well-being* results from success. I feel very good while painting and with colours anyhow, quite the same as I love colours in nature. With Brain Painting *happiness* is higher, because I am *productive* and thus maybe also *useful*, in the way that I can make other people happy with my paintings. For me, being useful means being productive for others. Because I am unintentionally this no longer, Brain Painting is a welcome opportunity for me." Regarding *ability to participate* HP stated: "This is very good for me, I have more contact to my external environment through exhibitions and requests by potential art buyers or people who simply wish to contact me. I mean others than patients".

Discussion: Brain Painting unequivocally contributes to the QoL of the artists in the locked-in state, even after 3,5 and 2 years of use.

Significance: BCI-controlled Brain Painting allows for maintenance of QoL and emotional well-being in patients with ALS, even in the locked-in state.

Acknowledgements: This work is supported by the Human Dynamics Centre (HDC) of the Faculty of Human Sciences of the University of Würzburg

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Unity Plugin for Immersive BCI Applications

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Introduction: Several groups have described BCI systems based on visual evoked potentials, including c-VEP and P300 based paradigms. In recent years, articles have drawn attention to new BCI applications with these and other BCI approaches, including immersive virtual reality (VR) for stroke rehabilitation, art, online interaction, and games [1, 2]. This represents a major shift from the conventional BCI approach, which aims to provide basic communication for people with severe motor disabilities that prevent them from communicating otherwise. However, several mechanisms for implementing BCIs in a VR have been described, and to our knowledge no plugin exists so far for the widely used Unity game engine (Unity Technologies, USA). In this paper, we introduce a new approach to BCI-based VR using the Unity game engine. It is optimized for VR development, and it contains a plugin for the Oculus VR Rift (Oculus VR, USA) head-mounted display. Thus, we developed a new plugin called screen-overlay control interface (SOCI) that combines Unity with our established BCI platform, which has already been validated with VEP BCIs [3].

Material, Methods and Results:
The plugin uses an OpenGL based flash module delivering visual stimulation for BCI applications. As shown in Fig. 1, a game object in Unity uses an instance of the SOCI display to either directly visualize a matrix on a 2D plane or to propagate flash states of BCI controls and to further assign the states to 3D game objects in the scene. To ensure proper usage of the BCI, the Unity game has to constantly run at 60 Hz refresh rate, while the integrated UDP handler in the SOCI plugin guarantees accurate trigger for a synchronous BCI. In a validation study two subjects participated in a P300 controlled simplified version of the board game Mastermind, where a 3x6 matrix was used to select color and position of a 3-digit color code. Initially, each subject performed a training run with 90 target and 540 non-target trials. Based on a training data a linear classifier (LDA) was used during the validation run, where S1 reached 100% accuracy for 8 selections with 15 trials per selection and S2 reached 100% accuracy for 8 selections with 5 trials per selection. Finally both subjects could complete the color code in an additional free run (10 selections for S1 and 5 selections for S2).

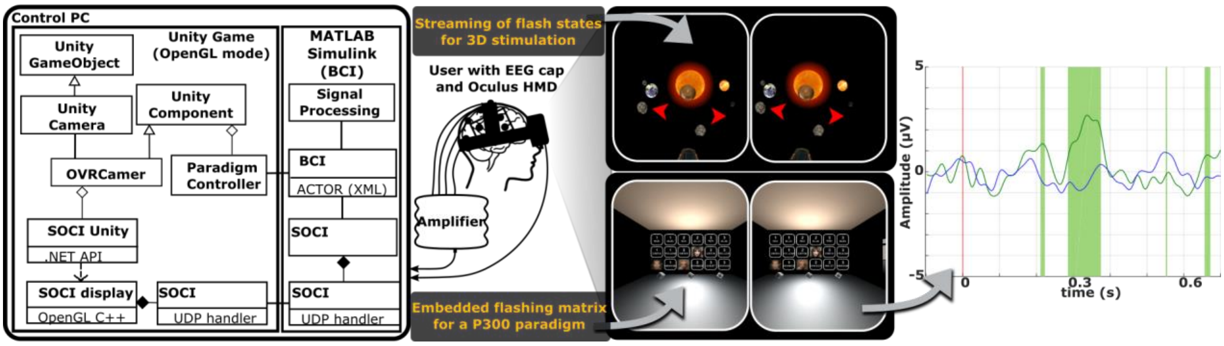

Figure 1. *Architecture of the SOCI Unity plugin (left) and stereoscopic view of two demo applications using a c-VEP (center, right) and P300 paradigm (center, bottom). On the right side the mean target (green line) P300 over Cz of S2 after 90 trials is plotted, while the green area indicates significant (p<0.05) deviation compared to a non-target average P300.*

Discussion: The platform described here introduces a new mechanism for developing immersive game-like environments with BCIs. Developers could easily adapt this new platform for a variety of applications to benefit different user groups. For example, we are currently testing different motor imagery BCI environments with stroke patients, and plan to explore new applications that use VEPs.

Significance: This new platform could greatly reduce development time and cost for many BCI applications, and foster development of innovative directions.

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Virtual Reality, Graphics and mVEP Classification

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Introduction: Brain computer interfaces (BCIs) have often been interfaced with video games however the impact that video games graphics complexity has on brain-computer games interaction (BCGI) performance has not been studied. Additionally, with more advanced visual displays such as the Oculus Rift Virtual Reality (VR) headset there is a need to investigate any (dis)advantages these variables may have on BCGI. This is particularly relevant for visual evoked potential (VEP) based paradigms where visual distractions may have an impact on the reliability of the EP. In this study we utilized an Oculus Rift headset as a visual display to present a motion-onset VEP (mVEP) controlled car racing game [1] and compared the offline mVEP classification performance with the same game presented on a standard 22 inch LCD computer screen. We also compared two different levels of graphical complexity and background styles for the mVEP evoking stimuli. mVEPs are elicited by the sudden, brief motion (lasting 140ms) of an attended target/stimulus and consists of a negative peak around 200ms (P2) after the evoked stimulus, followed by a positive peak at around 300ms (P3) (Fig. 1a). mVEP stimuli are more elegant as they are motion related, do not require long training periods and are less visually fatiguing than other VEP stimuli [2].

Material, Methods and Results: Electroencephalography (EEG) with a twelve channel montage covering the occipital areas was recorded (Fig. 1b) whilst fourteen participants viewed five mVEP stimuli presented along with a car racing game. One session employed VR and the other a 22inch LCD monitor to display the stimuli/game. To compare graphical complexity and mVEP stimuli background variations, the participants were presented with four game levels in each session. Two levels offering different graphics (complex (Fig. 2a) and basic (Fig.2b)) and two levels with different stimulus background settings namely, stimuli overlaid onto the game environment using a non-white background (Fig. 2a) vs. stimuli placed on a white background (Fig. 2b). Five mVEP stimuli were employed, each corresponding to a different command (five classes). Each stimuli was activated sixty times yielding a total of 300 trials for each game level.

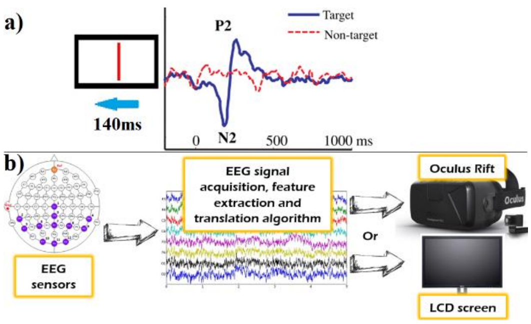

Figure 1. ***a)*** *mVEP stimuli details and* ***b)*** *BCI loop.*

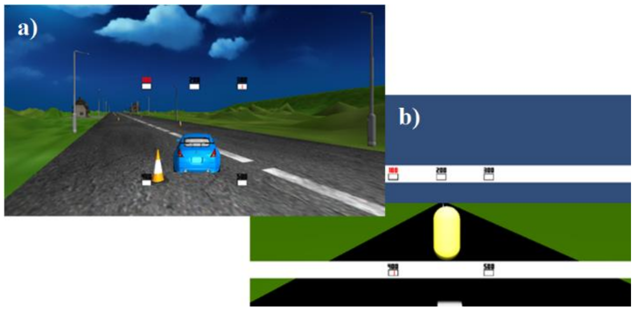

Figure 2. ***a)*** *Complex level no with white and* ***b)*** *basic level with white background.*

Offline analysis of mean accuracy across subjects for both target vs. non-target (two class) and five class mVEP classification indicates that VR presentation does not differ significantly from LCD presentation (69% and 70% for two class and five class respectively)(p>0.05). The differences between basic (69%) vs. complex (73%) graphics were significant (p<0.05). The differences using non-white (68%) vs. white (69%) backgrounds for mVEP stimuli are insignificant when basic graphics are presented (p>0.05), however the differences are significant when complex graphics are presented (non-white (70%) vs. white (74%), p<0.05).

Discussion: Offline analysis of results provide evidence for the first time that the Oculus Rift can be used for presenting low visually fatiguing mVEP stimuli without influencing classification performance and that the mVEP stimuli can be overlaid on basic games graphics without impacting performance significantly. The results however indicate that complex graphics improved mVEP classification performance and that when using complex graphics the mVEP stimuli should be presented onto a dedicated background and not overlaid on the games graphics i.e., a clear mVEP stimulus presentation area [3].

Significance: This pilot study provides evidence that realistic graphics and aesthetically pleasing game environments may be employed for BCGI using an mVEP paradigm, however the mVEP 'controller' should not be overlaid on game graphics but have consistent background (white tested here). The results will be validated in an online car racing game controlled using an mVEP paradigm taking into account the findings of this pilot study.

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"Brain Invaders 2": an open source Plug & Play multi-user BCI videogame

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Introduction: In 2011 we proposed « Brain Invaders » [1], a BCI videogame inspired from the vintage game Space Invaders. The software was released open source and was compatible with OpenVIBE [2]. The system is based on ERP classification using the oddball paradigm with a grid of 36 possible targets. This second version extends the game to the multi-user scenario. It includes four game modes namely *Solo*, *Collaboration*, *Cooperation*, *Competition* which are suitable for hyperscanning studies. Thanks to a classification algorithm based on Riemannian geometry, the system shows very good accuracy and is fully "Plug & Play", no calibration phase is needed.

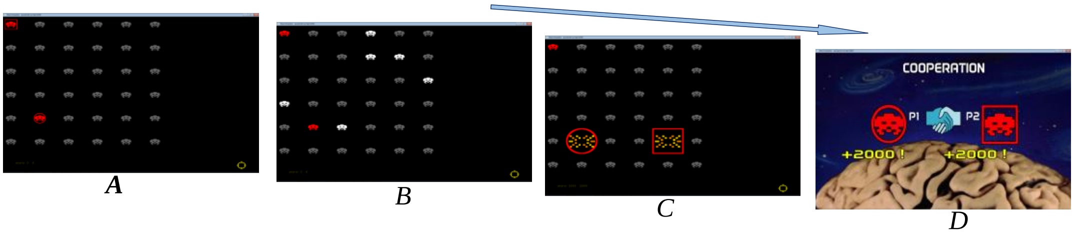

Figure 1. *Brain Invaders v2: (A) Level initiatilization. (B) After a short delay, the game flashes randomly all the aliens. (C) The game destroys the most likely alien(s) according to the classification.(D) If the player(s) succeed(s) at destroying the target(s), s/he (they) is awarded by a fixed amont of points or by a factor proportional to the number of repetitions required.*

Material, Methods and Results: "Brain Invaders 2" includes several characteristics that make it suitable for recreational, educational and research purposes: ■ Random alien target and alien distractor localization on a 6x6 grid (see Fig. 1A). Unpredictable flashing pattern (see Fig. 1B) with pseudo-random generated inter-stimulus interval (ISI) according to an exponential distribution. ■ Supervised adaptive classification method using the minimum distance to mean (MDM) of covariance matrices according to the Fisher information metric [3] and extended in the multi-user case according to [4]. This classification method has shown state-of-the-art performances, yet is simple, and can run on modest computers. ■ The system has been tested extensively on more than 250 subjects in controlled conditions (see Table 1) and also on hundreds of subjects during numerous public demonstrations and competitions (not presented here). It has been described by the participants as engaging and entertaining.

Table 1 *List of the experiments using the Brain Invaders software with the minimum, average and maximum online classification performance of the participants. Chance level is 1/36.*

Database	Mode(s)	# subjects	# sessions	Electrodes	Min (%)	Av (%)	Max (%)	Ref.
bi2012a	solo	26	1	17-wet	28.19	47.79	68.94	
bi2013a	solo	24	Up to 8	16-wet	42.86	62.88	92.31	[5]
bi2014a	solo	71	3	16-dry	16.67	35.55	72.97	
bi2014b	solo-collaboration	38	4	2x32-wet	36.73	68.30	94.74	[4]
bi2015a	solo	50	3	32 wet	33.33	68.04	100	
bi2015b	cooperation-competition	44	4	2x32 wet	27.5	74.0	98.75	

Discussion: The authors propose a complete state-of-the-art ERP-BCI chain for single-/multi-user. The use of open source code and OpenVIBE allows quick experimental protocol design and classification methods prototyping. This is part of an ongoing research and development effort concerning the Brain Invaders.

Acknowledgements: The software is freely available on the GPL license into the package "openvibe-gipsa-extensions". This research is partially funded by the European Research Council project CHESS 2012-ERC-AdG-320684. The authors would like to thank Ekaterina Ostaschenko and Martine Cederhout for the experimental support.

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A method for estimating emotional arousal changes of a group of individuals during movie screening using SSVEP

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Introduction: Neurocinematics is an emerging research area in neuroscience and passive BCI, which aims to provide new filmmaking techniques by analyzing viewers' brain activities [1]. There are an increasing number of neurocinematics studies that attempt to track temporal changes in cognitive and/or emotional states of the brain during movie screening; e.g., attention, emotional engagement, and cognitive load. However, it is generally difficult to find efficient and robust EEG features that can be used to track brain states over a long period of time. In the present study, we propose a method for estimating changes in emotional arousal of a group of individuals during movie screening, using a new type of visual stimuli that can elicit SSVEP.

Material, Methods and Results: Six male subjects participated in the preliminary experiments. A short video clip (~ 5 min) that was designed to elicit fearful emotion was prepared. Each frame of the movie clip was adjusted for the movie clip to keep a constant luminance throughout the whole screening time. Then, white-noise-like random chromatic dots flickering at 6 Hz were superimposed on the video clip with 20 % transparency, in order to elicit SSVEP responses. The EEG data were recorded at 2048 Hz sampling rate from 12 electrodes (Fp1, Fp2, F3, Fz, F4, Cz, PO3, POz, PO4, O1, Oz and O2). After the EEG recording, each participant was presented with the same video clip again to report two most impressive (most fearful or most arousing) scenes.

The recorded EEG data were downsampled to 512 Hz, and the temporal changes in spectral power at 6 Hz were evaluated using fast Fourier transform (FFT) with a 10-second moving window (90 % overlap). The spectral power series were averaged across channels O1, Oz, and O2, and then grand averaged over all study participants. The preliminary result of the averaged SSVEP responses during screening the 'fear' video clip is depicted in Fig. 1, where the overall temporal pattern of the SSVEP power changes coincided well with the questionnaire result.

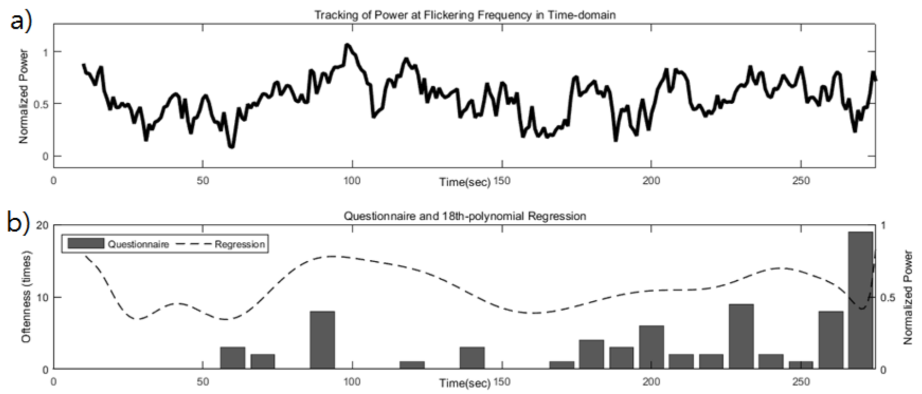

Figure 1. *Changes in normalized SSVEP power during watching 'fear' video: a) Grand averaged SSVEP power changes; b) Result of 18th-order polynomial regression of the power change (dashed line) presented with the questionnaire result (bar graph).*

Discussion: In this study, we proposed a new method for estimating emotional arousal changes of a group of individuals during movie screening by overlaying SSVEP stimuli on the original video clips. Our preliminary experimental results coincided well with a previous SSVEP study that reported the positive correlation between the SSVEP amplitude and the emotional arousal [2]. Further studies with more video clips and participants will be conducted soon, and the results will be presented at the conference.

Significance: Our preliminary results showed the possibility that a new SSVEP-based visual stimulation method might be used to track continuous emotional arousal changes of a group of individuals during movie screening.

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Affective BCI for characterizing museum visitors response

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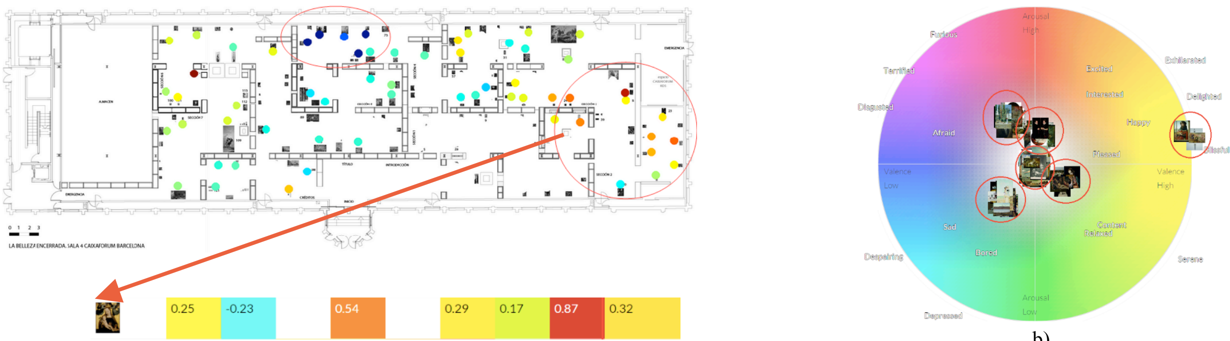
Introduction: We present a novel methodology based on affective BCI (aBCI) for the analysis of subject emotional response during art exhibitions. The proposed methodology provides tools for better understanding visitors reaction to exhibition layout and art pieces. Starlab's ExperienceLab system was adapted to record electrophysiology signals during visitors' activity. We analyze 20 volunteers' data. The signals were mobile recorded while the volunteers visited the exhibitions on 14^{th}-19^{th} century paintings, and S. Salgado's photography at the museum CaixaForum. The emotional state is characterized following the circumplex model [1]. The used valence and arousal features are directly taken from current state of the art, whereas we propose novel fusion and clustering techniques for the final interpretation tools.

Material, and Methods: Three different electrophysiological signals were recorded for emotional characterization, namely Electroencephalogram (EEG), Electrocardiogram (ECG), and Galvanic Skin Response (GSR). Enobio was used for wireless recording EEG and ECG, whereas a Shimmer device recorded the GSR. The synchronization of all signals and positioning video was made using a tablet PC, which was carried by volunteers. The emotional subjective response is obtained through questionnaires, which were realized once the volunteer finished the visit. We select one clean signal interval pro art piece by visual inspecting the signals and associating it through the video sequence. Once done 4s epochs are cut and used for feature computation. We extract 2 valence features: EEG parieto-temporal gamma asymmetry [2], and frontal alpha asymmetry [3]. Eight arousal features are used: EEG frontal alpha-beta ratio [4], EEG parieto-occipital gamma power [5], heart rate and its variability, and GSR variance and number of events. The interested reader is referred to the original papers for further details on features. The U-test is then applied for evaluating the statistical significance of the features taking the questionnaire answers as ground truth. The obtained p-vales are first used to compute the weights within a weighted sum that fuses the 2 valence features into a unique final value. The 8 arousal features are fused analogously. Both fused values are lastly scaled into [-1,1] and used for the *exhibition highlight maps*. On the other hand a clustering analysis is used on the 10-dimensional feature set based on K-means (K=6). This allows establishing groups among art pieces in the circumplex space. The prototype of each cluster is transformed into coordinates of the final *circumplex representation* by independently fusing the valence and arousal components of the prototypes.

Results: The EEG gamma asymmetry ($p<0.01$) is the most significant valence feature. Significant arousal features are the EEG alpha-beta ratio ($p<0.01$) and the GSR variance ($p<0.001$). The fused valence and arousal are topographically registered with the exhibition map for associating individual subject and grand responses with exhibition layout in what we denote as *exhibition highlight maps* (see Fig. 1a). Lastly the *circumplex representation* is used for depicting art piece groups and its associated emotional complex response, e.g. blissful, serene, sad (see Fig. 1b).



a) b)

Figure 1. *Informative visualization system output. a) Highlight map and detail for 1 art piece (where color codes arousal/valence values). b) Art piece clustering (color codes areas in the circumplex).*

Discussion: The significance of GSR arousal confirms the existing literature. The significance of the arousal and valence EEG features proves its applicability. Obtaining unique arousal-valence values through data fusion constitutes a novel approach in aBCI, which increases the features significance level. Moreover novel methods for transforming aBCI results into information both on the highlights of the exhibition layout, and the value of the exhibited pieces from an emotional point of view are proposed and exploited for generating the final results.

Significance: A multimodal aBCI system including statistically significant EEG-based arousal and valence is successfully applied out-of-the-lab. Here the employed wireless EEG technology shows its potential. The proposed data fusion and clustering methods constitute a novelty, which empower the outcome visualization tools for museum aBCI applications.

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An Affective Brain-Computer Music Interface

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Introduction: Music is a powerful method for evoking emotions in music therapy. We develop a hybrid affective Brain-computer music interface (aBCMI) for modulating its user's affective (emotional) state via a music generation system. The aBCMI aims to passively modulate a user's affective state by first identifying their current affective state and then generating appropriate music to move them to a new affective state.

Methods and Results: The aBCMI consists of four components: (1) electroencephalogram and physiological signals recorded from the user, (2) an affective state detection system [1], (3) a case based reasoning system to identify the best method to move the user to a target affective state, and (4) a music generator to produce novel piano music to dynamically target different affective states [2].

Eight participants (ages = 20-23, 6 female, all right handed, recruited by flyer from the student population, and naive to experiment details) attended 5 sessions over several months. In each session participants had their EEG (32 channel, impendence < 10kΩ, 1kHz) and physiological signals (galvanic skin response, electrocardiogram, respiration and pulse oximeter) recorded by a BrainAmp amplifier (BrainProducts, Germany).

The first four sessions were used for offline training of the affective state detector (a support vector machine classifying EEG band-powers and physiological signals) and the case based reasoning system. The final session was used to test the efficacy of the aBCMI during online use. Participants listened to generated music targeting discrete regions in the valence-arousal space, while reporting their current felt emotions via FEELTRACE [3].

The online session attempted to verify whether the aBCMI could be used to successfully move the user from their current affective state to a new target affective state. Each trial was 60s long and was used to attempt to achieve one of the objectives listed in table 1.

The objectives were achieved significantly often in 7 participants ('make happy' and 'calm'), 6 participants ('reduce stress'), and 1 participant ('excite'). Participants reported affective state changes during use of the aBCMI that matched the objective. An example is illustrated in figure 1 for 'reduce stress', note that arousal is decreased and valence is increased by the aBCMI.

Table 1. Testing session objectives.

Aim	Affective state transition
Make happy	Low valence -> High valence
Calm	High arousal -> Low arousal
Reduce stress	High arousal, Low valence ->Low arousal, Neutral valence
Excite	Low arousal -> High arousal

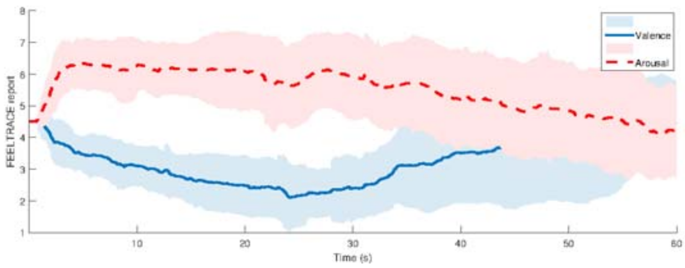

Figure 1. *Mean FFELTRACE reports (shaded area = ±1 STD.) of felt valence and arousal from participant 2 during the 'reduce stress' condition.*

The aBCMI was able to detect felt affective states with a mean accuracy of 0.54 (3 class) for valence and 0.46 for arousal classification. Significant ($p<0.05$) classification (measured against a null binomial distribution, chance level of 1/3) was achieved with 7 participants for valence and 2 participants for arousal classification.

Discussion: Our aBCMI is able to modulate a user's current affective states significantly more often than chance for the majority of participants. This is most effective for calming, pleasing, and de-stressing participants. Thus, the developed system provides a unique tool to allow it's users to interact with music in a way that could be potentially beneficial for their emotional state.

Significance: Our work represents the first attempt to use affective Brain-computer music interfacing to passively modulate emotions. This has potential applications in music therapy. Our future work will seek to explore this work further with patient groups with the potential to benefit from our aBCMI.

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Competitive and Collaborative Multiuser BCI

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Introduction: In recent years, brain-computer interface (BCI) applications for gaming of healthy individuals have gained a considerable interest [1]. Multiuser BCI games are still rare and mostly limited to motor imagery as a control strategy [2]. Here we propose BCI games based on simple operant conditioning that can be used for gaming of healthy people or for therapeutic purposes [3]. We compare collaborative and competitive strategies in a group of healthy naïve BCI users.

Material, Methods and Results: Six naïve pairs of healthy volunteers (age 24±7) took part in the study. Their EEG was recorded with usbamp (Guger technologies, Austria), bipolarly between F3 and F4 (control BCI signal) and monopolarly at AF3,AF4,A3,A4,FC3,FC4,C3,Cz,C4,O3,Oz,P4,O1,O2 (post-hock analysis). A sampling frequency was 256sam/s, impedance below 5kΩ, ear reference, on-line filter 5-30 Hz. A moving average window of 0.5s was used to calculate EEG power in alpha (8-12 Hz) and beta (13-30 Hz) band and in 5-30 Hz band. A relative power was calculated as power(alpha or beta)/power(5-30 Hz) to eliminate between-subject differences in EEG amplitude. Participants sit in the front of a computer looking at the screen showing a simplified 'see-saw'. In a collaborative game their used the alpha band power (strategy: relaxation) to keep the see-saw in balance. When player's 1 power was within ±7.5% of player's 2 power for 1 s they scored one point. In a competitive game (strategy: concentration), when player's 1 beta power was >20% of player's 2 power for 1s, player 1 scored a point. After an initial training, players played 2 runs of collaborative and 2 of competitive games, each run lasting 200s. Signal processing was performed in Simulink/Matlab (Mathworks, USA) while Java was used for visualization. Figure 1a shows the alpha power of two players in a collaborative game and Fig 1b shows their beta power in a competitive game. Fig 1c presents scalp maps of alpha power during rest and a collaborative task, showing the shift of maximum activity from the occipital towards frontal regions during game. The average score for 6 pairs in a competitive task was for run1: winner 39±24 and looser 13±12; run 2: winner 49±19 and looser 16±14. In a collaborative task the score was 42±12 for run1 and 55±19 for run2. A score was slightly better in a collaborative than in a competitive task, either due to the nature of the task (relaxation vs concentration) or a strategy (collaboration vs competition).

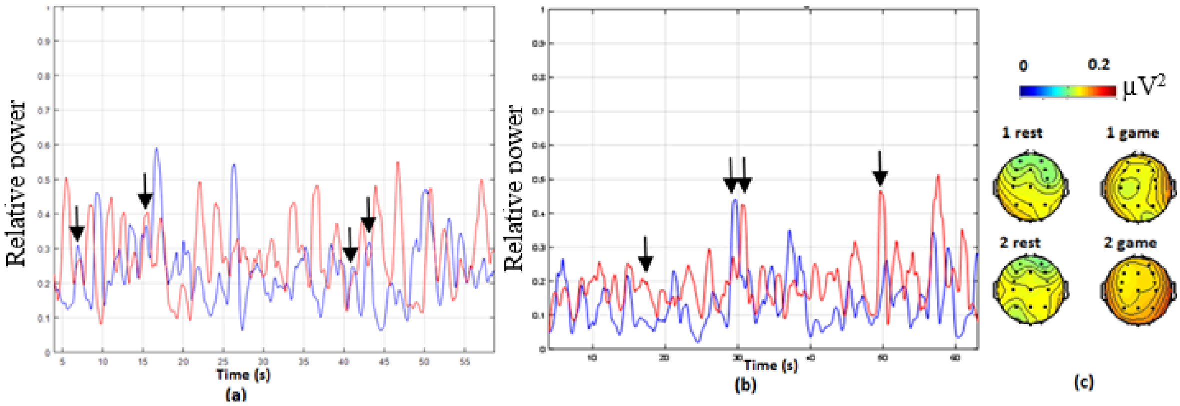

Figure 1. Relative alpha power of two players (red and blue color) during a colaborative task. b) Relative beta power dring a competitive task. Arrows show examples when points were scored. c)Scalp maps of alpha power in one couple, notice spatial shift of the maximum power towards the frontal region.

Discussion: The study shows that naïve participants can learn how to collaborate/compete using their brainwaves within one training session. Brain computer games can be used as inclusive gaming strategy for both able-bodied and heavily physically disabled. Group BCI games can also be used to enhance brain training strategies [3].

Significance: Collaborative/relaxation game strategies might be easier to learn than competitive. Voluntary modulation of brian activity from one cortical site causes wide spread changes that can be utilised for complex neuroodulation strategies but could also have a detrimental effect.

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Prediction of Difficulty Levels in Video Games from EEG

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Introduction: Changes in workload have been shown to be accompanied by power modulations in EEG frequency bands such as theta (4-7 Hz) and alpha (8-12 Hz)[1]. In a typical video game that requires continuous mental and visuomotor effort, an increase of difficulty is expected to increase the player's workload. In this contribution, we tested whether it is possible to predict the current difficulty level of a video game by using only the ongoing EEG activity of the player. The game we chose is a modified version of the classical Tetris, in which the current difficulty level can be set by the experimenter.

Methods and Results: Six subjects participated in the experiments during which they played nine Tetris games, with each game lasting ten minutes. Every 60 seconds during gaming, the difficulty level was changed at random to one of 10 predefined levels. EEG data was recorded from 32 channels. Preprocessing included removal of eye artifacts via regression from EOG signals and rejection of single levels or channels based on excess variance.
For the regression of multiple difficulty levels based on neural bandpower dynamics, we applied the Source Power Co-Modulation (SPoC) analysis[2]. SPoC optimizes spatial filters such that their corresponding spectral power dynamics of a given frequency band maximally covary with the given difficulty levels. The frequency band of interest is a parameter of the method.

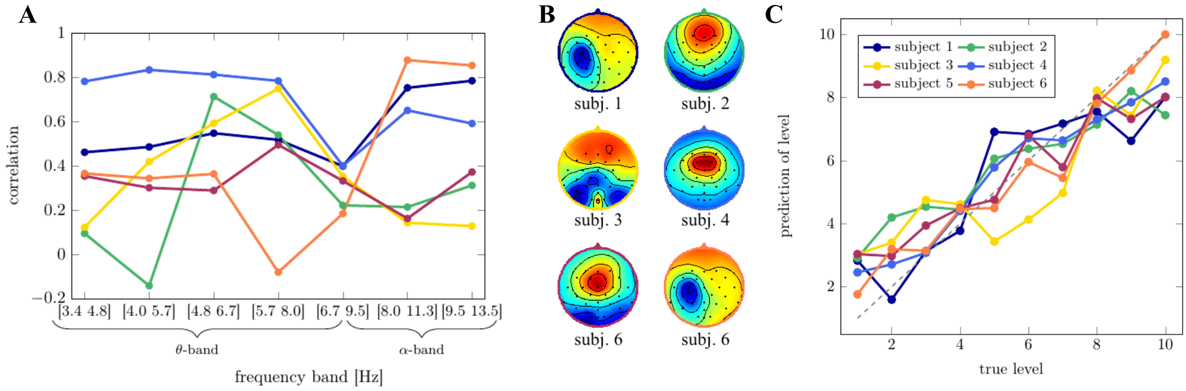

Figure 1. ***A:*** *Correlation between predicted and target levels as a function of frequency band used for SPoC analysis.* ***B:*** *Activation patterns of the first SPoC components for each subject.* ***C:*** *Mean predicted level versus true level for single subjects using the subject-specific optimal frequency band. Gray dashed line indicates a perfect prediction. Single subjects are color-coded equally in all three panels.*

To determine the optimal frequency band for each subject, a crossvalidated SPoC analysis was performed for different frequency bands (Fig. 1A). In each fold, one game was left out during the training of SPoC components. Performance of the prediction on the test dataset was measured as correlation between the regression output and the true levels. While for subjects 1 and 6 the frequency band that yields the best prediction is in the alpha range, for subjects 2-5 the best prediction is achieved in the theta range. The spatial patterns of the corresponding SPoC components are representative for the frequency bands and physiologically plausible (Fig. 1B). We found that for all subjects, one SPoC component is sufficient to yield high levels of prediction accuracy. The predictions roughly cover the levels from 1 to 10 (Fig. 1C), the mean correlation between predicted and true difficulty level across subjects was 0.802±0.036 SEM.

Discussion: Inspecting the optimal frequency band and the resulting spatial pattern indicates that for subjects 1 and 6 the best prediction was based on the sensorimotor rhythm (SMR), while workload related mid-frontal theta activity was the optimal predictor for the remaining subjects. However, even for subjects 1 and 6 the correlations obtained from theta activity (r=0.55 and r=0.36, respectively) are statistically significant as revealed by a permutation analysis. Our findings demonstrate that difficulty levels of a video game can be predicted with high accuracy solely from ongoing brain signals by employing a state-of-the-art EEG spatial filtering method. Finally, our approach can be extended to an online application, e.g. for adaptive gaming.

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Sheet Music by Mind: A BCI for Composing

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Introduction: A direct connection between the human brain and a computer is a so called brain-computer interface (BCI). P300-based BCIs are often used for communication and control and various applications (e.g., speller [1], brain painting [2], environmental controller [3] and web browser [4]) are already implemented. Our aim is to provide a composing system comparable with the brain painting system [2], which can be used in real-world settings.
Material, Methods and Results: We connected a P300-based BCI system with a powerful music composing software (MuseScore, http://www.musescore.org). This software enables the user to compose music for several voices, instruments, and other composing tools. The composed music can either be listened immediately within the application or exported to a MIDI file to be used with real instruments.
Five volunteers (3 male; mean age 24.0±1.7 years) participated in this study. Eight EEG channels (Fz, FC1, FC2, Cz, Pz, PO7, PO8, and Oz) with water-based sensors were used. The biosignal amplifier (Mobita) uses wireless technology to transmit the signals with 24 bit resolution. A classical P300-based BCI (7x6 matrix) using famous faces was setup, see Fig. 1. The first two rows of the matrix are to select the note value and other features of the actual note or bar. The third row represents the different pitches. The following rows are to select other features of the application e.g., next or play bar. Calibration was performed with fifteen highlightings per row and column. The music composing task was started by the operator by selecting "Music Composing" in the user interface menu. The composing application started automatically on a second screen placed above the matrix screen and the "letter" matrix from the calibration changes to the "main menu" matrix (3×6 matrix) of the composer software. First, the participants had to select the "compose" element out of three other elements ("New", "Open", "Save"). If the "compose" element was selected the matrix switched automatically to the 7×6 "composing" matrix, see Fig. 1, left. Then the participants were asked to copy-compose the first six bars of Alouette, a famous French Canadian children's song, Fig. 1., right.
Three out of the five participants were able to copy-compose the given melody. Their accuracies were 57%, 58%, 78% 83 and 96%, whereas the best performing participant (P5) needed on average 3.9 (±1.1) sequences until the system stopped highlighting and presented the classifier result.

Fig. 1: Left: P300 matrix. Right: music to be composed in the upper row. The base line was given already, to present a nicer music to the participants after the composing task.

*Discussion:*In this pilot study, the idea to compose music with a BCI was introduced and successfully tested. We could show that it is possible to setup a P300-based BCI system (8 channels) and copy-compose a short melody (25 notes, min. 42 selections) within 45 minutes. Three out of five volunteers were able to operate this brain composer with excellent success.

Significance: With this brain composer system it is nicely possible to also really compose music, an example is given in the following video: https://youtu.be/sW9nkC06D94

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BCI-controlled Brain Painting at home: years of use

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Introduction: Brain Painting (BP) is a P300-BCI controlled application that allows for creating pictures [1]. BP has been adapted for home use following the user-centred design (UCD) approach [2] and was installed at two patients' home (JT and HP). Both patients were diagnosed with amyotrophic lateral sclerosis (ALS) in the locked-in state. Since January 2012 (HP) and September 2013 both end-users have been painting at home independently of experts being present. Caregivers and family members were trained to set-up the system. After every session end-users are asked to rate their satisfaction, frustration, and joy. Here we report painting duration and satisfaction across the entire time of enrollment.

Material, Methods and Results: End-user HP: female, 76, diagnosed with ALS in 2007, locked-in state, retired teacher, impressionist lay painter, communication with eye movements possible. BP installed at home 26th January 2012; Einstein face stimulation [3] was added October 19, 2012 after 96 sessions. End-user JT: male, 74, diagnosed with ALS in 2006, locked in state, retired architect and professional painter, communication with eye movements possible. BP installed at home 16th September 2013, after 158 BP Version 2 was installed December 10, 2014. At the end of each session satisfaction is rated on a visual analogue scale (range 1-10; 1 = not at all satisfied, 10 = absolutely satisfied). All results are stored on the local PC and automatically transferred to a remote server owned by UNI WUE. LB and EH provide remote supervision and technical support if necessary.
Until December 10, 2015 HP has been painting for N=418 sessions with an average duration of 93.7 min SD=51.4. Satisfaction was on average M=7.11, SD=3.42 (see Fig. 1 left). JT has been painting for N=222 with an average duration of 59.6 min, SD=34.2. Satisfaction was on average M= 7.56 SD= 2.57 (see Fig. 1 right).

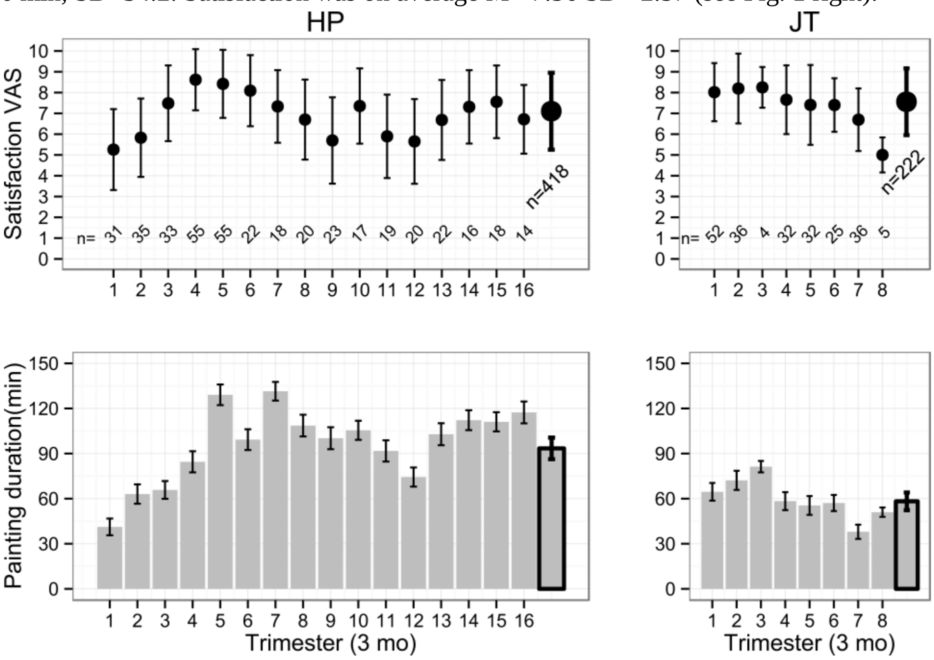

Figure 1. *Satisfaction (top) and painting duration (bottom) for HP (left) and JT (right). Due to the high number of sessions, single sessions were summarized in 3-months periods. Most right data of each plot show the average across the entire painting years.*

Discussion: BP has been used for 4 (HP) and 2 (JT) years. Fluctuations in satisfaction did not lead to abandoning of BP. P300-BCI use requires attention and concentration and has been used between 1 and 2 hours, which may be indicative for the maximum duration of BCI use per session.

Significance: BCI-controlled applications can be long-term used at home independent of experts being present. If the application matches end-users needs, they keep using the BCI despite known shortcomings (EEG cap, fluctuations in performance). Simple metrics to monitor satisfaction with the device are tolerated by the end-users and can be applied after each session.

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Brain Painting V2: long-term evaluation by an end-user at home – an update

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Introduction: Brain Painting (BP) is a brain-computer interface (BCI) application that allows for creative expression using P300 event related potentials [1]. BP has been adapted for home use and benefited to two users (JT and HP) with amyotrophic lateral sclerosis (ALS) and was reported to increase their quality of life [2]. The new version BP2, providing features and the possibility to draw lines, was created following a user-centered design (UCD) approach [3]. It was installed at the home of JT and was evaluated across a period of 3.5 months [4]. We present here new evaluation results of JT from another 3 months.

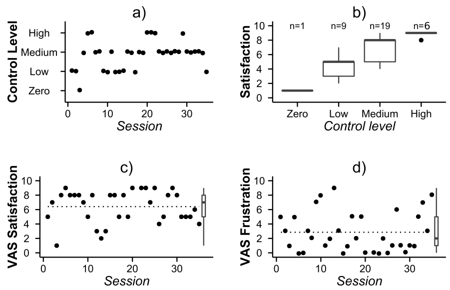

Figure 1. *Control level (a), VAS for Satisfaction (c), VAS for Frustration (d) as a function of sessions. Boxplot (c,d) represent quartiles and dotted line the mean. (b) Boxplots show Satisfaction depending on control level.*

Methods: End-user JT, male, 74, diagnosed with ALS in 2006, in the locked in state, retired architect and professional painter regularly using BP for more than 2 years. EEG was measured with 8 channel and digitized by a g.USBAmp amplifier (g.Tec). BCI was calibrated prior to the evaluated period [4]. All sessions were initiated by caregivers, in complete autonomy. After each session, JT evaluated the session following the UCD framework [3] ("Effectiveness", "Efficiency", NASA TLX, "Satisfaction", QUEST 2.0 for BCI. NASA-TLX and QUEST were answered after the evaluated period.

Results: n=35 sessions occurred within 3 months, painting duration was M=40.8min (SD=21.5), 17 Brain Paintings were produced. "Effectiveness": Level of control (see fig.1.b). "Efficiency": exhaustion was low n=28, medium n=7, high n=0. Workload was 70 (out of 100), with subscales mental demand 25.3, physical demand 18, temporal demand 12, performance 8.3, effort 6 and frustration 0. Selection/min: 2.47. "Satisfaction": (means in fig.1.c-d) no significant variation in satisfaction (M=6.4), enjoyment (M=6.0) and frustration (M=2.8) was found over time. Subjective level of control predicted satisfaction (R^2=.52, F(3,30)= 13,1 p<.001). The QUEST 2.0: high satisfaction M=4.7 (out of 5) and M=5 for BCI related questions.

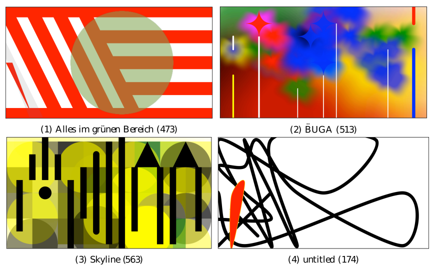

Figure 2. *JT's creations made using BP2, demonstrating the use of lines. Number of selections under parenthesis.*

Discussion: JT painted often and showed good overall satisfaction, although it was inferior to the previous 3.5 months of use [4]. Once again, satisfaction was highly dependent on the BCI performance. The home setup remained functional, until JT complained about blur vision due to cataract. After visual inspection of every painting session, the subjective control level appears negatively biased, as the control is sufficient for JT to paint and cancel wrong selections. Thus, low control may also refer to general dissatisfaction with the painting. Workload did not differ from former use of BP. Still, selections per minute and performance were inferior to what most ALS patients expect from BCI technology [5]. Nevertheless, the high results in the QUEST and the high involvement of JT show that following the UCD leads to applications that match users' needs.

Significance: If a BCI and its application is tailored to individual needs following the UCD, it is used in daily life independent of experts being present and despite shortcomings such as perceived low control. The metric to implement the UCD suggested by [3] can be implemented in a long-term independent home setting.

Acknowledgements: This work was supported by the European FP7 grant 288566 (Backhome) and the Volksbank Würzburg. This abstract only reflects the authors' views.

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Influence of cognitive variables in a Brain-Computer Interface driven application

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Introduction:

Sensorimotor rhythms Brain-Computer Interfaces (SMR-BCIs) allow users to actively control a device with cortical, muscle independent, activity. This characteristic has drawn attention to possible uses within environments richer and more interactive than laboratories, in particular for unpaired people. Nevertheless rates of success in using BCI vary widely and, although it has been demonstrated that several cognitive variables might affect BCI performances [1], such a relationship has not been fully investigated in interactive BCI driven applications.

Participants and method:

Data were acquired from ten subjects (four female, average age 23.1 ± 2.9 years). Participants gave informed consent to the study and received no remuneration. They performed three recording sessions of a two-classes SMR-BCI [2]: in the first session (CALIBRATION condition) 4 offline runs with positive feedback were exploited to calibrate the system; the second session (ONLINE condition) was devoted to test the BCI online with a cue-based visual protocol (4 runs of 30 items each); finally, the third session involved the control of the BCI Race Game "Brainrunners" of the Cybathlon Rehearsal 2015 (http://www.cybathlon.com). The videogame consisted in making a virtual avatar avoid obstacles by delivering the correct BCI commands. In this session, subjects performed 3 runs without opponents (GAME-SOLO condition, 42 items) and 3 runs playing versus virtual opponents (GAME-GROUP condition, 42 items).

For the psychological data acquisition, we used the Questionnaire of Current Motivation BCI edition (QCM-BCI) to investigate motivation [3], The Positive and Negative Affect Schedule (PA and NA) to assess mood [4] and the Mini Locus of Control Scale [5].

Results and discussion:

Results show a significant decrease of the BCI accuracy in the GAME-GROUP condition versus the ONLINE condition ($p<0.01$). Performance in the ONLINE condition correlates positively with the PA scale ($r = 0.645$, $p<0.05$) and the QCM-BCI Mastery Confidence ($r=0.676$, $p<0.05$) and negatively with the NA scale ($r= -0.74$, $p<0.05$) and the QCM-BCI Fear of Incompetence scale ($r= -0.539$, $p<0.05$). Overall performance moderately correlates with Internal Locus of Control ($r=0.38$, $p<0.01$).

Results show how cognitive variables affect the performance during an SMR-BCI task. However no effect could be observed in the GAME condition, probably due to the difficulty of the task and the increasing number of visual stimuli that need to be processed. Although we cannot exclude that such psychological variables influence BCI accuracy, external and environment-related conditions (e.g. competitiveness, application complexity) may be predominant.

Condition		**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**	**Average**
ONLINE	[%]	95.0	65.0	95.0	89.2	95.0	80.8	97.5	100.0	78.3	99.2	89.5 ± 11.35*
GAME-SOLO	[%]	83.3	50.0	42.9	59.5	100.0	73.8	90.5	100.0	78.6	92.9	77.1 ± 20.4
GAME-GROUP	[%]	85.7	42.9	28.6	52.4	100.0	61.9	100.0	100.0	90.5	92.9	75.5± 26.7*

Table 1. Percentage of correct commands delivered for each condition. Statistical significance has been found between ONLINE and GAME-GROUP conditions (* $p<0.01$).

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Social inclusion as feature to improve BCI skill training: A feasibility case study in cerebral palsy

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Introduction: Operating brain-computer interfaces (BCIs) that are based on modulation of spontaneous electroencephalogram (EEG) rhythms is a skill that users have to learn. Training time varies significantly among users and it can take up to several months of time before minimum BCI control becomes possible. One reason for this may be the design of BCI training paradigms [1]. Trials of mental activity are collected prior to BCI use and used to calibrate BCI model parameters. During this initial data collection no feedback is provided to users. This is not very motivating and engaging for users. Recently, we introduced a thought-based one-switch row-column communication board for users with cerebral palsy [2]. To make BCI skill learning more motivating, we lately also introduced a jigsaw puzzle game-based training paradigm [3] that presents feedback from the very start. Initially sham feedback and once enough data is available for BCI calibration, online feedback. Moreover, the game was designed following user-centered design principles and explains the concept of BCI use and allows users to get familiar with the dynamics of BCI control. A pilot study in four users with cerebral palsy (CP) showed that the acceptance was high and users liked the game-based training approach [3]. Three out of the four users achieved performance better than chance level after about 30 minutes of training. Fig. 1 shows a user assembling a puzzle. Here, we propose social inclusion as another feature for improving BCI training. End users should not perform training alone but engage in direct competition with other persons.

Material, Methods and Results: One CP user participated in this single-case study. The user learned to operate the BCI-based one-switch row-column communication board by undergoing the jigsaw puzzle game-based training as described in [3]. After about 30 minutes of training, the CP user played three times the Tic-Tac-Toe game against his caregiver. Tic-Tac-Toe is a paper-and-pencil game for two players, “Lion” and “Elephant,” who take turns marking the spaces in a grid composed of three rows and three columns. The player who succeeds in placing three respective marks in a horizontal, vertical, or diagonal row wins the game (Fig. 1). The game, implemented for Android OS tablet computers, accepts BCI input by using the one-switch row-column paradigm [2, 3] and by touch (caregiver). The results of the three games were a win, a loss and a tie.

Figure 1. *User training with the Puzzle game app (left). Graphical user interface of the Tic-Tac-Toe game (right). Modified from [4].*

Discussion: Investigation of BCI performance and game moves confirms that the user had control over the BCI and was able to place game characters in accordance with the game rules.

Significance: Enhancing BCI training and improving social inclusion is crucial for CP users. The proposed approach combines both issues successfully.

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