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tools for brain-computer interaction

Proceedings of TOBI Workshop IV

Practical Brain-Computer Interfaces for End-Users: Progress and Challenges

Sion, Switzerland, January 23-25, 2013

SEVENTH FRAMEWORK PROGRAMME

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Local Organising Staff:

Nancy-Lara Millán, Robert Leeb, José del R. Millán,
Najate Guechoul, Tom Carlson, Aleksander Sobolewski,
Andrea Biasiucci, Marco Creatura, Serafeim Perdikis, Luca Tonin.

Preface

The brain–computer interface (BCI) technology uses brain signals to directly drive external devices. Over the past decade, BCIs have begun to provide basic communication and motor control abilities to people with severe motor disabilities, thus offering a unique opportunity to improve their quality of life.

The European TOBI project (www.tobi-project.org), and similar efforts worldwide, promised to push the field forward, from laboratory to home environments, from research experimental setups to real-world prototypes, and from healthy participants to end-user studies. Progress along all these lines has been made, mainly because of a holistic user-centered approach and the integration of novel research components in areas such as hybrid BCI, online adaptation and mental states, as well as human-computer interaction. Yet, we are still facing challenges in bringing BCI to end-users for their daily use.

Goals of this workshop

The 4th and final TOBI workshop seeks to bring together all researchers, rehabilitation professionals, clinicians, and potential end-users in the field of BCI to share their progress, experience and prospects in practical BCIs for the end-users. We are thus soliciting contributions reporting progress in end-user studies as well as basic research facing the challenges in bringing BCI to end-users for their daily use.

Topics of interest, but not limited to, include:

- End-user studies and experiences with BCI technology
- User-centered approaches and user training
- Development and benefits of hybrid BCIs
- Online adaptation and monitoring of mental states
- Ethical issues in BCIs
- Technology transfer to industrial products
- Human-computer interaction
- Novel BCI principles and paradigms

Proceedings

These proceedings contain all contributions to the 4th TOBI Workshop that were accepted for presentation. All contributions were reviewed by independent reviewers. The submissions with the highest review scores and aligned with the workshop goals were assigned to an oral presentation.

Reviewers were selected among members of the partners' institution:

- Ecole Politechnique Fédérale de Lausanne, Lausanne, Switzerland
- Technical University of Berlin, Berlin, Germany
- Graz University of Technology, Graz, Austria
- Fondazione Santa Lucia, Rome, Italy
- University Clinics, Heidelberg, Germany
- University of Glasgow, Glasgow, Scotland
- AIAS, Bologna, Italy
- Clinique Romande de Réadaptation, Sion, Switzerland
- University of Würzburg, Würzburg, Germany

We would like to thank all reviewers for their valuable contribution. In particular, we thank the Ricardo Chavarriaga, Tom Carlson, Aleksander Sobolewski, Maria Laura Blefari and Robert Leeb for the second round of reviews to help authors address reviewers' comments.

We hope you enjoy the 4th TOBI Workshop 2013 in Sion!

The Organizing Committee

Nancy-Lara Millán, Najate Guechoul, Robert Leeb, José del R. Millán.

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Poster session 2 (Thu Jan. 24, 2013 / 14:00-15:30)

Keynote Speakers

1. Grégoire Courtine

Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland

"Neuroprosthetic Technologies to restore Motor Functions after Severe Paralysis"

Grégoire Courtine was trained in Mathematics and Physics, but received his PhD degree in Experimental Medicine from the Inserm Plasticity and Repair, France, in 2003. After a Post-doctoral training at the University of California (UCLA), he established his own laboratory at the university of Zurich in 2008. He recently accepted the International paraplegic foundation (IRP) chair in spinal cord repair in the center for neuroprosthetics at the Swiss Federal Institute of Technology, Lausanne (EPFL).

Over the past 15 years, Grégoire Courtine has implemented an unconventional research program with the aim to develop a radically new treatment paradigm to restore motor function in severely paralyzed people. Recently, he introduced a combinatorial intervention that restored supraspinal control over complex locomotor movements in rats with a spinal cord injury leading to permanent paralysis. The first testing in a paraplegic man suggested that this therapeutic approach may restore some degree of function in humans with severe paralysis. He received numerous honors such as the UCLA Chancellor's award, the Schellenberg Prize for his advances in spinal cord repair, and a fellowship from the European Research Council (ERC). Several of his works received substantial press coverage in the national and international media, including radio stations and TV channels from different countries worldwide.

Relevant references

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Dominici N, Keller U, Vallery H, Friedli L, van den Brand R, Starkey ML, Musienko P, Riener R, Courtine G (2012) Novel robotic interface to evaluate, enable, and train locomotion and balance after neuromotor disorders. Nature Medicine.

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Courtine G., Gerasimenko Y. P., van den Brand R., Yew A., Musienko P., Zhong H., Song B., Ao Y., Ichyama R., Lavrov I., Roy R. R., Sofroniew M.V., Edgerton V.R. (2009) Transformation of nonfunctional spinal circuits into functional and adaptive states after complete loss of supraspinal input Nature Neuroscience. 12(10):1333-1442.

Courtine G, Song B, Roy RR, Zhong H, Edgerton VR, Sofroniew MS (2008) Recovery of supraspinal control of stepping mediated by indirect propriospinal relay connections after severe spinal cord injury. Nature Medicine. 14: 69-74.

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2. Niels Birbaumer

University of Tübingen, Tübingen, Germany

"Brain Machine Interfaces in Paralysis"

Niels Birbaumer is Professor and Director of the Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Faculty of Medicine as well as the director of the Magnetoencephalography (MEG)-Center. His research interests are wide-ranging. Among other things he is dealing with neuronal plasticity and learning, with aspects of epilepsy, of Parkinson's disease and pain disorders. Prof. Birbaumer also conducts research on brain-computer interfaces (brain-computer interfaces , BCI), which should make it possible to exchange information without the use of the limb between the brain and machines. This research is intended as patients with end-stage amyotrophic lateral sclerosis (ALS) allow to communicate in spite of complete paralysis with their environment.

Professor Birbaumer obtained his Ph.D. degree in psychology from the University of Vienna in 1969. Since then he has had a very active and prolific research carreer represented amongst other by the prices and awards listed below.

Prizes and awards recipient

1985: the Roemer Award for outstanding scientific achievements in Psycho-somatic Medicine (DKPM)

1992 and 1999: Award of the Deutsche Gesellschaft zum Studium des Schmerzes for Research on the Treatment of Chronic Pain (together with H. Flor) and Experiments on Neural Pain Mechanisms

1993: full member in the Academy of Sciences and Literature.

1994: Nordmark Neuropharmaka Award for Behavioral Research in Parkinson's disease

1995: Gottfried Wilhelm Leibniz Prize award & Psychologie-Preis of the Deutsche Gesellschaft für Psychologie (DGfP) and the Christoph-Dornier-Stiftung.

1996: Distinguished Scientist Award of the American Association for Applied Psychophysiology and Biofeedback

2000: the Wilhelm Wundt Medal of the German Society for Psychology; award for Research in Neuromuscular Diseases of the Deutsche Gesellschaft für Muskelkranke & Sertürner Preis, Mundipharma, for research on pain treatment with opiates.

2001: Albert-Einstein-World-Award of Science of the World Cultural Council

2003: he was elected a member of the Leopoldina

2009: Distingiushed Scientist Award of the Society of Psychophysiological Research (SPR)

2010: awarded the Helmholtz Medal of the Berlin-Brandenburg Academy of Sciences Award, which is awarded every two years to an outstanding scientist .

For further detail on his biography, please refer to http://www.mp.uni-tuebingen.de/mp/index.php?id=62

3. José L. Pons

Spanish Council for Scientific Research (CSIC), Madrid, Spain

"Multimodal BNCIs: Sourcing Information from Motor Planing through Motor Execution. The Case of Suppression of Pathological Tremor"

Prof. José L. Pons obtained his PhD in Physics, Universidad Complutense Madrid, in 1997. In 1998 he was appointed as Postdoctoral Fellow at the Institute for Industrial Automation of the Spanish Council for Scientific Research, CSIC. In 1999 he was awarded a position as Tenured Scientist, in 2007 a position as Research Scientist and, eventually, in 2008 a position as Full Professor, all of them at CSIC.

Prof. Pons has published along the last ten years over 80 articles in highly ranked international journals in Robotics (Robotica, Autonomous Robots, Mechanism and Machine Theory), Smart Materials, Sensors and Actuators (Sensors and Actuatos A & B, Journal of the European Ceramic Society, Bol. Soc. Esp. Cerám. V., Journal of Electroceramics, IEEE Trans. on Ultr., Ferr., and Freq. Contr.), Neuroscience (The Cerebellum, Eur. J. Neurol.), Physiology (IEEE Engineering in Medicine and Biology magazine, Physiological Measurement, Medical Biological Engineering & Computing, Technology and Health Care) or Biomechanics (Gait & Posture, Applied Bionics and Biomechanics). His current interests are Neurorehabilitation, Rehabilitation Robotics and Neuroprosthetics.

TOBI Invited Speakers and Committee Members

1. TOBI Invited Speakers

G. R. Müller-Putz – Institute for Knowledge Discovery, Graz University of Technology, Graz, Austria
"Hybrid Brain-Computer Interfaces: Technology and Current and Future Applications"

J. Williamson – University of Glasgow, Glasgow, UK
"Designing for Unreliable Input Channels"

M. Tangermann – Technische Universität Berlin, Berlin, Germany
"Machine Learning as a Key Technology for BCI"

D. Mattia – IRCCS Fondazione Santa Lucia, Rome, Italy
"Harnessing Hybrid Brain-Computer Interactions for Stroke Rehabilitation"

R. Rupp – University Hospital, Spinal Cord Injury Center, Heidelberg, Germany
"BCIs for Control of Upper Extremity Neuroprostheses - Facts, Challenges and Visions"

A. Kübler - University of Würzburg, Würzburg, Germany
"Bridging Gaps: the User-centered Design for Bringing BCI to End-users"

A. Al-Khodairy – Clinique Romande de Réadaptation SUVACARE, Sion, Switzerland
"Brain-Computer Interfaces: A Rehabilitation Team Perspective"

J.d.R. Millán – CNBI, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland
"Design Principles for Neuroprosthetics"

2. Program Committee

José del R. Millán – Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland
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Andrea Kübler – University of Würzburg, Würzburg, Germany
Roderick Murray-Smith – University of Glasgow, UK
Klaus-R. Müller – Technische Universität Berlin, Berlin, Germany
Michael Tangermann – Technische Universität Berlin, Berlin, Germany
Rüdiger Rupp – University Hospital, Spinal Cord Injury Center, Heidelberg, Germany
Abdul Al-Khodairy – Clinique Romande de Réadaptation SUVACARE, Sion, Switzerland
Evert-Jan Hoogerwerf – AIAS, Bologna, Italy
Elizabeth Hildt – Eberhard-Karls Universität Tübingen, Tübingen, Germany
Peter Schoenknecht – Medel GmbH, Hamburg, Germany

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4. Local Organizing Staff

Nancy-Lara Millán, Robert Leeb, José del R. Millán, Najate Guechoul, Tom Carlson, Aleksander Sobolewski, Andrea Biasiucci, Marco Creatura, Serafeim Perdikis, Luca Tonin.

Agenda

Wednesday, January 23, 2013

Time	Title
08:30-09:00	**Registration**
09:00-09:30	**Opening: welcome and general information:** Prof. José del R. Millán - *Ecole Polytechnique Fédérale de Lausanne, Lausannne, Switzerland* Dr. Abdul Al-Khodairy - *Clinique Romande de Réadaptation SUVACARE, Sion, Switzerland*
09:30-10:15	**Keynote: Prof. G. Courtine** - *Ecole Polytechnique Fédérale de Lausanne, Lausannne, Switzerland* Neuroprosthetic Technologies to restore Motor Functions after Severe Paralysis
10:15-10:45	**Coffee Break**
10:45-11:05	Hybrid Brain-Computer Interfaces: Technology and Current and Future Applications *G. R. Müller-Putz - Institute for Knowledge Discovery, Graz University of Technology, Graz, Austria*
11:05-11:25	Assessing the User Experience with Hybrid BCIs R. Lorenz - *Berlin Institute of Technology, Berlin, Germany*
11:25-11:45	Towards a Hybrid Control of a P300-based BCI for Communication in Severely Disabled End-users *A. Riccio - IRCCS Fondazione Santa Lucia, Rome, Italy*
11:45-12:05	The Riemannian Potato: an Automatic and Adaptive Artifact Detection Method for Online Experiments using Riemannian Geometry *A. Barachant - Team ViBS (Vision and Brain Signal Processing), GIPSA-lab, CNRS, Grenoble University, France*
12:05-12:35	Designing for Unreliable Input Channels *J. Williamson - University of Glasgow, Glasgow, UK*
12:45-14:00	**Lunch**
14:00-15:30	**Poster Exhibition I and Industrial Exhibition**
15:30-16:00	**Live Demos**
16:00-16:30	**Coffee Break**
16:30-16:50	Online Covert Visuospatial Attention based BCI: A Study with Neutral Background and Natural Images *L. Tonin - CNBI, Ecole Polytechnique Fédérale de Lausanne, Lausannne, Switzerland*
16:50-17:10	Evaluation of Three BCI-controlled AT Devices in a Highly Paralyzed End User *M. Rohm - University Hospital, Spinal Cord Injury Center, Heidelberg, Heidelber, Germany*
17:10-17:30	An Adaptive Bandit Procedure to Explore User-specific Motor Imagery Tasks *M. Clerc - Athena, INRIA Sophia Antipolis, France*
17:30-17:50	Machine Learning as a Key Technology for BCI *M. Tangermann - Berlin Institute of Technology, Berlin, Germany*
18:00-20:00	**Aperitif**

Thursday, January 24, 2013

Time	Title
09:00-09:45	**Keynote Lecture: Niels Birbaumer** - *Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Germany* Brain Machine Interfaces in Paralysis
09:45-10:05	Harnessing Hybrid Brain-Computer Interactions for Stroke Rehabilitation *D. Mattia - IRCCS Fondazione Santa Lucia, Rome, Italy*
10:05-10:25	How to decrease BCI Performance Variability? A Machine Learning Approach Applied to End-user Data. *M. Schreuder - Berlin Institute of Technology, Berlin, Germany*
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11:00-11:20	BCIs for Control of Upper Extremity Neuroprostheses - Facts, Challenges and Visions *R. Rupp - University Hospital, Spinal Cord Injury Center, Heidelberg, Germany*
11:20-11:40	Sensorimotor Oscillatory Reactivity of the Stroke Affected Hemisphere is increased by EEG-based BCI Training: A Study in Subacute Patients *M. Petti - IRCCS Fondazione Santa Lucia, Rome, Italy*
11:40-12:00	Brain Controlled Functional Electrical Stimulation for Motor Recovery after Stroke *A. Biasiucci - CNBI, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland*
12:00-12:20	A Preliminary Fundamental Study of Ambulatory SSVEP *M. Duvinage - TCTS Lab, University of Mons, Belgium*
12:20-12:40	Bridging Gaps: the User-centered Design for Bringing BCI to End-users *A. Kübler - University of Würzburg, Würzburg, Germany*
12:45-14:00	**Lunch**
14:00-15:30	**Poster Exhibition II and Industrial Exhibition**
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16:20-16:40	Bridging Gaps: Long-Term Independent BCI Home-Use by a Locked-In End-User *E.M. Holz - Institute of Psychology, University of Würzburg, Würzburg, Germany*
16:40-17:00	Two Approaches to Communicate with Patients in Minimally Conscious State *C. Pokorny - Graz University of Technology, Graz, Austria*
17:00-17:20	Information Processing in Patients with Chronic and Severe Disorders of Consciousness *R. Real - University of Würzburg, Würzburg, Germany*
17:20-17:40	The Importance of User-centred Design in BCI Development: A Case Study with a Locked-in Patient *T. Kaufmann - University of Würzburg, Würzburg, Germany*
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Friday, January 25, 2013

Time	Title
09:00-09:45	**Keynote Lecture: J. L. Pons** - *Spanish Council for Scientific Research (CSIC), Madrid, Spain* Multimodal BNCIs: Sourcing Information from Motor Planning through Motor Execution. The Case of Suppression of Pathological Tremor
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10:05-10:25	A Hybrid BCI for Telepresence *T. Carlson - CNBI, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland*
10:25-11:00	**Coffee break**
11:00-11:20	A tactile P300-BCI for Communication *R. Ortner - g.tec Guger Technologies OG, Austria*
11:20-11:40	A 2D Cursor Control Based Brain-Computer Interface Speller *B. Xia - Shanghai Maritime University, Shanghai, Shanghai, China*
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3	Offline Muscle Synergies Decoding from EEG *N. Beuchat, R. Chavarriaga, S. Degallier, J. d. R. Millán*
4	Asking the Practioneers – Requirements Concerning a New EEG-based Diagnostic Battery *H. Erlbeck, A. Kübler*
5	A Pilot Study on Mental Workload Detection during Operation of a Self-paced ERD BCI *J. Faller, G. Bauernfeind, R. Scherer, G.R. Müller-Putz*
6	Connecting the Disabled to their Physical and Social World:The BrainAble Experience *J.M. Fernández, S. Dauwalder, S. Torrellas, J. Faller, R. Scherer, P. Omedas, P. Verschure, A. Espinosa, C. Guger, C. Carmichael, U. Costa, E. Opisso, J.M. Tormos, F. Miralles*
7	Spatio-temporal Discriminant Analysis for ERPs using Inverse Solution *M. K. Goel, R. Chavarriaga, M. Ušcumlic, J.d.R. Millán*
8	Freeing the Visual Channel – Feeling the BCI Vibe! *K. Gwak, R. Leeb, D-S. Kim, J.d.R. Millán*
9	A Portable Auditory P300 BCI using Directional Cues and Natural Stimuli *S. Halder, N. Simon, C.A. Ruf, I. Käthner, E. Pasqualotto, A. Kübler, N. Birbaumer*
10	Increasing Tactile ERP-BCI Performance using Generic Models *A. Herweg, T. Kaufmann, A. Kübler*
11	Extraction of Oscillatory EEG during Palm and Finger Movements *S. Kanoh, R. Scherer, K. Miyamoto, T. Yoshinobu*
12	A BCI using Electrocorticographic VEPs *C. Kapeller, R. Prückl, R. Ortner, C. Guger*
13	Face Stimuli Prevent ERP-BCI Inefficiency in users with Neurodegenerative Disease *T. Kaufmann, S. M. Schulz, A. Köblitz, G. Renner, C. Wessig, A. Kübler*
14	Empathy and Motivation in BCI performance *S. C. Kleih, N. Grüneberg , A. Kübler*
15	Sensitivity and Specificity of the Studentized Continuous Wavelet Transform for ERP Detection – A Simulation Study *R. Real, S. Veser, B. Kotchoubey, A. Kübler*
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17	Non-invasive Decoding of Hand Movements from Brain Signals - Influence of Execution Velocity *M. Schneiders, R. Rupp*
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20	Using random forests for classifying motor imagery EEG *D. Steyrl, R. Scherer, G. R. Müller-Putz*
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23	Robust User Interfaces for Motor Imagery Channels *J. Williamson*

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2	Brains of Proficient and Less than Proficient BCI Users: Is there a Difference? *M.L. Blefari, R. Martuzzi, A. Sobolewski, O. Blanke, J. d. R. Millán*
3	Wavelet Tools for the Detection of Error-related Potentials *P. Borsò, R. Chavarriaga, J. d. R. Millán*
4	Relaxation Exercise improves SMR-BCI Performance *L. Botrel, L. Acqualagna, B. Blankertz, T. Kaufmann, A. Kübler*
5	P300-speller Adaptivity to Change with a Backspace Key *E. Daucé, T. Proix*
6	Effects of Attention and Passiveness on Event-related Potentials *H. Erlbeck, A. Kübler, B. Kotchoubey, S. Veser*
7	Steering Timing Prediction in a Driving Simulator Task *L. A. Gheorghe, R. Chavarriaga, J.d.R. Millán*
8	Hybrid-P300 BCI: Usability Testing by Severely Motor-restricted End-Users *E.M. Holz, A.Riccio, J. Reichert, F. Leotta, P. Aricò, F. Cincotti, D. Mattia, A. Kübler*
9	Comparison of Asynchronous SSVEP-based BCI Detection Approaches for Assistive Technologies *D. Ibanez, A. Soria-Frisch*
10	Towards Realtime Detection of Anticipatory Brain Potentials *Z. Khaliliardali, R. Chavarriaga, L. A. Gheorghe, J.d.R. Millán*
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14	Designing Wearable BCIs: A Software Framework *A. Ottaviani, C. Breitwieser, A.Kreilinger, M. Tavella, M. Rohm, M. Schreuder, R. Leeb, J.d.R. Millán, G.R. Müller-Putz, R. Rupp, F. Cincotti*
15	Effects of Adaptation Intensity in Motor Imagery BCI *S. Perdikis, R. Leeb, J.d.R. Millán*
16	Attention and P300-based BCI Performance in People with Amyotrophic Lateral Sclerosis *A. Riccio, L. Simione, F.Schettini, A. Pizzimenti, M. Inghilleri, M. Olivetti, D.Mattia, F. Cincotti*
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18	Evaluation of MI-BCI Performance in Ten Spinal Cord Injured End Users *M. Rohm, M. Schneiders, R. Rupp*
19	Prediction of Fast and Slow Delivery of Mental Commands in BCI *S. Saeedi, R. Chavarriaga, J.d.R. Millán, M.C. Gastpar*
20	The Concept of ECG-based Hybrid BCI *S. Shahid, A. Ramsay, M. Quek, R. Murray-Smith*
21	Error Processing of Self-paced Movements *A. Sobolewski, R. Chavarriaga, J. d. R. Millán*
22	Liquid Cursor for Multimodal Funnel Display of SMR modulation *T. Sollfrank, A. Ramsay, S. Perdikis, J. Williamson, R. Murray-Smith, R. Leeb, A. Kübler*
23	Fixed-Sequence Stimulus Presentation in ERP-BCI *M. Tangermann, J. Höhne, M. Schreuder*
24	Predict Driver's Turning Direction through Detection of Error Related Brain Activity *H. Zhang, R. Chavarriaga, L. A. Gheorghe, J.d.R. Millán*

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Assessing the User Experience with Hybrid BCIs

R. Lorenz[1], J. Pascual[1], B. Blankertz[2], C. Vidaurre[1]
[1]*Machine Learning Group;* [2]*Neurotechnology Group, Berlin Institute of Technology, Berlin, Germany*

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Abstract. Within the context of the MUNDUS project [Pedrocchi et al., 2010], three graphical user interfaces (GUIs) were designed for their prospective use in controlling a brain-computer interface (BCI)-driven upper-limb neuroprosthesis. The action selection was divided into two stages: selection and confirmation that were controlled using event-related potentials (ERP) or motor imagery (MI). By assessing pragmatic as well as hedonic quality aspects of User Experience (UX), the study attempts to bridge the existing gap of proper UX evaluations in current BCI research [Plass-Oude Bos et al., 2011]. The in-depth comparison of UX between two hybrid BCIs and a conventional BCI approach provided valuable insights into the underlying dynamics causing the users' experience to differ across the GUIs.

Keywords: User Experience, Usability, User-Centered, Hybrid BCI, Motor Imagery, ERP, Neuroprosthetics

1. Introduction

In contrast with the consistent increase of UX evaluations in the field of human-computer interaction, a user-centered perspective in the field of BCI assistive devices for patients is only scarcely adopted. Most BCI systems are exclusively evaluated in terms of classification accuracy and speed [Pasqualotto et al., 2012]. Besides including these common efficiency measures, the evaluation of further usability aspects such as ease of use, learnability and mental workload (hereinafter referred to as pragmatic quality of UX) could improve user efficiency and satisfaction [Plass-Oude Bos et al., 2011]. In order to gain a holistic perspective on UX, hedonic quality aspects [Hassenzahl, 2005] have also been taken into account. Measuring UX and improving BCIs accordingly could boost user acceptance, enjoyment and BCI task performance [Plass-Oude Bos et al., 2011]. That this is not just important concerning BCIs for entertainment can be construed from a study with ALS patients [Nijboer et al., 2010] in which motivational factors indeed seem related to BCI performance. Other studies point towards frustration as having a detrimental impact on BCI performance [Reuderink et al., 2009]. Within the context of the MUNDUS project, three different BCI interfaces were proposed for a prospective use in controlling a neuroprosthesis [Pascual et al., 2012]. By assessing the UX of the three GUIs, the present work reveals from a user's perspective whether one of the interfaces is most suitable for this application.

2. Material and Methods

Twelve healthy subjects (6 female; mean age: 26.2 ± 2.9 years) took part in the one-session study. Brain activity was recorded from the scalp with multichannel EEG amplifiers using an active electrode system with 64 electrodes placed according to the extended international 10-20 system (Fp1,2;AF3,4,7,8;Fz; F1-10;FCz;FC1-6; FT7,8;T7,8;Cz;C1-6;TP7,8;CPz;CP1-6;Pz;P1-10;POz;PO3,4,7,8;Oz and O1,2). First, the participants performed an ERP and MI calibration to compute one classifier for each paradigm. This was followed by a feedback recording, in which three different GUIs were presented to the subjects in a randomized order. The task for each GUI consisted of a two-stage action-selection task. First, subjects selected one of six symbols representing possible actions executed by a neuroprosthesis, and then users had to confirm or cancel this selection. For the experiment, a solely ERP-based and two hybrid combinations were tested (see Fig. 1): (1) selection with ERP, confirmation with ERP (ERP-ERP), (2) selection with ERP, confirmation with MI (ERP-MI), (3) selection with MI, confirmation with ERP (MI-ERP). For the assessment of UX, the NASA-TLX [Hart and Staveland, 1988] and the User Experience Questionnaire [UEQ; Laugwitz et al., 2008] were administered after each GUI. The UEQ contains the three dimensions attractiveness, use (pragmatic) quality and design (hedonic) quality.

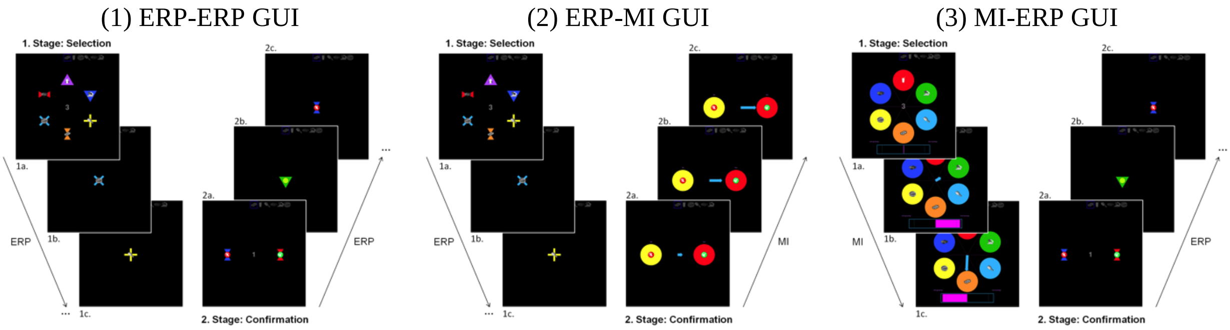
3. Results

NASA-TLX and UEQ scores were analyzed using one-way repeated measures ANOVAs (α-level: 0.05). Due to one subject's inability to control either one of the hybrid GUIs and another participant's loss of control over the MI-ERP GUI, two subjects were excluded for the analyses. NASA-TLX results showed a significant effect of workload ($F_{(2, 18)}$ = 19.627, $p < .001$). The lowest workload score was reached by the ERP-ERP GUI (28.83; NASA-TLX scale: 0 to 100), followed by the ERP-MI GUI (35) while the MI-ERP GUI achieved the highest workload score (62.5).

Dimension scores of UEQ

Dimension	*ERP-ERP*	*ERP-MI*	*MI-ERP*
Attractiveness	1.73	1.45	0.6
Use Quality	1.83	1.33	0.79
Design Quality	1.48	1.53	1.33

Post-hoc tests using the Bonferroni correction revealed a significant difference between the ERP-ERP and MI-ERP GUI (p = .002) as well as between the ERP-MI and MI-ERP GUI (p = .005). The highest overall UEQ score was attained by the ERP-ERP GUI (1.69; UEQ scale: -3 to +3), followed by the ERP-MI GUI (1.42) and the MI-ERP GUI (0.91). This effect was also found to be significant ($F_{(2, 18)}$ = 4.003, p = .036). Post-hoc tests indicated no specific pairwise differences between the GUIs. Regarding the dimensions attractiveness and use quality, the ERP-ERP GUI again scored the highest and the MI-ERP GUI the lowest (Table 1). A significant effect was found for both dimensions (attractiveness: $F_{(2, 18)}$ = 5.264, p = .016; use quality: $F_{(2, 18)}$ = 4.913, p = .020). Post-hoc tests unveiled that solely the difference between the ERP-ERP and MI-ERP GUI was statistically significant (attractiveness: p = .041; use quality: p = .038). For the dimension design quality no significant difference was observed ($F_{(2, 18)}$ = 0.408, p = .671, *n.s.*).



ERP: *For the ERP trials the symbols were presented repeatedly in a sequential fashion at a single central position of the screen.* ***MI:*** *For MI selection the six symbols were equidistantly distributed in a circle on the screen. By exceeding the thresholds of the power bar the subject could rotate the arrow until reaching the desired action, and then increase its length to select it. For the second stage, the OK and CANCEL symbols appeared randomly on each side of the screen, and the direction and length of the arrow was controlled through the output of the MI classifier.*

4. Discussion

The results clearly show that both the conventional ERP-based approach and the hybrid ERP-MI interface surpassed the MI-ERP GUI in terms of pragmatic quality aspects of UX. Both GUIs were perceived as less mentally demanding (NASA-TLX), more easy and efficient to use and more easy to learn (use quality items). Alongside these findings all three GUIs seem equally exciting, interesting and motivating to the user (design quality items). Hence, the MI-ERP GUI might be more appropriate for a BCI gaming application than for its use in a neuroprosthesis. The best overall results were achieved with the conventional non-hybrid approach.

Acknowledgements:

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Towards a *Hybrid* Control of a P300-based BCI for Communication in Severely Disabled End-users

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Abstract. A hybrid (electromyographic, EMG) control devoted to the correction of spelling errors was introduced in a previously implemented P300-based BCI system designed to control an assistive technology software (Riccio et al., 20111; Zickler et al., 2011). The *hybrid* version of such system would provide severly disabled end-users with a way to exploit not otherwise functionally reliable residual muscular activity. Six healthy subjects and one severly motor impaired end-user participated to the system testing. Preliminary findings are in favour of the superiority in *efficiency* of the *hybrid* control with respect to the *no-hybrid* (only BCI-based) as indicated by the observed improvement of the performance (expressed as time for selction and number of errors) that was associated with a decrease of the system usage frustration perceived by the users.

Keywords: Brain computer interface, Hybrid, Electromyography, Event related potential, Communication

1. Introduction

1.1 The Hybrid BCI

A hybrid Brain Computer Interface (BCI) is a BCI combined with at least one other system or device enabling people to send information (Müller-Putz et al., 2011). In a previous study, we reported on a developed system in which a P300-based BCI was combined with a QualiWorld Assistive Technology (QW) software for communication and environmental control (Riccio et al., 2011). Such BCI-based system was successfully tested with severely disabled potential end-users (Zickler et al., 2011) and according to their feedbacks on system's usability, we endowed the system with a *hybrid* control that subserved the function of deleting uncorrected selections by means of electromyographic (EMG) signal generated by the end-user's residual muscular activity.

2. Material and Methods

2.1. Participant

Six healthy volunteers (3 males, 3 females; mean age 30) and one severely disabled end-user (female, 48 year old) participated to the study. The end-user, had tetraplegia with severe dysarthria due a brainstem ischemic stroke and she could communicate her primary needs only with the support of the caregivers.

2.1. Hybrid system

To fully adhere to a user-centered design, the *hybrid* system is adaptable to several degrees of residual motor activity and the customization of the EMG control channel is obtained during a screening session wherein the end-users' target muscle is identified on the basis of their residual functional voluntary movements. For the same reason the visual stimuli eliciting P300 are adaptable to user's needs in terms of shape, colors, dimension and position (Holtz et al., 2013). The visual stimulation is overlaid on top of the QW window through a proxy and the system is based on the TOBI common implementation platform both for the biosignal acquisition (signal server) and for the exchange of messages (Breitwieser et al., 2012).

2.3. Protocol and Data Acquisition

A calibration session was performed in order to define the EMG control features, such as the onset and offset of signal amplitude thresholds and the optimal time window for the EMG signal onset and offset to occur in order to operate the delete command. The same session was also devoted to identify the best stimulation modality (least number of sequences needed to achieve the 100% offline accuracy) within four stimuli changing for shapes (dot vs. grid) and colors (red vs. green) (Holtz et al., 2013). In a different session, participants were asked to spell online three predefined words (21 characters) using the system under two conditions: *(i) No-hybrid task*: uncorrected letter selections were deleted by means of the BCI control operating a backspace command integrated in the QW virtual keyboard; *(ii) Hybrid task*: the errors were canceled by exploiting the EMG control signal; in case of failure, the user had to delete the wrong letter as in the previous condition. For between conditions comparative purposes, the number of sequences of stimulation was set at the minimum number of sequences needed by a given user to reach 80% of accuracy in order to artificially introduce spelling errors in a controlled manner. EEG and EMG signals were acquired using 8 EEG (Fz, Cz, Pz, Oz, P3, P4, Po7, Po8) and 2 EMG active electrodes, respectively. All EEG channels were referenced to the right earlobe and grounded to the left mastoid, amplified using a g.tec USB amplifier (Graz, Austria) and recorded by the BCI2000 software.

2.4. Data Analysis

The *efficiency* of the *hybrid* BCI-system was evaluated in terms of performance estimated as *i)* time for selection (*TIME*; ratio between the total time to successfully complete the task and the minimum number of selections needed to execute it); percent of errors (*ERRORS*; ratio between the number of BCI errors and the total number of BCI selections) and users *FRUSTRATION* (as a workload factor by means of the NASA-tlx). The comparison between the two modalities was performed by means of a non-parametric Wilcoxon test.

3. Results

As shown in Figure 1, the *efficiency* of the *hybrid* BCI-system was higher as compared to that of the *no-hybrid* system version, as indicated by the significantly lower scores relative to *TIME* and *ERRORS* obtained in the *hybrid task* ($p < 0.05$) with respect to those observed in the *no-hybrid task*. Further, the level of *FRUSTRATION* perceived by the healthy users resulted significantly lower for the *hybrid* condition ($p<0.05$). The end-user achieved *TIME* and *ERRORS* mean values lower in the *hybrid task* (*TIME*=19.13 sec; *ERRORS*=19.3%) as compared to the *no hybrid task (TIME*=34.8 sec; *ERRORS*=33.9%). The perceived *FRUSTRATION* was also lower while using the *hybrid* modality function (3.3) with respect to the *no-hybrid* (4.6).

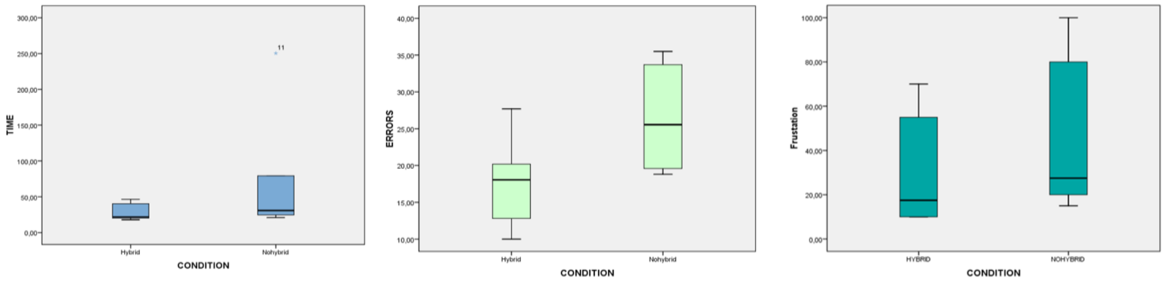

Figure 1. *Plots showing statistic comparison between the "hybrid task"and the "no-hybrid task" on the time of selection (TIME), percentage of errors (ERRORS) and perceived frustation (FRUSTRATION).*

4. Discussion

These preliminary findings support the initial assumption that the integration of the EMG channel into the system would yield to an improvement of the system *efficiency*, as indicated by the significant decrease of the *time for selection* and of the *percentage of errors* in an on line spelling task performed under the *hybrid* and *no-hybrid* task modality. One can speculate that the observed decrease of the *percentage of errors* under the *hybrid* task might be ascribed to a reduced psychological demand of the BCI-based spelling letters due to the possibility of correcting errors by exploiting the EMG channels. The lower level of perceived *frustration* associated with the *hybrid* task could be a consequence of the performance enhancement. The similarity in the system usage performance showed by the end-user corroborates the added value of the hybrid control concept. In severely disabled end-users, the residual muscular activity could be indeed, easily fatigable or not reliable and consequently not functionally useful to operate a control of a standard assistive device.

Acknowledgements

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The Riemannian Potato: an Automatic and Adaptive Artifact Detection Method for Online Experiments using Riemannian Geometry.

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Abstract. Artifacts management is a critical problem in any applications involving on-line processing of EEG signals. This paper presents a multivariate automatic and adaptive method for identifying artifacts in continuous EEG data.

Keywords: EEG, Artifact detection, Riemannian geometry, BCI.

1. Introduction

In this work we consider as artifacts any kind of EEG signal different enough as compared to the normal baseline signal. Based on this new definition, covariance matrices are used as descriptors of EEG signals and a Riemannian metric is employed to compare these covariance matrices with an average covariance matrix estimated on the signal baseline. This framework is not specific to a particular kind of artifacts and allows us to take into account the spatial properties of the artifacts. A practical implementation of this method will be described, and results of the online detection will be shown.

2. Methods

The goal of the detection algorithm is to determine if a portion of EEG signal $X \in \Re^{N \times T}$ recorded during a time window of T samples over N electrodes contains artifacts. In order to achieve this, a trial X will be represented by its spatial covariance matrix $C = \frac{1}{T-1} XX^T$ and the criterion for the detection will be based on a Riemannian distance computation. The main idea is to estimate a reference covariance matrix $\overline{C}$ and reject every trial which is too far, in term of Riemannian distance, from this reference matrix. The Riemannian distance between C and $\overline{C}$ is defined by [Förstner and Moonen, 1999]:

$$d_R(C, \overline{C}) = \sqrt{\sum_{n=1}^{N} \log^2(\lambda_n)} \quad (1)$$

with λ_n the eigenvalues of $C^{-1/2} \overline{C} C^{-1/2}$. The trial corresponding to C will be considered as an artifacts if d_R is greater than a threshold th. Thus, the detection algorithm requires two parameters: $\overline{C}$, the reference point in the Riemannian manifold and the threshold th for the detection. The estimation of those two parameters is the important part of the algorithm. The reference point could be estimated in an adaptive manner during the whole recording session according to the following equation:

$$\overline{C}_{t+1} = (\overline{C}_t)^{1/2} \left[(\overline{C}_t)^{-1/2} C (\overline{C}_t)^{-1/2} \right]^{1/\alpha} (\overline{C}_t)^{1/2} \quad (2)$$

with $\overline{C}_t$ the reference matrix from the previous iteration, C the current covariance matrix and α a coefficient which defines the speed of the adaptation. This adaptation is done only when clean signal is detected, i.e., the distance is lower than the threshold. The threshold th is estimated based on the mean μ and standard deviation σ of the distance to the reference matrix defined in Eq. 1 :

$$th = \mu + 2.5\sigma \quad (3)$$

These two parameters define a region of interest in the Riemannian manifold. Since the Riemannian metric is non-linear, this region of interest corresponds to a “potato” in the Riemannian manifold. Fig. 1 shows the potato for a dataset of 100 2x2 covariance matrices on simulated data.
Each point represents a covariance matrix in the manifold. The big black point corresponds to the reference matrix and the grid represents the edge of the potato where the Riemannian distance to the reference point is equal to *th*.

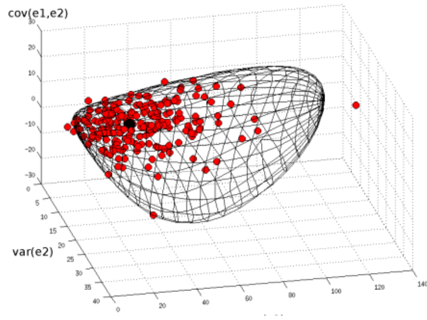

Figure 1: Riemannian potato for a set of 100 2x2 covariance matrices on simulated data.

3. Results

This algorithm was implemented in the OpenViBE software [Renard et al., 2010], and applied during a P300 experiment. EEG signals were recorded using a g.tec amplifier and 16 dry active electrodes. After a bandpass filtering (1-20Hz), signals are epoched using a sliding window of 1s (with a step of 100ms). The parameter α of the adaptation is set to 100, and the initialization of the reference point is done at the beginning of the session, where the user is instructed to stay still for 10 seconds.

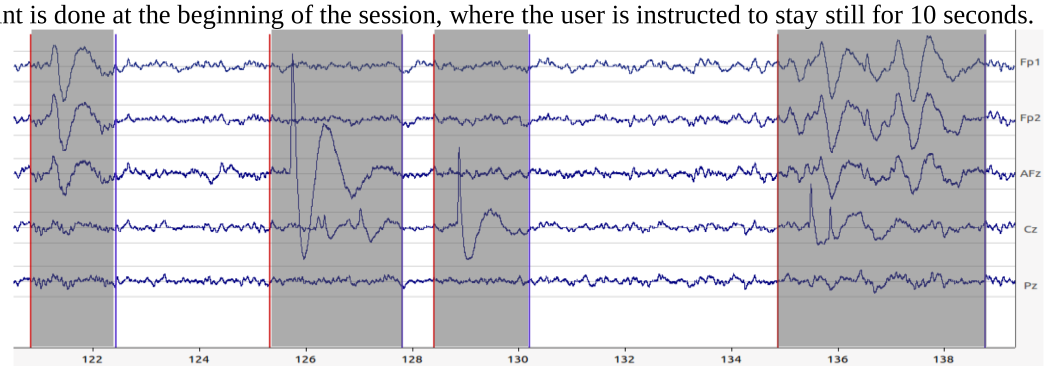

Figure 2: Results of the online detection for 20 seconds of signals recorded in OpenViBE. Only 5 electrodes are shown (Fp1,Fp2, AFz,Cz, Pz) .Grey areas correspond to time intervals where artifacts were detected.

In the example Fig. 2, the potato rejects blinks (1st artifact), electrodes movements (2nd and 3rd artifacts) and eye movements (4th artifact).

4. Discussion

The efficiency of this method is based on two facts: first, we use multivariate statistics by considering the covariance matrices as EEG signal descriptors. This allows us to take into account the spatial structure of the artifacts. For this reason the artifact detection is sensitive to the correlation structure of the EEG channels. Second, by using a strategy where an artifact is everything different enough from the reference activity, the algorithm is sensitive to many kinds of artifacts. Nonetheless, the initialization of the reference point is critical for the good functioning of this algorithm and its sensitivity and specificity strictly depend upon its correct initialization and correct adaptation. On the other hand, because of the good sensitivity of the Riemannian metric, the artifacts usually lie several standard deviations away from the reference point, so the threshold estimation is not critical.

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Online Covert Visuospatial Attention based BCI: A Study with Neutral Background and Natural Images

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Abstract. The main aim of this study is to demonstrate the reliability of an online EEG based BCI using covert visuospatial attention. For this purpose the BCI system has been tested across different days and in two different conditions: with neutral background and with natural images. The achieved classification performances achieved (70.6±4.3% in average, in case of neutral background) makes this mental signal as a promising candidate for BCI control. Although the performances dropped (61.2±3.3% in average) with natural images, this was the first attempt of a comparison between these two conditions in the case of a covert visuospatial attention task.

Keywords: Covert visuospatial attention, EEG, BCI, Online

1. Introduction

Recently, several studies have started to explore covert visuospatial attention as a control signal for Brain-Computer Interfaces (BCI). These studies are mainly based on steady-state visual evoked potential paradigms [Treder et al., 2011] or on more flexible and spontaneous voluntary attention mechanisms without any external stimulation [Andersson et al., 2012]. However, the latter modality has not been yet fully explored in the case of EEG based BCIs. In [Tonin et al., 2012] we proposed a new method based on a time-dependent approach in order to enhance the classification accuracy of this particular paradigm. The main aim of the current work is to verify the aforementioned method online and furthermore to demonstrate the reliability and the robustness of this EEG based BCI. For the first time, we tested the BCI system in a more real condition wherein natural images were presented on the background of the screen. The results reported demonstrated the possibility of using this mental task as control signal for BCI.

2. Material and Methods

Eight healthy volunteers (age 29.3±4.8) participated in this study. Each subject performed two recording sessions separated by 1-2 days. The study was conducted in two conditions: covert visuospatial attention with neutral background (black) and natural images. The structure is illustrated in Table 1. Notice that the classifier was calibrated with only the first four runs from day 1 and therefore tested online across days and conditions.

Table 1. *Study structure. Between brackets the number of trials. Calibration runs were performed during day 1.*

	calibration	*day 1*	*day 2*	*total*
Neutral background	4 runs (160)	4 runs (120)	4 runs (120)	12 runs (240)
Natural images	0 runs (0)	2 runs (60)	6 runs (180)	8 runs (240)

Participants were instructed to fixate a cross in the middle of screen (for 2000 ms) and after a symbolic cue (100 ms) to focus their attention at one of the two predefined locations for 3000-5000 ms. The to-be-attended locations were defined as two circles continuously displayed at the bottom left or bottom right of the screen. During the whole trial period a black background or an image from a real environment was continuously presented according to the current condition. In the case of natural images condition they were randomly selected from a dataset with indoor pictures and they changed at beginning of each trial. At the end of the trial a red circle appeared at one of the locations (1000 ms) as feedback of the classification procedure. During the calibration, the feedback appeared always at the correct location in order to inform the subject of the end of the trial. It is worth to notice that there was no external (bottom-up) stimulation during the covert attention period but the images in the related condition.

EEG signals were acquired with an active 64-channels system at 2048 Hz. Data processing and classification were performed according to [Tonin et al., 2012]. Briefly: we preselected parieto-occipital electrodes and computed the envelop of the signals for seven different sub-bands in the alpha range (from 8 to 14 Hz). Then, the trial period was split in consecutive, non-overlapping windows of 150 ms. During the calibration, the most discriminative features in each window were selected and used to setup a classifier for the given interval. During the testing, the classifiers were applied online according to the belonging window. Finally, the resulting probability vector was accumulated in a Bayesian framework in order to make the final decision about the trial.

In parallel, gaze positions were recorded by means of a commercial eye-tracker system. This data was used offline in order to ensure that subjects were doing the task covertly. We defined two Region of Interest (RoI) overlapping each one of the to-be-attended locations. A trial was considered contaminated by eye movements if the gaze position was in one of the RoI at least once during the covert attention period.

3. Results

Figure 1A depicts the performances for each subject averaged across the two recording days. The first outcome is that all subjects performed better than random. In the case of neutral condition, the overall accuracy across subjects was 70.6±4.3%. In addition, four subjects (s1, s4, s5 and s8) reported high performances (88.7%, 70.8%, 73.0% and 74.6%, respectively). Only three subjects showed a drop in performances during the second day. This suggests that generally no shift in the features space happened across sessions. Conversely, with natural images in the background (red bars in figure) subjects did not reach high classification accuracy (in average 61.2±3.3%). Only subject s1 reported results comparable with the first condition (83.0%). In Figure 1B we report the percentage of trials contaminated by overt eye movements. The percentage is relatively low for all subjects (in average 3.6±1.4% and 3.2±1.2% respectively for the two conditions). This outcome supports the fact that subjects were correctly performing the covert attention task.

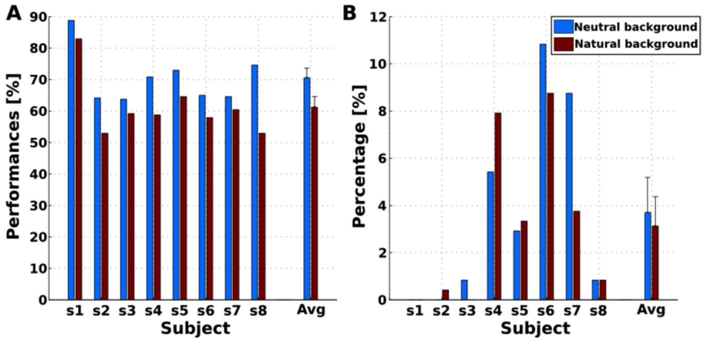

Figure 1. (A) Classification performances for each subject for the two conditions. (B) Percentage of trial contaminated by overt eye movements. Average across days and standard error are reported.

4. Discussion

This study highlights three different novelties in the field. For the first time, we demonstrated (i) the feasibility of an online EEG BCI based on covert visuospatial attention without any external stimulation. The classification accuracy achieved (70.6±4.3% in average, in case of neutral background) makes this mental signal as a promising candidate for BCI control. (ii) This was the first attempt in literature studying covert visuospatial attention with more natural and daily like images, although in this condition the performances dropped considerably (61.2±3.3% in average). It is worth to notice that the calibration phase was based only on runs with neutral background in order to avoid any possible bottom-up arising by the images themselves. This might be an explanation for the lower classification performances. Nevertheless, further analyses are needed in order to understand the underlying processes in this particular condition. Finally, (iii) for the first time -in the case of covert visuospatial attention- the stability of the classifier was tested across different days. This is a fundamental requirement to prove the robustness and the reliability of this mental signal for BCI control.

Acknowledgements
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Evaluation of Three BCI-controlled AT Devices in a Highly Paralyzed End User

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Abstract. Three BCI-controlled AT devices namely a Functional Electrical Stimulation (FES)-hybrid orthosis, a telepresence robot and a music player were tested and evaluated in a highly paralyzed subject (C3 Tetraplegic since 2010, 42 years old, BCI-naïve). He went through an extensive Motor-Imagery-Brain-Computer Interface (MI-BCI) training of 102 runs and achieved an average performance >80%. He successfully passed all three testing protocols, stated a low to medium workload and was satisfied with their use. He could imagine using improved versions in his daily life.

Keywords: Electroencephalogram (EEG), Brain-Computer Interface (BCI), Evaluation, Assistive technology

Introduction

Spinal cord injured (SCI) individuals suffer from restricted limb functions depending on the level of lesion. [Zickler et al., 2011] has shown that the main needs of highly paralyzed individuals are manipulation and communication. However, in high lesioned tetraplegic subjects only a few residual motor functions are preserved that can be used for control of conventional assistive devices (ADs). For this purpose Brain-Computer Interfaces (BCI) exploiting the subject's electroencephalogram (EEG) are connected with such ADs offering a new opportunity for access. In even higher lesioned subjects in whom residual movements are mostly absent, a BCI remains the last option for control of ADs.

The aim of this study is to evaluate the BCI performance and end user satisfaction for three different AT prototypes namely an upper extremity hybrid neuroprosthesis [Rohm et al., 2011], a telepresence robot [Tonin et al., 2011] and a music player in a highly paralyzed end user.

Study participant and methods

The individual (G.S.) included in this single case study is a right-handed 42-year-old man with a traumatic spinal cord injury since August 2010. He is affected by a motor complete lesion with a level of injury of C3. He has a limited passive range of motion in the elbow with a flexion deficit at 110°. He has no active hand, wrist and elbow movement on both sides, only pro-/retraction and elevation/depression of his shoulders and head movements are preserved.

He has never participated in any clinical trial before and was naïve to BCI or FES applications. The TUEBS questionnaire, the ATDPA and a Visual Analog Scale (VAS) were used to assess the user satisfaction and the NASA-TLX to measure the subjective workload.

Results

3.1. Results from MI-BCI Online Training Sessions

Due to the fact that G.S. lives 400km away from Heidelberg, only five sessions of BCI training have been conducted. 102 MI-BCI runs have been recorded since August 2011. 65 of these runs were recorded with feedback (online sessions) and 51 were evaluated. With the Graz-BCI he achieved an average performance of 78%, with the EPFL-BCI 85%.

3.2. Prototype Testing

G.S. drove a telepresence robot which was located ~720km away from his home along three different paths in a real working space, passing through pre-defined target locations first controlled mentally and, second by two buttons activated by residual head movements. During the telepresence trial G.S. was able to complete all the paths in both conditions. The times to complete the tasks were similar (on average 96.80+/-35.83s (BCI) and 82.6+/-32.25s (buttons)). These results are in line with previous work [Tonin et al., 2011]. He stated that he likes how the device looks and that it is small and can turn quickly. He could imagine using it as intended. However, he'd like to have a smaller system with a smaller display integrated in his bed/wheelchair. He liked the device (VAS 9/10, TUEBS 4.3/5) and stated a low workload (NASA-TLX: 30/120).

G.S. also tested the FES hybrid-orthosis, which aims at restoring grasping and reaching function via muscle stimulation, a passive orthosis and an electrical drive to lift the lower arm. He was quite satisfied with the device (TUEBS: 4/5) and claimed a low workload (NASA-TLX: 24/120). However, assessing the ATDPA the end user found both devices semi-useful (31/60 and 34/60). He securely grasped an ice cone from a special holder, lifted it to its mouth and licked it without haste (Fig. 1). During the task he elicited one unintended switch from arm- to hand control that he undid in a few seconds. All other BCI switches were elicited as intended. He overall liked the neuroprosthesis (8/10) but he stated that the whole system could be smaller when produced by a company and tailored to his body. Concerning aesthetic design, he stated that it does not matter in his highly paralyzed state.

On day three, G.S. reported being rather fatigued and his classifier appeared biased towards one class. By the end of the experiment, his NASA-TLX scores for the binary BCI feedback paradigm were 98/120, 62/120 for the REx paradigm and 49/120 for the music player. He was able to complete 19/20 of the music player tasks with an effective accuracy of 80%. G.S. overall liked the music player (4/5). Further discussion about the end user's performance and preferences regarding the music player can be found in [Quek et. al. (in the same proceedings)].

A B

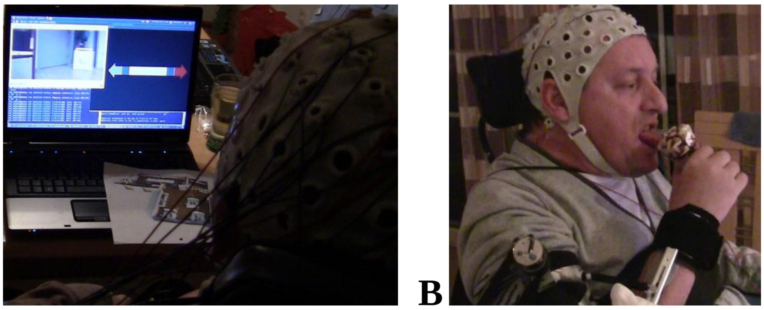

Figure 1. A *demonstrates the setup of the telepresence trial and* **B** *of the neuroprosthesis trial.*

Discussion

It was shown that all three BCI controlled prototypes worked well in the highly paralyzed subject and provided the functionality as intended. He liked all three devices and could imagine using them in his daily life and gave recommendations for their future improvement.

It is worth noticing that if there was no actual task, G.S. became tired easily. In contrast a demanding task made him completely attentive. He needed several breaks during the testing sessions.

During the music player trial he desired to select a particular album for himself and achieved this goal with an accuracy of 100% (13/13 selections). He reported that he really liked to be able to select his own album ("this is cheering me up more than the other BCI trials"), and that it was quickly done. However, the workload was fairly high. It is unclear whether this was due to the novel control paradigm, the high number of preceding trials or the biased classifier.

At the end of day three, G.S. was unhappy that the BCI experiments were finishing and that he really hopes this research work will continue.

Acknowledgments

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An Adaptive Bandit Procedure to explore User-specific Motor Imagery Tasks

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Abstract. In Motor Imagery BCI, a preliminary step for each new user is to find which motor tasks elicit the best discrimination. The user is customarily asked to repeat the imagination of different movements (typically three or four), and an offline analysis determines the best tasks among these. Because quite a number of repetitions are needed to afford a correct estimation of the classification rates, it is not possible to explore many tasks. A radically new way of selecting the best tasks is to optimize online the sequence of tasks. This idea is implemented, using a multi-armed bandit procedure, to select a single task, which can best be discriminated from the idle state. The performance of the method is evaluated in offline and online analyses. We demonstrate a significant reduction in calibration time compared to the uniform procedure.

Keywords: BCI Calibration, EEG, Motor Imagery, Reinforcement Learning, Online Adaptation, Multiarmed Bandit.

Introduction

A major concern in the BCI community is to produce systems that adapt automatically to the specificities of the user [Wolpaw et al., 2002]. The calibration phase can greatly benefit from such automatic calibration, allowing earlier feedback, because users who receive feedback at early stages in an experiment achieve better performance [Vidaurre et al., 2010]. Task selection is a prerequisite to setting up a Motor Imagery (MI) BCI, because the tasks that afford best classification performance vary between subjects. But automatic calibration research has so far limited its scope to the features and the classifier: so far, very few studies have paid attention to the time-consuming step of task selection [Dobrea et al., 2009].

In this automatic task selection study, we focus on a simple BCI paradigm, aiming to control a button [Solis-Escalante et al., 2010]. Reinforcement Learning (RL), aiming to optimize an *exploration-exploitation* trade-off, is particularly well-suited for optimizing the sequence of task presentations: *exploration* is being made with little prior information, and new information can be *exploited* incrementally. In this abstract we summarize recent findings, showing how the multi-armed bandit model, and an Upper-Confidence Bound algorithm, can be used to optimize the task presentation procedure [Fruitet et al., 2012; Fruitet et al., 2012b].

Material and Methods

Parameters: a, N, q

Present each image q times.

For $t = qK+1, \ldots N$

  Evaluate the performance $r_{k,t}$.

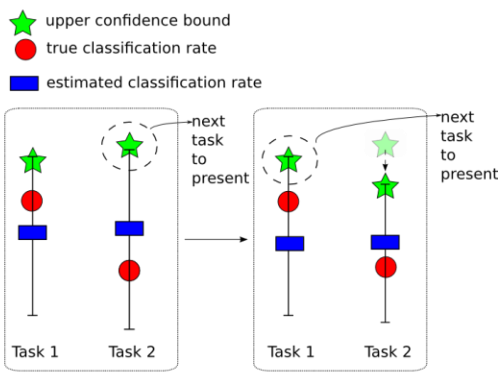
  Compute the Upper Confidence Bound: $B_{k,t} = r_{k,t} + \sqrt{\frac{a \log N}{T_{k,t-1}}}$

  Select the next image to present: $k_t = argmax_{k \in [1,\ldots,K]} B_{k,t}$

  Update T: $T_{k_t,t+1} = T_{k_t,t} + 1$ and for all other k $T_{k,t+1} = T_{k,t}$

Endfor

(a)



(b)

Figure 1 **(a)** *The UCB-classif algorithm.* **(b)** *The iterative task selection procedure.*

An offline study (10 subjects) was conducted to compare the automatic and the traditional (uniform, all tasks presented equal number of times) task selection procedures. An online study (4 subjects) was run to demonstrate that the automatic task selection indeed performed well online. The experiments were designed and run using OpenViBE [Renard et al., 2010]. The subjects were asked to imagine moving their right hand, both feet, or the tongue, during cued intervals lasting 2 seconds, with an inter-cue interval lasting 2.5 to 9.5 seconds (in order to record data in the idle condition). In the offline experiment, MI from the left hand was also recorded, and four

sets of artificially degraded features were produced (by combination of features of the idle state) resulting in 8 “tasks”.
As the goal of this study was not to optimize the features, six features were chosen according to a preliminary experiment with one of the subjects: the power around 11 and 20 Hz, on 3 Laplacian-filtered electrodes (C3, Cz and C4), and on two time windows (duringand after MI). The classifier was a linear SVM, and the criterion to maximize was the classification performance of a task with respect to the idle condition.
We adapted an Upper Confidence Bound algorithm [Auer et al., 2002] to optimize a classification problem. The resulting algorithm, called *UCB-classif,* is presented in Figure 1. It optimizes the exploration-exploitation tradeoff between exploring different tasks, and exploiting data from the most promising ones.

Results

The offline study shows that the total number of task presentations leading to the selection of a good task is much reduced with UCB-classif compared to the traditional uniform task presentation method. This reduction increases with the number of tasks (example, for 8 tasks, 150 presentations instead of 250).

Online results are presented in Table 1. For 3 out of 4 subjects, the task selected on each of the runs was the best-performing one. For Subject 2, two tasks had very similar performance so that UCB-classif could not distinguish between the two, but succeeded in eliminating the worst-performing task.

Average results of the online task selection procedure, for 60 total task presentations per run.

	Avg RH classification rate	*Avg RH presentations*	*Avg Feet classification rate*	*Avg Feet presentations*	*Avg Tongue classification rate*	*Avg Tongue presentations*
Subject 1 (3 runs)	74	20.0	**83**	**30.3**	61	9.7
Subject 2 (5 runs)	**75.6**	**24.6**	**79.8**	**23**	67	12.4
Subject 3 (5 runs)	**84.4**	**31.8**	65.4	15.6	54.8	12.6
Subject 4 (5 runs)	71.8	17	**88.8**	**30.8**	61.2	12.2

4. Discussion

These first results of an automatic task selection are very promising for developing BCIs that are faster to set up. It is all the more worthwhile as the number of tasks is large: for only 3 tasks, as customary in BCI today, it does not offer much advantage over uniform task selection. But, by accommodating a large number of tasks, one can explore different movement strategies. In selecting 1 out of 8 tasks, only 150 total presentations are necessary to obtain the performance achieved by 250 uniform presentations (20 minutes instead of 35).
This method saves time in task selection, and can lead to better BCI performance, by exploring a greater repertoire of imaginary movements. This work should be combined with a feature adaptation method, to further improve the classification performance. Extension to more control classes could be performed by building all bandits whose arms consist of pair-wise classification rates.

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How to decrease BCI Performance Variability? A Machine Learning Approach applied to End-user Data

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Abstract. Brain-Computer Interfaces (BCI) must deliver accurate and stable decoding of the user's intention in order to be become a useful instrument in clinical practice, for example in the context of restoring motor functions of severely disabled patients. In this work we re-analyzed a data set containing 30 days of BCI recordings of a spinal cord injury patient. Using state-of-the art machine learning methods, we were able to increase the mean performance from 73.7% to 81.9% and to decrease the standard deviation from 8.7% to 5.9%.

Keywords: EEG, BCI, CSP, classification variability, end-user

1. Introduction

An important clinical application domain for BCIs is to aid in restoring motor functions as well as to provide alternative methods for the substitution of motor function in severely physically disabled persons (e.g. Rupp & Gerner 2004, Tavela et al. 2010). A major requirement of such a clinical BCI system is not only *high* classification performance but also long-term reliability, i.e. *stable* classification performance. Thus, a successful BCI setup will have to be (i) tailored to the daily states of the user in order to ensure high and stable classification accuracy, and (ii) deliver this adaptivity with minimal intervention from the operator (e.g. the clinical personal).

In this contribution we investigate a 30 day data set of a single end-user and aim to reduce classifier error and variability by combining state-of-the machine learning approaches and dynamic training data selection.

2. Material and Methods

The end-user is an individual with a chronic spinal-cord injury (SCI). He sustained a traumatic SCI in 2009 with a neurological level of injury of C4. He is not able to generated functionally relevant movements of the elbows, hands or fingers on either side. Since August 2011, the end-user participated in a two class motor imagery BCI training using foot imagery vs right hand imagery. A 9 electrode EEG setup was used with a Laplacian montage over electrodes C3 and Cz.

The data set consists of 30 separate measurement days, with a variable number of days between measurements and with a variable number of runs per day (see Figure 1.A). A single run consisted of 24 consecutive trials (12 trials for each class, in random order), after which there was a short break for the subject to relax before the next run of 24 trials began.

Frequency-dependent class-discriminability was assessed using the signed r-square ('signed-r2') measure (Blankertz et al. 2011), which was computed on spectral power of Laplace filtered EEG channels C3 and Cz. Non-significant ($\alpha < 0.05$, bootstrapping) r2-values were set to zero.

Two LDA classifiers were compared in the offline re-analysis, of which both were based on spectral power features of spatial filter outputs. The first classifier uses 2 features from two Laplace-filtered channels (C3, Cz). This *Laplace feature classifier* was actually used during the recording to give feedback to the subject. The spatial filters for the second classifier were not fixed. Instead, 2 filters were optimized for 3 bands separately using the Common Spatial Pattern (CSP) algorithm (e.g. Blankertz et al. 2008). This *mbCSP feature classifier* was recomputed for each recording day using the following dynamic retraining scheme: For a given day, the first three runs were classified using a classifier that was trained on data from all available previous days. For the following runs of that day, mbCSP was re-computed using (i) data from the first three runs and (ii) all the data from the (maximally) previous 5 days that had the most similar profile of signed-r2 values.

3. Results

Figure 1.B and 1.C show the frequency-dependent r2-square values for Laplace-channels C3 and Cz. It can be seen that the strength of class-specific neural sources varies considerably across days, despite the fact that experimental paradigm was the same on all days. For instance, for days 1, 2, 4, 13, and 14 a much stronger discriminative beta-band power is found for the foot class in Cz than for the other class in C3. Whereas in days 6 and 8, for example, the picture is reversed. Also, for the foot class in Cz, there are 8 days in the second half of

the data set (days >15) with no significant r2 values in the entire spectrum, compared to only 2 days in the first half of the data set (days < 15).

Figure 1.D shows the resulting day-wise classification performance of the two classifiers described in section 2. In this plot, the variability of classification performance becomes evident: There are days for which the Laplace feature based classifier performs barely above chance (days 3, 7, 16, and 17), while at other days (e.g. days 18 and 21) the performance is above 80%. The average classification performance of the classifier based on Laplace features is 73.7%, while the CSP-feature based classifier achieves 81.9% accuracy. The difference is statistically significant with $p<0.001$ (Wilcoxon rank sum test). Notably, the standard deviation of performance for the two classifiers is 8.7% and 5.9%, respectively, yielding a reduction of about one third for the CSP featured based classifier. This reduction is statistically significant with $p<0.05$ (Bartlett test for equal variances).

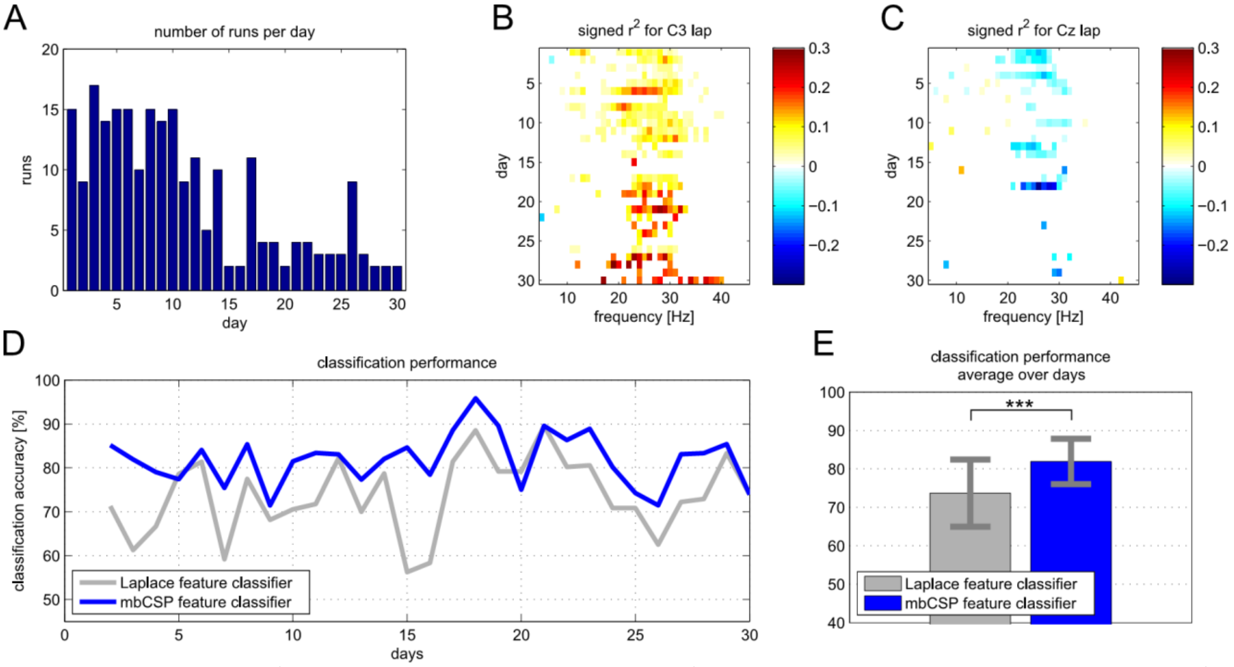

Figure 1. ***(A)*** *Number of recording runs per day. Each run consisted of 24 trials.* ***(B)*** *and* ***(C)*** *Color-coded measure (r2-square) for frequency dependent class-discriminability for each day (y-axis). Shown separately for Laplace-channels C3* ***(B)*** *and Cz* ***(C)****. Color intensity represents strength of class-discriminability, while hue represents which motor imagery class is best decoded: red – right hand, blue – foot.* ***(D)*** *Classification performance for each day (starting from day 2) for LDA classifiers based on either Laplace-features or multi-band Common Spatial Patterns (mbCSP) features.* ***(E)*** *Classification accuracy averaged over days. Error bars indicate standard deviation.*

4. Discussion

We have demonstrated that state-of-the machine learning approaches can yield high classification rates with reduced variability. Our dynamical retraining scheme automatically adapts the classifier and feature extraction process to the daily state of the BCI user, which was in this case a target end-user.

However, our results were obtained in an offline re-analysis of previously recorded data of a single subject. Therefore, it remains to be shown whether the increased classification performance and decreased variability can be transferred to the online application of the system at the clinical evaluation site and whether our approach is beneficial to other end-users. The online BCI system of the clinical partner in this study has been adapted accordingly, and online evaluation of the setup are currently under way. We will present results of the online evaluation during the workshop.

Acknowledgments

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Sensorimotor Oscillatory Reactivity of the Stroke Affected Hemisphere is increased by EEG-based BCI Training: A Study in Subacute Patients

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Abstract. Motor imagery (MI) was proposed to enhance arm motor recovery after stroke. EEG-based BCIs operated by MI can provide a valuable method to support mental motor practice by allowing direct monitoring of the patient's adherence to such task-specific training. In this paper we describe MI-related EEG patterns of 11 subacute stroke patients who underwent a one-month BCI-supported motor imagery training with a specifically developed BCI-based device. Significantly higher involvement of the affected hemisphere was observed at the end of the one-month training as revealed by higher desynchronization values in motor relevant scalp areas of the ipsilesional hemisphere in the lower Beta range of frequencies.

Keywords: BCI, stroke, rehabilitation.

1. Introduction

Motor Imagery (MI) was proposed to enhance arm motor recovery after stroke; however recent evidence reported no significant improvement from MI as an add-on to intensive therapy alone [Ietswaart et al., 2011]. One possible reason for this lack of effect could be attributed to an unclear definition of the content of such mental practice (i.e., the impossibility to verify the actual brain activity related to the MI task). In this context, EEG-based BCIs operated by MI can provide a valuable approach to support mental motor practice by allowing direct monitoring of the patient's adherence to such task-specific training. It is widely agreed that a stroke lesion may results in a functional reduction of activity of the ipsilesional hemisphere associated with a correspondent increase in the contralesional one. Based on this assumption, rehabilitation strategies aim at increasing the excitability of the affected hemisphere and/or decreasing that in the unaffected [Dimyan and Cohen, 2011]. Here we propose sensorimotor (SMR)-BCI training as a tool to boost motor-related neuroelectrical responsiveness of the affected hemisphere. In particular, we highlighted the reinforcement of motor-related EEG patterns generated from the affected (lesioned) hemisphere of subacute stroke patients provided by a specifically developed BCI-based training device [Pichiorri et al., 2011].

2. Material and Methods

Eleven subacute stroke patients (age: 61.9 ± 6.9 years; first ever, unilateral stroke causing paresis or plegia of the affected upper limb) underwent a BCI–assisted MI training preceded by a screening session, from which *control features* for BCI training were spatially selected over the damaged hemisphere at frequency ranges typical of sensorimotor rhythms (alpha and beta). The training protocol included 4 weeks of MI-based BCI training (3 sessions per week), during which the patient was asked to control the movements of a virtual representation of his own stroke-affected hand throughout the imagination of simple hand movements. Each training session contained from 4 to 8 runs (20 trials per run). Trials consisted of a baseline period (4 sec) followed by MI (max 10 sec). EEG signals were collected from 31 positions (frontocentral, central, centroparietal and parietal lines), sampling rate 200 Hz. In order to assess the BCI training effects, 2 training sessions were analyzed for each subject: an "*EARLY*" session, namely the second session for all subjects and a *"LATE"* session corresponding to the best session in the last week of training, selected according to patient's performance rate. After preprocessing – downsampling at 100 Hz, band pass filtering (1-45 Hz), artifact rejection, CAR (*Common Average Reference*) spatial filtering – the power spectral densities (PSD) of the task- and baseline- related EEG signals were computed and averaged within five frequency bands defined according to Individual Alpha Frequency (IAF, 9.7±0.5): theta [IAF-6;IAF-2], alpha [IAF-2;IAF+2], lower beta [IAF+2;IAF+11], upper beta [IAF-11;IAF+20] and gamma [IAF+20;IAF+35] [Klimesch, 1999]. To highlight spectral activity related to the task, a statistical comparison (Student's t-test) for a significance level of 5% was computed between MI and baseline PSDs. False Discovery Rate correction for multiple comparisons was applied to the statistical tests to avoid the occurrence of type I errors. In order to evaluate the efficacy of the BCI–assisted MI training and its consistency across patients, a statistical comparison between t-values associated to EARLY and LATE sessions was performed for each channel and frequency band. Data from patients with lesion of the right hemisphere were flipped in order to visualize the affected hemisphere on the left for the whole population.

3. Results

Statistical scalp maps (MI vs baseline) for a representative patient in alpha and lower beta bands for EARLY and LATE sessions are reported in Figure 1. The color of each pixel codes for the correspondent t-value: gray for not significant differences, hot (yellow-red) and cold (blue) color scales for the level of significant synchronization and desynchronization, respectively. In the EARLY session, the pattern elicited in both bands is bilateral and *t* values are just above threshold. In the LATE session, higher involvement of the affected hemisphere (AH) was observed mainly in lower beta band. In fact, an increase of spectral desynchronization was bilaterally visible in both frequency bands (absolute *t* values are greater than 10), mainly on the affected hemisphere. A similar SMR reactivity was observed in all patients. Group analysis revealed significant statistical differences ($p<0.05$) only in lower beta band oscillations recorded over the affected hemisphere sensorimotor strip (Table 1).

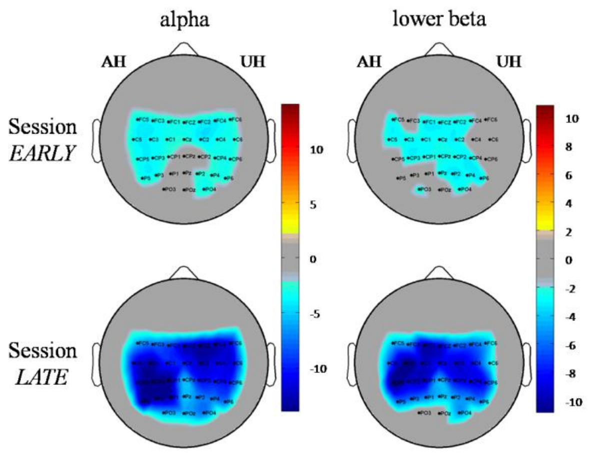

Figure 1. *Statistical scalp maps of a subacute stroke patient: MI vs baseline in alpha and lower beta bands for the EARLY and LATE training sessions. Unaffected and Affected Hemisphere (UH; AH) are represented on the right and left of each scalp map, respectively. Color bars code for t-values.*

	Channel	theta	alpha	lower beta	upper beta	gamma
Affected Hemisphere (AH)	***FC3***	0,776	0,131	*** 0,036**	0,119	0,138
	C3	0,735	0,336	*** 0,024**	0,161	0,289
	CP3	0,849	0,231	*** 0,004**	0,171	0,655
Unaffected Hemisphere (UH)	***FC4***	0,794	0,109	0,146	0,741	0,601
	C4	0,843	0,312	0,054	0,534	0,61
	CP4	0,828	0,54	0,171	0,507	0,612

Table 1. *p values of the statistical comparison EARLY vs LATE sessions for 6 channels over the motor cortex: FC3, C3, CP3 (Affected Hemisphere, AH) and FC4, C4, CP4 (Unaffected Hemisphere, UH). Significant Results (p<0.05) are highlighted in red.*

4. Discussion

A growing literature suggests that BCI-supported MI training could be proposed in stroke patients, to potentially improve post-stroke recovery. In support of this application, our findings show that reactivity of the affected hemisphere of subacute, severely motor-impaired stroke patients is effectively modulated by a specifically designed training supported with a BCI device for motor rehabilitation. A higher involvement of the affected hemisphere was observed across training, possibly reflecting a motor cortex functional recruitment moving closer to normal, as disclosed by EEG patterns elicited by MI in a BCI context. How this increased motor-related brain activity can impact on the actual fucntional motor recovery of subacute patients remains to be elucidated in future controlled studies.

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Brain Controlled Functional Electrical Stimulation for Motor Recovery after Stroke

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Abstract. In the recent past, Brain-Computer Interface (BCI) have been proposed as a potential mean to maximize the output of standard motor therapy after stroke, providing access to the damaged motor network of the brain. Also, Functional Electrical Stimulation (FES) is often applied during rehabilitation to directly engage muscles of the affected side of the body. In this paper, we describe a BCI system for stroke rehabilitation that decodes the engagement of motor areas of the brain and activates FES of a target muscle on the affected arm, accordingly. The system allows the physical therapist to monitor current brain activity through a EEG-guided visualization . Preliminary results on 4 patients show consistency in the EEG features selected for further training. Two of the patients completed the testing, and both show recovery of target muscle function. Our results support the idea that BCI can be used to promote beneficial brain plasticity, and justify further testing on a larger population.

Keywords: Rehabilitation, Stroke, Brain-Computer Interface, Functional Electrical Stimulation

1. Introduction

Every year, approximately 10 million people worldwide are left disabled after a stroke [Roget et al., 2012]. Research in the direction of more efficient, faster rehabilitation is then crucial. Brain-Computer Interfaces (BCI) provide a mean to decode mental states and activate devices according to user intentions, and could provide a direct feedback on the engagement of motor areas of the brain surrounding the lesion site [Millán et al. 2010]. Functional Electrical Stimulation (FES) is often used to directly engage muscles on the affected side of the body during physical therapy. Still, no commercial system provides a mean to directly link the intention to move with the muscular response.

In this paper, we report preliminary results of a BCI system for stroke rehabilitation initially described in [Cincotti et al., 2012]. User's intention to perform an extension movement of the affected hand is detected through a BCI and used to activate a FES device. A physical therapist receives the visual feedback about BCI performance, motivates the end-user and avoids compensatory behaviors in executing the task through a visualization of current EMG activity on the arm.

2. Material and Methods

The EEG was acquired through a gUSBamp with 16 active electrodes mounted in correspondence of the central sulcus and motor cortices. Bipolar EMG derivations of the extensor digitorum (target muscle), biceps, flexor carpi radialis and triceps were also recorded. The data were digitalized at 512 Hz and band-pass filtered in the range [0.1 70] Hz. One FES channel is applied to the extensor digitorum during the on-line sessions.

The experimental protocol consists in three different phases: first, patients undergo an EEG pre-screening session to characterize the initial state of the brain and calibrate the BCI classifier. In the following 2 months, they are trained with on-line BCI feedback and FES for at least 10 sessions. Finally, they perform a post-screening to determine changes in EEG patterns following the treatment.

During both the pre- and post-screening sessions, users are asked to perform (or attempt performing) a full sustained finger extension of approximately 4s. Each run is composed of 15 trials of motor task and 15 trials of resting, for both the affected and unaffected hand (AH, UH, respectively). For the on-line training sessions, the number of runs varies between 3 and 6 depending on user fatigue. Each run is composed of 15 trials where the user is asked to concentrate on his affected hand, trying to execute a full sustained finger extension of approximately 4s. FES of extensor digitorum is activated every time the BCI is sufficiently confident of motor engagement.

We have been working with 4 stroke patients up to now, all of them suffering a left hemisphere ischaemic infarct. Two chronic stroke patients completed the prototype testing. Two additional chronic patients are currently in the testing process.

3. Results

In this paper, we present the most discriminant EEG features used by the BCI, extracted from the initial EEG screening session [Galán et al., 2007]. These features are used to train a classifier that judges whether each sample belongs to a motor task or to a resting task (samples with a probability < 0.6 will be rejected). Table 1 reports some information about the 4 end-users, the classifier performance on the pre-screening session data, the number of on-line BCI sessions done so far and the functional Fugl-Meyer (FM) indexes. Figure 1 shows the experimental setup and the selected EEG electrodes and features in terms of spatial and frequency location.

Table 1. *Patients information, off-line classifier performance, number of already recorded BCI sessions and functional indexes (Fugl-Meyer) of a movement involving the extensor digitorum*

Subject ID (Age, Lesion site, Gender)	*tse (i.e. time since stroke event)*	*BCI Classifier Performance / Rejection*	*BCI sessions (on-line)*	*Fugl-Meyer Upper Limb (pre-screening)*	*Fugl-Meyer Upper Limb (post-screening)*
S1 (64, L, M)	10	*0.9 / 0.43*	10	7 / 66	17 / 66
S2 (71, L, M)	14	*0.91 / 0.68*	11	31 / 66	40 / 66
S3 (49, L, M)	10	*0.91 / 0.45*	9 – in progress	36 / 66	–
S4 (50, L, F)	19	*0.89 / 0.41*	8 – in progress	30 / 66	–

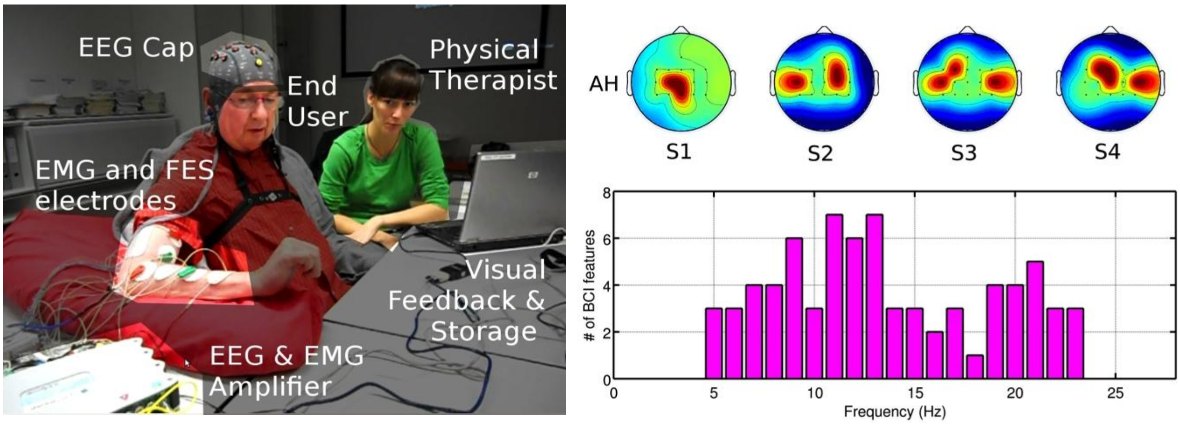

Figure 1. *Experimental Setup (left), spatial (right, top) and frequency (right, bottom) location of the EEG features extracted from the pre-screening session. The number of frequency features is the sum over all 4 patients.*

4. Discussion

The spatial distribution of EEG discriminant features is fairly consistent over our 4 patients: they all have a rather bilateral representation of the motor action, except subject S1 that shows a central representation. Regarding the discriminant frequency components, they consistently localize in the mu and beta bands, except subject S1, who presents very low alpha features. BCI features for the other patients are rather aligned to those of healthy subjects. Interestingly, subject S1 was the most severed individual of our group.

Regarding the two subjects that completed the testing, we observed functional improvements in both, especially in movements involving the extensor digitorum, as reflected by the Fugl-Meyer index. Remarkably, also subject S1, for whom the BCI features were rather different from those of the other patients and from healthy subjects, showed functional recovery passing from a totally paretic arm to a very limited but still noticeable voluntary activity of the fist. These results confirm the beneficial effects of direct muscle stimulation according to user intention to perform a motor task. Nevertheless, these initial findings need to be confirmed on a larger population and as compared to a control group.

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A Preliminary Fundamental Study of Ambulatory SSVEP

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Abstract. To bring BCIs outside the lab, researchers are focusing on studying standard BCI paradigms under ambulatory conditions. Although the P300 has been widely studied in such circumstances, the SSVEP potential has not got such a specific attention so far. This preliminary study aims at getting some evidence of the gait impact on the SSVEP SNR distribution and magnitude. Basically, gait seems to impact the SSVEP response measurement. After being confirmed, this result could help to improve the design of BCI dedicated to both sitting and ambulatory conditions.

Keywords: Ambulatory Conditions, Fundamental Analysis, Luminosity Effect, Signal-to-Noise Ratio, SSVEP

1. Introduction

For a few years, researchers have attempted to bring BCIs outside the lab. Among the different aspects, ambulatory BCI efficiency is an important part. Up to now, P300-based BCIs have been thoroughly analyzed [Castermans et al., 2011]. The main conclusion is that it is feasible and performance is not dramatically affected by gait-related artifacts or altered by modifications of the brain responses.

However, none of the recent studies have focused on the SSVEP potential, which is though the quickest BCI paradigm. Indeed, only a one-subject SSVEP analysis was reported using 4 Hz and 6 Hz. Its main conclusion was the SSVEP is still working while walking [Touyama et al., 2010]. Obviously, this paper provides anything but a deep understanding of gait effects. Therefore, the aim of this paper is to show preliminary results on how movements can affect SSVEP responses according to two parameters: stimulus luminosity and frequency.

2. Experiment and Methods

In this section, the experiment is firstly described. Then, the analysis method is detailed.

2.1. Experiment

Basically, the experiment consisted in comparing the SSVEP brain response under different conditions: sitting/walking and normal/high luminosity. During the experiment, the subject had to focus on a 63-LED panel (7 x 9 cm), whose flickering frequency was increased from 10 to 46 Hz (to avoid low-frequency mechanical gait artifacts) by 2 Hz step (scanning of 19 frequencies). The distance between the LEDs and the subject's eyes was checked during the whole experiment and fixed at 70 cm. For each flickering frequency, two recording sessions were performed while walking on a treadmill at 3 km/h and two others were recorded while sitting on a chair. These two sessions encompass two luminosity conditions, which were the same for each subject: one that could be used for a daily life application and one that tends to the supportable limit. For each session and for each frequency, a 30-second EEG dataset was recorded leading to a total of 76 recordings per subject. A 32-electrode ANT EEG cap was used with a common average reference [Ding et al., 2006]. Three healthy subjects participated in this study.

2.2. Methods

To detect the SSVEP response across all the channels and scanned frequencies, local Signal-to-Noise Ratios (SNR) were calculated as proposed in [Ding et al., 2006]. To depict the results that are not due to statistical fluctuations of noise, a one-tailed 95% distribution threshold was applied. Indeed, SNR fluctuations were measured by computing SNRs at non-flickering frequencies, excluding harmonics, in order to estimate the distribution, which was Gaussian. This allows to only focus on SSVEP SNRs that are unlikely due to noise. For each dual condition, all the SNR results across frequencies and electrodes are depicted in a matrix figure.

3. Discussion

This section is composed of two main analyses. First, the luminosity influence is discussed. Then, the SSVEP responses under sitting and walking conditions are analyzed.

3.1. Luminosity Effect

As expected, the increase of the LED luminosity increases the SSVEP SNR. On Fig. 1, it clearly appears that a higher luminosity improves the contrast between areas with and without SSVEP responses. Logically, when a SSVEP response is insufficient compared to the noise level for a given luminosity, a higher luminosity allows it to be observed. Thereby, it is important to know the luminosity parameter when analyzing which areas are responding to the stimulus. However, some of the luminosity effect could lead to an artificial increase of the SNR in non-responding areas simply due to the common average referencing.

3.2. SSVEP Responses Under Sitting and Walking Conditions

As shown in Fig. 1, under sitting conditions, although the results are somehow heterogeneous among the subjects, a fairly standard behavior is observed. The SSVEP potentials are mainly located in the occipital/parietal areas as expected. Moreover, some significant -but lower- responses are elicited in the central/centro-parietal area close to the midline (not detected in Fig. 1). These results are coherent with the literature.

In comparison, walking conditions may not be seen as a transparent process for the SSVEP paradigm. For some subjects, the occipital SNR magnitude appears to decrease (and sometimes disappear). This could be due to EMG artifacts. On the other hand, the SNR magnitude seems to be reinforced in the fronto-central, central and centro-parietal areas close to the midline below 16 Hz. This likely corresponds to the feet localization on the homunculus over the motor/sensorimotor areas. Moreover, just by walking, some frequency band responses vanish. Differences between luminosity conditions may suggest the main reason could be artifacts but it needs to be confirmed by EMG sensors on the neck. Future work will be devoted to determine whether these effects occur on larger population and if they are due to gait artifacts or a specific brain behavior.

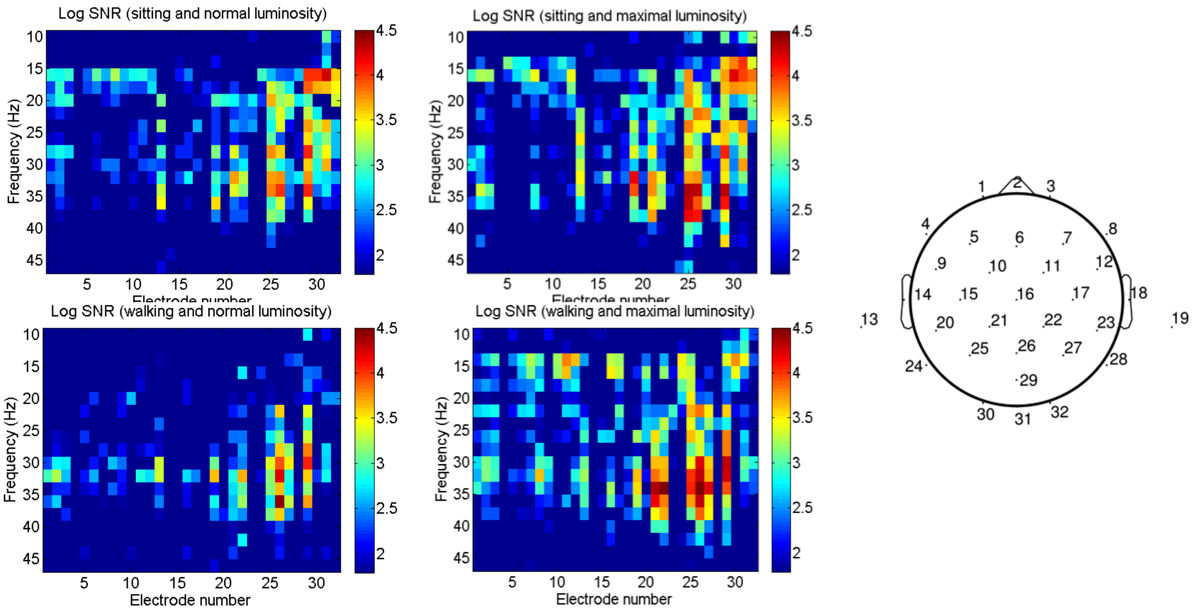

Figure 1. *On the left: Luminosity and gait obviously impact the SSVEP log SNR distribution and magnitude. The former one allows the SSVEP response to emerge from the background noise. The latter one could slightly affect the SSVEP through artifacts. On the right: the electrode number and their localization are depicted.*

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Bridging Gaps: Long-Term Independent BCI Home-Use by a Locked-In End-User

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Abstract. In the current study the BCI controlled application Brain Painting was installed at a locked-in ALS-patient's home. Family and caregivers were trained to set-up the EEG-cap and amplifier and to start an easy-to-use interface for the brain painting application. BCI data, duration of painting time, and evaluation were saved automatically on a server. The Brain Painting was evaluated in terms of satisfaction, frustration and enjoyment using a visual analogue scale. In over 8 months the end-user painted in 86 BCI sessions (and ongoing). Overall, satisfaction was moderate to high (*M*=6.2 of 10, *SD*=3.65). The study demonstrates that expert-independent BCI use is possible. Nevertheless, independent BCI use is challenged by technical problems and variable BCI control.

Keywords: Brain Computer Interface (BCI), independent home-use, P300, user-centered design, evaluation, locked-in state

1. Introduction

Brain-Computer-Interfaces enable the severely motor impaired person to communicate without muscular pathways. Despite intensive research, BCIs could hardly be established at the patient's home [Sellers et al., 2010]. Main problems are e.g., too complex and not ready to use software and time-consuming set-up, e.g. placement of EEG-cap. Another problem is the very expensive EEG equipment, e.g. EEG cap and amplifier. The BCI-application Brain Painting, which was successfully tested and evaluated in healthy subjects [Münßinger et al., 2010] and patients [Zickler et al., submitted], was implemented at the end-user's home.

2. Material and Methods

2.1. Subject

One female, 72 years old, locked-in ALS-patient was considered as end-user for this study. The end-user is artificially ventilated and fed, using an eye-tracker (eye-gaze system) for communication. She is living with her family and has a 24-hours care. She used to be a painter.

2.2. BCI-set-up and application

The easy-to-use P300-driven Brain Painting application was installed at the end-user's home. An initial calibration was performed in this first meeting and the family was trained how to set up and start the BCI. After 2 months the family was visited for a second time, in which a second calibration was made. The end-user was using the BCI independently at home, while the researcher team was in close contact to the family and the end-user. Evaluation reports (see below) and BCI data were automatically transmitted and stored on a remote server, enabling the experts to follow BCI usage and end-user's experience. The BCI experts intervened only few times, e.g., when technical problems occurred or BCI parameters had to be changed. This was always realized via remote control. EEG was recorded using a 8-channel active electrode cap (g.tec, Austria) from centro-parietal regions.

2.3. Evaluation

After every Brain Painting session the end-user was asked to answer evaluation questions. The end-user rated her *satisfaction* with the BCI session, her experienced *frustration*, and the level of *enjoyment* on a visual analogue scale (VAS). Furthermore *subjective level of BCI control* was rated, choosing between zero (0-50%), low (50-70%), medium (70-90%) and high control (90-100%). Accordingly, high control means that 90 to 100% of all selections were correctly made. In the initial test phase, only VAS satisfaction was rated (first 8 sessions). After this proof-of-principle phase the extended evaluation was assessed (reported for session 9 to 86). Furthermore a command line enabled the end-user to give further feedback or report on errors.

3. Results

The end-user painted in about 86 sessions within 8 months. Mean total painting time of *M*=66.21 (*SD*=38.19). Overall, the end-user was moderately to highly *satisfied* (*M*=6.20, *SD*=3.65). Ratings for VAS Satisfaction across all 86 sessions can be seen in **figure 1**. *VAS enjoyment* ratings indicated that the end-user enjoyed the painting in most of the sessions, with an average of *M*=6.81 (*SD*=3.57). On the other hand, *frustration* was rather low, with an average over all sessions of *M*=3.74 (*SD*=3.66). One of the main reasons for her dissatisfaction and frustration were technical problems, especially in the first BCI sessions. Further sources of dissatisfaction were bad or not good control due to possibly not sufficient electrode gel or bad cap placement, tiredness/bad concentration and loss of control due to drying electrode gel or shifting of cap after 2-3 hours of painting. Dissatisfaction also occurred when she could not produce the painting that she desired. The end-user indicated the *subjective level of BCI control* in 33.33% of all sessions being zero, in 26.92% low, in 25.64% medium and in 14.10% high. Setup of BCI equipment took around 20-40 min, while setup and operation of the application took around another 10-20 min, as reported by the family.

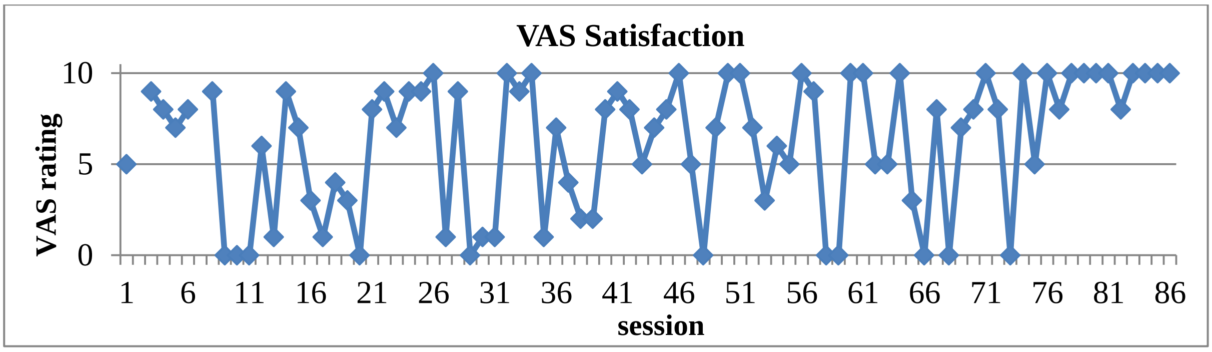

Figure 1. ***VAS Satisfaction****: Satisfaction was rated on a visual analogue scale from 0 (not satisfied at all) to 10 (very satisfied).Note that ratings in session 2 and 7are missing.*

4. Discussion

The results of the study demonstrate independent home-use of BCI. However, BCI usage is challenged by technical problems and varying BCI control. It cannot be excluded that control could have been better and less varying, if calibration would have been performed regularly. The moderate to high ratings in satisfaction and enjoyment and the number of sessions conducted, notwithstanding the occurring problems with the BCI, indicate that in this case the BCI well matched the patient's needs. For the end-user, Brain Painting has become an important part of her life (personal statement). Further steps to increase *effectiveness*, *efficiency* and *satisfaction* are planned, comprising inclusion of face stimuli in the Brain Painting matrix [Kaufmann et al., in press] and to integrate the optimized computer interface for autocalibration [Kaufmann et al., 2012].

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Two Approaches to Communicate with Patients in Minimally Conscious State

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Abstract. Two different EEG-based BCI approaches to communicate with minimally conscious patients were applied. In an auditory P300 paradigm, tone streams composed of short beep tones with infrequently appearing deviant tones at random positions were used as stimuli. In a mental imagery paradigm, the patients were instructed to perform imagined sports, navigation and feet movements. In the P300 paradigm, averaged results were significant in all four patients, but not on single-trial basis. Classification accuracies above chance were reached by three of the patients performing mental imagery tasks indicating the feasibility to use this paradigm to communicate with minimally conscious patients.

Keywords: EEG, BCI, auditory P300, mental imagery

1. Introduction

Brain-computer interfaces (BCIs) based on electroencephalography (EEG) can provide severely motor-disabled people with a new output channel for communication [Birbaumer et al., 1999]. To provide a simple and robust means of communication, the BCI should reliably detect one specific brain pattern, such as P300 potentials or a task specific event-related (de)synchronization (ERD(S)) pattern.

2. Material and Methods

Two different approaches to communicate with patients were applied, namely detecting P300 potentials in an auditory P300 paradigm, and detecting ERD(S) patterns due to mental imagery tasks. Four male patients in minimally conscious state aged between 21 and 65 years participated in this study at Albert Schweitzer Clinic in Graz. Informed consent was obtained from the patients' legal representatives. This study was approved by the Ethics Committee of the Medical University of Graz.

Monopolar EEG was recorded at 32 positions with a sampling rate of 512 Hz. The patients were either sitting in a wheelchair or lying in bed with their upper part of the body slightly elevated. Each patient participated in two P300 sessions and in three to four mental imagery sessions.

2.1. Auditory P300

Two intermixed tone streams composed of short beep tones with infrequently appearing deviant tones at random positions were used as stimuli. The beep tones were arranged according to the tone stream pattern LHL_LHL… ('L' = low tone, 'H' = high tone, '_' = silent gap). The inter-stimulus interval (ISI) was 300 ms in the low tone stream (LTS) and 600 ms in the high tone stream (HTS). The low (deviant) tones had a frequency of 396 Hz (297 Hz), the high (deviant) tones a frequency of 1900 Hz (2640 Hz). By intentionally shifting attention from one stream to the other the P300 response elicited by the deviant tones in the attended stream should be modulated [Müller-Putz et al., 2012].

A stepwise linear discriminant analysis (SWLDA) classifier together with 10x10 cross-validation was used to infer which tone stream was attended. Moreover, all data segments of one participant were averaged according to stimulus type and target stream and significant differences (α = 5 %, length $L \geq 30$ ms) were estimated by bootstrapping using 1000 bootstrap samples.

2.2. Mental Imagery

The patients were instructed to perform different mental imagery tasks which should induce distinctive ERD(S) patterns [Goldfine et al., 2011]. In the sports task (S), they should imagine performing one sport of their choice. In the navigation task (N), they should imagine navigating through their house and looking around in each room. In the feet task (F), they should repeatedly attempt to perform a feet dorsiflexion.

A linear discriminant analysis (LDA) classifier based on logarithmic band power features calculated for multiple frequency bands (ϑ: 4-7 Hz; α: 7–13 Hz; β_L: 13-19 Hz; β_M: 19-25 Hz; β_U: 25-30 Hz) was used. A nested blockwise cross-validation (10x10 inner fold; leave-one-out outer fold) was applied to estimate the classification accuracy of each task versus reference.

3. Results

In Table 1, all significant results of the P300 and the mental imagery paradigm together with the mean Coma Recovery Scale-Revised (CRS-r) scores of the patients across all sessions are summarized. In the P300 paradigm, all single-trial classification results were below chance level (not reported). On average, significant positive (P) or negative (N) deflections within one stream (deviant vs. standard tones) or across streams (target vs. non-target deviants) could be detected in all patients. Only significant results in any of the channels Fz, Cz and Pz are reported. In the mental imagery paradigm, classification accuracies above chance (α = 1 %) were reached by three patients in the F or S task. Only the Laplacian channel derivation yielding the highest accuracy is reported.

Table 1. *Summary of all significant results of the auditory P300 and the mental imagery paradigm.*

Patient ID	*Mean CRS-r*	*Auditory P300*				*Mental Imagery*				
		Session	*Condition*	*Target*	*Deflection*	*Session*	*Task*	*Accuracy*	*Channel*	*Band*
PA_{01}	*18*	*2*	*within*	*LTS*	*P390*	*1*	*F*	*70 %*	*Cz*	α
		2	*across*	*LTS*	*P300*	*1*	*S*	*68 %*	*C2*	α
						2	*S*	*76 %*	*C2*	α
PA_{02}	*14*	*1*	*across*	*LTS*	*P680*	*1*	*F*	*69 %*	*FC1*	ϑ
						1	*S*	*75 %*	*Fz*	ϑ
						3	*F*	*71 %*	*FC1*	ϑ
PA_{03}	*13*	*2*	*within*	*LTS*	*N210*					
		2	*within*	*LTS*	*P810*					
PA_{04}	*9*	*1*	*across*	*HTS*	*N730*	*1*	*S*	*69 %*	*Fz*	α
		2	*within*	*LTS*	*N760*	*2*	*S*	*68 %*	*CPz*	β_m
		2	*within*	*HTS*	*N800*					

4. Discussion

The single-trial classification results of the auditory P300 paradigm are not sufficient for communication. To improve the paradigm, different stimuli (e.g., words) that may be easier to distinguish or elicit a stronger P300 response might be beneficial in future. Nevertheless, since significant deflections were found on average, this paradigm might still be useful to support clinical assessment of patients by averaging data over many trials. Some of the P300 deflections showed delayed latencies, as also reported previously [Perrin et al., 2006]. The negative deflections might indicate (possibly delayed) mismatch negativities instead of P300 potentials.

Using mental imagery, on the other hand, seems to be a promising approach for some patients to communicate their intent using EEG. Classification accuracies above chance were reached in the F or S but not in the N task. This is in line with previous findings indicating that, among other tasks, motor imagery rather than spatial navigation most frequently results in better classification performance [Friedrich et al., 2012].

Acknowledgements

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Information Processing in Patients with Chronic and Severe Disorders of Consciousness

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Abstract. *To study the prevalence of the N100, P200, and P300 event related potentials (ERP) in patients with chronic and severe disorders of consciousness, ERPs were recorded in 19 long-term vegetative state and minimally conscious state patients during an auditory oddball paradigm in a passive – listen only – and an active – count the odds – condition at two time points. Significant ERPs were detected in all patients. N100 was significantly more frequent than the P300. No evidence was found for differential activity between the passive and the active condition.*

Keywords: EEG, t-cwt, wavelet, P300, disorders of consciousness, vegetative state, minimal conscious state, ERP

1. Introduction

The event-related potential (ERP) P300 has been linked to the processing of attention-demanding stimuli. For example, in categorization tasks its amplitude is larger for stimuli belonging to the attended category as compared to non-matching stimuli. It is thus, thought to indicate the intactness of a wide cortical network ranging from prefrontal to temporal-parietal areas [Polich, 2007].

The vegetative state (VS) is a severe disorder of consciousness (DOC), presumably characterized by a complete loss of conscious experience despite preserved wakefulness. It is sometimes followed by a minimally conscious state (MCS), in which weak and inconsistent signs of awareness can be detected. In a previous study, up to 32% of DOC patients showed a P300 in an auditory oddball paradigm [Kotchoubey et al., 2005]. Here we report on the distribution of the N100, P200 and P300 ERPs recorded during an auditory oddball paradigm in 17 DOC patients and nine healthy controls in two conditions. A passive ("listen only") condition served as a baseline to which responses during an active condition ("count the odd tones") were compared. We hypothesized that healthy subjects would show an increased P300 in the active condition, and we were interested in whether DOC patients would show a similar increase. Such an increase could be an indicator of preserved command following and thus, consciousness and cognition.

2. Material and Methods

Participants 19 patients with disorders of consciousness (sex: 11 male, 8 female; age: M = 50, SD = 14.19; diagnoses: 5 MCS, 14 VS; years since onset: M = 6.18, SD = 3.17; aetiology: 10 hypoxia, 3 trauma-related, 3 intra-cerebral haemorrhage, 3 other; hemispheric localization of lesions: 4 left, 2 right, 3 both, 10 none), whose legal guardians gave informed consent, and nine healthy subjects participated in the study. Patients' diagnoses were ascertained using the Coma Recovery Scale (CRS-R) immediately before EEG measurement.

Procedure Subjects listened to an auditory odd-ball paradigm (60 odd and 420 frequent tones) in a passive ("listen only"), and an active ("count the odd tones") condition (T1). In 17 patients, the experiment was repeated after a minimum interval of 1 week (T2) to compensate for the possibility of fluctuating arousal levels.

EEG recording and analysis EEG and EOG was recorded (512Hz) from 31 standard 10-20 system electrode locations. Offline, the EEG was bandpass (0.01 – 70Hz, 12dB) and notch filtered, epoched into 850ms long intervals, and aligned to the 100ms pre-stimulus baseline. Ocular artefacts were corrected using a regression procedure and trials with absolute voltages in excess of 100 µV excluded. Only datasets with at least 20 trials in each condition (n = 17) were considered for the remaining analyses and re-referenced to linked mastoids. ERPs were detected using the t-CWT procedure [see abstract Real et al., Bostanov, 2003; Real et al., 2012]. ERPs were defined as follows, N100: negative peak between 50 and 200ms at Fz or Cz, P200: positive peak between 100 and 250ms at Fz or Cz, P300: positive peak between 250 and 500 ms post stimulus onset at Fz, Cz or Pz. All available trials were used for N100 and P200 detection, whereas all odd tone and the immediately preceding frequent tone trials were used for P300 analysis.

3. Results

Healthy participants All healthy subjects showed significant activation in the N100, P200 and P300 ranges in all conditions, with the exception of one subject in which no P200 could be detected in the active condition. Seven of nine healthy subjects showed a significantly larger P300 in the active than passive condition.

Patient participants Reliable ERPs were detected in all 17 patients entering the analysis. A P300 was found in two VS, in one MCS and in one patient who was diagnosed as MCS at T1 but VS at T2. No significant difference between the P300 in the active and passive conditions was found in any patient.

The N100 was found more often than the later P300 in both experimental conditions (binomial tests, all $p < .05$) at T1 but not at T2. No difference was found for the P200.

Table 1 *Frequency of ERPs by experimental condition and time points in patients*

	T1		*T2*	
ERP	*passive*	*active*	*passive*	*active*
N100	12/13	10/10	5/5	9/10
P200	6/13	6/10	4/5	3/10
P300	2/13	1/10	1/5	3/10

Discussion

Our results replicate previous findings of a comparatively higher prevalence of the N100 in comparison to the P300, and an overall rare occurrence of a P300 (4/17 = 24%) in DOC patients [Kotchoubey et al., 2005]. In contrast to healthy subjects, in DOC patients the P300 of the active condition was not enhanced compared with the passive condition. This may indicate that patients did not perform the task for multiple reasons, like lack of language understanding, insufficient attention span, lack of motivation or cognitive abilities, or indeed disrupted conscious awareness. Future analyses, based on an extended sample, will also test whether the time since the event predicts absence/presence of the P300 ERP.

Acknowledgements

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The Importance of User-centred Design in BCI Development: A Case Study with a Locked-in Patient

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Abstract. Although Brain Computer Interfaces have been proposed as communication devices for those with severest motor impairment, research is rarely performed with this target population, i.e. people in the locked-in state. Usually, developments are tested in healthy samples and assumptions are made regarding generalization of results to patient samples. Herein we report a case study with a user in the locked-in state. Different paradigms on different modalities were applied and far best performance was achieved in the tactile modality, usually regarded as inferior to the visual and auditory modality. Although she displayed distinct ERPs in a visual oddball, the visual channel could not be utilized for communication – even a so-called gaze independent speller failed. Our results thus highly encourage BCI development in the frame of a user-centered approach. Generalization from healthy participant data to patient samples should be treated with great caution and cannot replace actual end-user testings. BCIs that may be regarded less effective or less practical, may be the only possibility for a specific end-user. Adjusting BCI development specifically to end-users' needs and requirements is mandatory and will thereby potentially allow for a transfer of BCI technology out of the lab into end-users' daily lifes.

Keywords: brain computer interface (BCI), event related potentials (ERP), end-users, user-centered design, visual, auditory, tactile

1. Introduction

Brain Computer Interface (BCI) developments are often tested in healthy samples and generalization to functionality in those with severest motor impairment is often assumed yet less often confirmed. It is well known that performance deteriorates when bringing this technology to potential end-users and that some users even lack sufficient control (BCI inefficiency). Retained abilities may greatly vary across potential end-users. Thus, there is an extensive need for testing BCI developments in patient samples. Their needs and requirements may well differ from those of healthy participants, care-givers or family members [Zickler et al., 2011]. Herein we present data from a case study which emphasizes the need of a user-centered design in BCI development.

2. Material and Methods

2.1. The case

The herein presented potential BCI end-user is a 46 year old woman who has been in the locked-in state for 7 years after a brainstem stroke in the pons. She has no reliable muscle control other than vertical eye movements. During the last year, control of the left thumb rehabilitated but is not yet fully reliable. She communicates by means of binary partner scanning (yes = eye lift; no = looking down). It is assumed that the lesion in the brain stem barely affected her cortical abilities (as confirmed by CT) and she was fully attentive during all sessions.

2.2. Experimental Design

Data was collected on five consecutive days and different setups tested for finding a reliable communication channel: (1) Oddballs in 3 modalities, i.e. visual (count Einstein face, ignore red squares), auditory (count high pitched tone, ignore low pitched tone) and tactile (count stimulus on one location, ignore the other; locations were switched between runs to account for sensitivity differences). All oddballs shared the same parameters except for the modality and stimulus duration (two stimuli, target to non-targets ratio: 1:5, 1000ms inter-stimulus interval; 2 runs per modality). (2) Matrix based visual ERP-BCI paradigms in different settings (6x6, 4x4; different sizes on screen) (3) A so-called gaze-independent visual ERP-BCI paradigm with characters displayed consecutively in the middle of the screen [Acqualagna et al., 2010]. Only 6 characters were used in this case to align the paradigm with the parameters (incl. timing) of the visual oddball. (4) Tactile paradigm in which letters were grouped into four categories that could be selected by focusing attention on one of four tactile stimulation units placed on the left arm (which was sensory-sensitive in her case). This paradigm was specifically designed to copy her partner scanning approach, thus allowing for communication in a well-known, long established setting.

EEG was obtained from 15 passive Ag/AgCl electrodes with mastoid ground and reference and sampled at 512Hz. All paradigms were implemented in Python 2.7 and connected to BCI2000 via UDP.

3. Results

Fig. 1 displays the average ERP at electrode Cz for each modality evoked in two runs of an oddball paradigm. To control for reliability of elicited ERPs we set up a classifier on one run and tested it on the second run (and vice versa). Tactile modality displayed most reliable ERPs that resulted in an average offline classification accuracy of M=100%, i.e. all trials were correctly identified (each run comprised 3 trials with 30 odds per trial). Visual modality was moderately accurate (M=66.5%), whereas auditory ERPs resulted in worst performance (M=33.0%). We thus tested only visual and tactile modalities with BCI systems.

(1) Visual BCI: Although she reported to fully perceive the entire screen, no matrix based BCI communication could be established. Interestingly, also the gaze-independent central speller paradigm did not yield positive results. From none of the acquired data sets, reliable classifier weights could be generated.

(2) Tactile BCI: Four tactile stimuli were the target once in a tactile BCI calibration session. Offline performance was estimated 100% with 8 stimulation sequences. Unfortunately, this system could not be tested online as the user had to cancel the last testing session due to strain. Online results are thus pending.

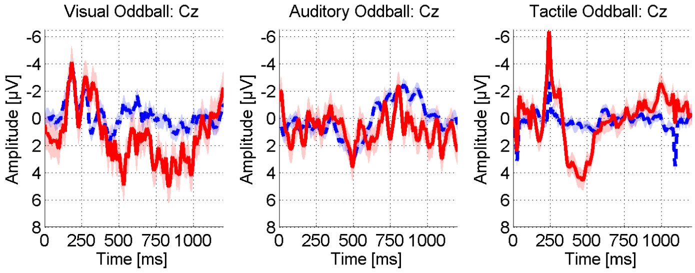

Figure 1: *Average ERP at electrode Cz from the oddball sessions in three different modalities*

4. Discussion

Results of our case study manifest the importance of testing BCI systems in the target population and developing systems specifically adjusted to their needs. To our experience, only such user-centered BCI design is able to account for the great variance of users' retained abilities. From the literature we expected visual (gaze-independent central speller) and auditory modalities to work with the locked-in patient. Although she was not able to fixate, she reported to fully perceive the entire screen. Compared to the visual oddball, in which a salient white face was used as rare stimulus, it may be much more difficult to identify a target character among others of same size and color if the user is not able to fixate the stimuli. This result may question the gaze-independence of gaze-independent spellers. From the auditory oddball results we assume that no auditory BCI would work in her case, yet no auditory BCI data were recorded for systematic investigation. Importantly, from the literature we expected tactile stimulation inferior over others [Aloise et al., 2007], as the only study reporting similarity of P300 amplitudes across modalities placed an odd stimulus on the sensitive belly while all other stimuli were on less sensitive locations [Brouwer et al., 2010]. In our case, tactile stimulation evoked large and reliable ERPs that could accurately be classified. Online results are pending but offline classification accuracy for discrimination between four tactile stimulation units is promising.

Consequently, we highly encourage to not exclude approaches that may not be feasible for effective communication from a healthy user's perspective and to test BCI technology in end-user samples.

Acknowledgements

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Continuous and Discrete Control of a Hybrid Neuroprosthesis via Time-Coded Motor Imagery BCI

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Abstract. The feasibility of using a time-coded motor imagery-based brain-computer interface (BCI) for the control of an elbow and hand neuroprosthesis was investigated in a study with nine healthy subjects and one person with spinal cord injury (SCI). Context-based BCI commands, which resulted from motor imageries with different activation lengths, were used to open/close the hand or to flex/extend the elbow. All participants had to follow a predefined activation sequence simulating a self-feeding procedure. On average 5.5 out of 10 sequences were successfully completed by the study participants. The SCI end-user was among the best subjects. The system was found to be feasible for persons with severely limited muscular functions by providing a control method purely based on mental activity.

Keywords: Electroencephalogram (EEG), Brain-Computer Interface (BCI), Functional Electrical Stimulation (FES)

1. Introduction

People with spinal cord injury (SCI) suffer from restricted limb functions to different degrees depending on the level of injury. Individuals with an injury above the 5th cervical vertebrae can greatly benefit from an upper extremity neuroprosthesis which can restore elbow extension/flexion and grasping function to a certain extent. Self operation of such a neuroprosthesis requires some kind of control signal. This signal can be derived from muscles not affected by the spinal cord lesion, e.g., shoulder, mouth, or cheek movements. However, in severely disabled people with SCI not enough muscles are under voluntary control. Therefore, signals derived from brain activity may be an alternative for such a neuroprosthesis control in this user population. One popular method is to measure electrical activity on the scalp of the user with electroencephalography (EEG). This activity can be classified and translated into commands by a brain-computer interface (BCI) [Wolpaw et al., 2002] which can be used to control neuroprostheses. The aim of this study was to investigate if time-coded motor imagery (MI) [Müller-Putz et al., 2010], generated by commands with different time lengths, can be used to either control the grasping of the hand or to move the arm up or down continuously. The time-coded BCI can be more difficult to master but has the benefits of needing only one changeable pattern for controlling more than one action and the effortless use of rest for a non-control state.

2. Material and Methods

Nine healthy subjects with BCI experience took part in the study (M=24.9, SD=1.7 years old). Additionally, one end-user participated: a 30 year old male, diagnosed with an incomplete/complete SCI at the level of C4/C5. The patient had no voluntary hand and restricted elbow function. MI BCI training (MI versus rest) was carried out to record data for preparing an LDA classifier. All healthy subjects used right hand MI; the end-user had to use feet MI because no reliable pattern was found for the right hand. Using the classifier online, subjects had to complete ten sequences (open hand→close hand→move arm up→open hand→return to starting position) with a time limit of 180 s. Intermitting break sequences of 60 s were used to count false positives (FPs). Muscles of the arm and hand were controlled by functional electrical stimulation (FES) with support from a hybrid orthosis (consisting of more than one component), which could read and control the angle of the elbow and further provided stabilization [Rohm et al., 2011]. Healthy users controlled the arm of a proxy-subject who was equipped with the hybrid FES orthosis to prevent undesired effects on the brain signals from sensory feedback due to FES. Users were provided with video feedback showing the controlled arm from a perspective above the shoulder. The SCI end-user underwent the same procedure without a proxy-subject for direct comparison of the results obtained in healthy subjects. In addition, he performed the experiment a second time with the hybrid FES orthosis mounted on his own arm. In his case, effects on the brain signals from sensory feedback could be neglected due to the absence of sensory function in his distal arm. A scheme of the setup can be seen in Fig. 1A. An abstract feedback, which was a schematic visualization of the arm, displayed the current angle of the arm and the state of the grasp. Fig. 1B shows all possible states and according effects of short and long MI commands. A short command was detected between 0.75 and 1.25 s; a longer detection was used to move the arm as long as the detection was active or until an end position was reached. A continuously filling bargraph informed the users about the current length of the detected command.

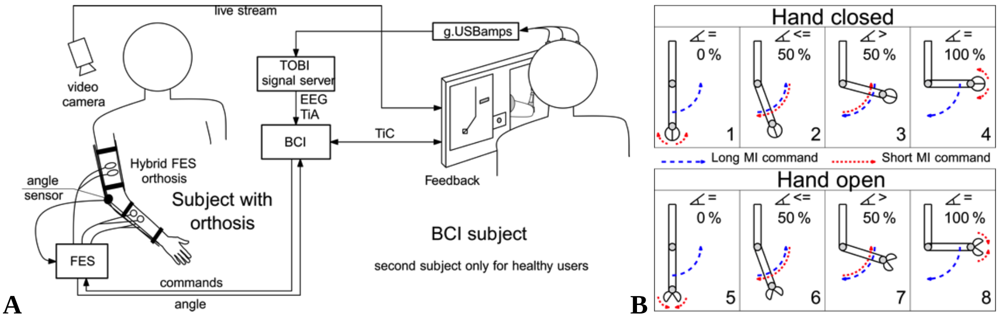

Figure 1. **A** *demonstrates the setup of the experiment. Two subjects were only used with healthy BCI subjects in order to avoid sensory feedback from FES stimulation.* **B** *shows the eight states the arm could reach and the context-based commands executed depending on the length of the MI command.*

3. Results

All subjects were able to generate more commands during the experimental than during break sequences (Tab. 1). Five participants could successfully complete more than half of the sequences, including the end-user who had the second best true positive (TP) rate (the percentage of correct context-based commands) when using the orthosis. The average time used to finish all ten sequences was 22.6 min, the maximum being 30 min plus some overtime to finish final commands.

Table 1. *TP rate, FP/min, commands/min, length of sequences, and number of successfully completed sequences for all healthy subjects and for two different sessions with and without the equipped orthosis on the end-user.*

	TP [%]	*FP/min*	*Commands/min*	*Length [min]*	*Successful [%]*
S1	45.9	3.2	8.3	26.2	30
S2	77.7	8.2	9.7	11.5	100
S3	49.9	1.5	6.7	28.9	20
S4	68.1	1.1	8.7	18.7	90
S5	45.8	7.4	8.4	26.9	30
S6	67.5	7.6	9.0	18.1	90
S7	50.6	5.7	7.7	30.4	0
S8	62.3	3.5	7.5	24.3	60
S9	54.0	4.3	6.5	29.1	20
End-user, - orthosis	66.4	7.3	10.5	14.5	90
End-user,+ orthosis	73.7	2.0	6.9	19.9	80
Average	60.2+/-11.4	4.7+/-2.6	8.2+/-1.3	22.6+/-6.4	55.5+/-36.2

4. Discussion

The TP rates for all subjects were relatively low, because for most of the subjects it was difficult to perform MI reliably for different time lengths. Some had difficulties with long MI while performing better for short MI and vice versa. Fortunately, the end-user could control the neuroprosthesis very well. The presented setup showed that signals derived from the brain may be an interesting alternative to systems based on EMG or muscular functions for continuous control of elbow and hand movements in very high lesioned spinal cord injured people.

Acknowledgments

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A Hybrid BCI for Telepresence

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Abstract. Previously we have shown that motor-disabled end users were able to drive a telepresence robot using a Brain-Computer Interface (BCI). However, to facilitate the interaction part of telepresence, users must be able to voluntarily and reliably stop the robot at any moment, not just drive from point to point. We propose to exploit the user's residual muscular activity to provide a fast and reliable EMG channel, which can toggle start/stop the telepresence robot. Our preliminary results show that not only does this hybrid approach increase accuracy, but it also helps to reduce workload and was the preferred control paradigm of all 4 participants in this study.

Keywords: Hybrid BCI, Telepresence, Mobile Robots, Motor Imagery, Shared Control

1. Introduction

We have already shown how a 2-class BCI can enable motor-disabled end users to successfully drive a telepresence robot in a complex environment [Carlson et al., 2012]. To date, these users have relied upon an assistant to start and stop the BCI feedback that allows them to drive the robot. Furthermore, they were only able to stop the robot when the shared control system determined that they wished to dock to a particular target. However, it is an important element of any telepresence system to be able to reliably start and stop the robot at any point, regardless of the interface [Tsui et al., 2011]. As a solution, we propose to exploit the hybrid BCI (hBCI) principle, which has already been shown to work well in the Braintree text entry prototype, whereby a complementary EMG channel is added to the EEG-based BCI [Perdikis et al., 2012].

2. Material and Methods

2.1. The Telepresence Platform

Our telepresence robot is driven using a 2-class asynchronous sensory-motor rhythm-based BCI. The robotic platform and the EEG-based BCI system (including pre-processing, feature extraction and classification methods) are described in detail in [Tonin et al., 2011]. The default behaviour of the robot is to move forward and avoid obstacles where necessary. The user can then voluntarily deliver one of the two classes (turn left or turn right), or decide not to issue a turning command, which yields an implicit third class known as intentional non-control, where the robot continues with its default behaviour. A shared control system takes the environmental context into account when interpreting these commands [Tonin et al., 2011].

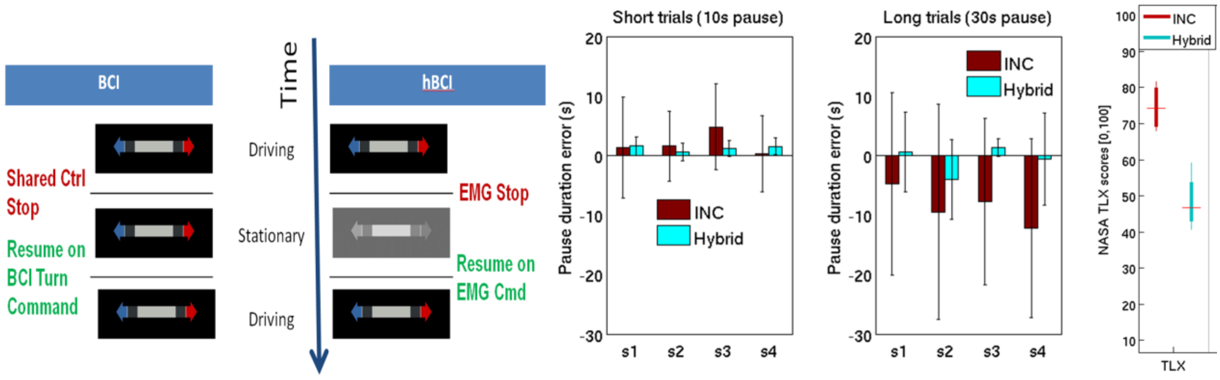
2.2. The Control Paradigms

We compare the existing BCI control paradigm with the new hybrid paradigm, which adds an EMG channel to the system. In the original paradigm, once the shared control system has automatically stopped the robot at an identified "target" location, to remain stationary, users must (intentionally) not deliver any commands, until they are ready to move on. This can be extremely demanding, especially if the user wishes to interact with someone (telepresence) whilst the robot is stationary. Conversely, in the new hBCI paradigm (see Fig. 1(a)), an additional bipolar EMG channel acts as an asynchronous toggle switch, which can start or stop the robot's motion and simultaneously (un)-pause the delivery of BCI commands. Motor-disabled end users often have some residual voluntary EMG activity that can be exploited for this purpose [Perdikis et al., 2012].

2.3. The Experiment Protocol

We perform a feasibility study with 4 healthy males aged 28±6 years. They were all able to reach >90% accuracy in delivering left and right commands in a cued protocol, prior to undertaking the experiment with the robot. The task involved driving the robot along 8 trajectories, each ~5m in length. The subject was audibly cued by the experimenter to pause and resume driving twice at predefined locations along each path. We compare the original BCI control paradigm (condition INC)—where the shared controller stops the robot and any BCI command resumes the motion—with the new hBCI paradigm (condition Hybrid), for both short (10s) and long (30s) pauses. The left and right turns and pauses were interleaved and counterbalanced within subjects, whereas the control paradigms were block-counterbalanced between subjects.

3. Results



(a) (b) (c)

Figure 1. *(a) The protocol: BCI (INC condition) vs hBCI (Hybrid condition). (b) The error in the duration of the pause for different length trials using both control paradigms, for each subject, s1-s4. Positive values indicate that they remained stationary too long, whereas negative values mean that they moved on too soon. (c) The task load index reported by all 4 subjects, higher values mean higher perceived workload.*

Although we do not yet have enough participants to give any statistically significant results, this pilot study does suggest some noteworthy trends. As can be seen in Fig. 1(b), it was much more difficult for participants to make the robot remain stationary for a precise period of time using intentional non-control, compared with using the hybrid BCI. This is especially the case for long trials, where participants were instructed to stop for a period of 30 seconds, but on average could only remain stationary for around 20 seconds, before they accidentally delivered a command. Furthermore, the variance of the INC trials is greater than that of the hybrid trials, which again highlights the difficulty of precise timing for BCI command delivery [Carlson et al., 2012]. In the hybrid condition, for one of the long pause trials, subject s2 relaxed and accidentally flexed his arm, which resulted in a false positive in the EMG and contributed to the larger negative mean error. Importantly, the subjects report a reduction in the perceived task workload, when using the hybrid approach, as can be seen in Fig. 1(c). Moreover, all 4 of them reported that they preferred to use the hybrid version for stopping, rather than relying upon the shared control in combination with intentional non-control.

4. Discussion

This pilot study suggests that not only does the hybrid approach provide a reliable and precise stopping mechanism, but that users are able to successfully complete the task with a lower perceived workload. These results may be transferred to representative end-users, who are able to produce reliable EMG activity (fatigue should be negligible given the sporadic nature of stop commands). The new hybrid control paradigm empowers users to start and stop the BCI controller, without having to rely upon an assistant. This, combined with the lower overall workload, is likely to enable BCI users to work independently for prolonged periods of time.

Acknowledgements

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A tactile P300-BCI for Communication

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Abstract. Brain-Computer Interfaces (BCI) for communication purposes are usually controlled via a P300 paradigm. There, a high number of different classes is presented to the user, thus enhancing the information transfer rate in comparison to e.g. motor imagery based BCIs. During the last years several P300 speller, based on visual stimulation, were developed. For people with visual impairments another stimulation strategy needs to be used. In this publication a tactile P300 based BCI was tested on nine healthy users, reaching an average control accuracy of 68.1 % after the first session. Three of the nine users performed additional sessions to evaluate the effect of training on the accuracy rate.

Keywords: EEG, P300, tactile stimulation, BCI, people with impairments

Introduction

The P300 approach is one of the most popular BCI control strategies currently used, especially for spelling devices. Guger et al. (Guger et al, 2009) investigated how many people are able to control a visual P300 based BCI. After five minutes of training 89% of 81 persons were able to spell with an accuracy rate between 80% and 100%, when using a row-column flasher (chance level was 1/50). Ortner et al (Ortner et al., 2011) investigated the control accuracy of a visual P300 speller for people with motor impairments, showing that one user suffering from locked-in syndrome, reached an accuracy of 40% (chance level: 1/50). But the P300 can also be elicited via auditory or tactile stimulation. This offers the possibility to control a P300 speller to people suffering from visual impairments. Also, a tactile P300 approach could be used to investigate the consciousness of nonresponsive persons. Brouwer et al. (Brouwer et al., 2010) investigated the feasibility of a tactile P300 speller with two, four or six vibrotactile elements placed around the user's waist. They reached a mean bitrate of 3.71 bits per minute in their best setup. In the work presented here eight elements were placed on the user's fingers (see Figure 1).

Material and Methods

EEG was measured on eight positions of the cortex (Fz, Fc1, FC2, C3, CZ, C4, CP1, CP2) and bandpass filtered between 0.1Hz and 30 Hz. The vibrotactile elements (tactors, produced of vibrating elements without specific control of the stimulation frequency) were fixed on the little finger, ring finger, middle finger and index finger of the left and right hand. The tactors were stimulated in randomized order. The stimulation time was set to 100 ms and the pause between the stimulations was 150 ms. As in a visual P300 speller the subject's task was to attend to one of the tactors and count each time this tactor vibrated. Each vibration of the target tactor elicited a P300 wave in the EEG. The classification was done using a multi-class linear discriminant analysis classifier. For each session a training run was used for setting up the classifier and a second testrun for testing the control accuracy was performed. A sequence of stimulations comprised 30 repetitions, the user had to attend during a sequence to the selected tactor, after the sequence was finished the selected tactor was visualized on the computer screen. For each run eight sequences were performed. For masking the acoustic noise produced by the tactors (that could also elicit P300 waves) the experimenter played brown noise via two earplugs to the user. After the testrun, the online classification accuracy was calculated. Three users (Subject 5, 6 and 9) performed additional sessions to see if their performance increases due to training.

Results

Results are summarized in Table 1. The mean accuracy was 68.1% but the performance of single subjects varied between 25% and 100%. The last row shows the accuracy of the three people who underwent additional training, the number of additional sessions is shown in parenthesis. S5 reached again 62.5% for the second session and finally 100% after the third session. The results of S6 in the additional sessions were: 62.5%, 87.5%, 87.5% 100%.

Figure 1. *Left: Eight tactors (blue) used for stimulation. The g.STIMbox is used to control the single tactors and turn them on and off. Right: Setup of the experiment. Four tactors are placed on the fingers of the left hand, the other four are placed on the fingers of the right hand. For electrical noise suppression in the EEG signal, the user is connected to ground (yellow stripe).*

Table 1. *Results of the nine users*

Subject ID	1	2	3	4	5	6	7	8	9	Mean	STD
Accuracy after one session in %	25	100	100	25	62.5	50	62.5	100	87.5	68.1	30.7
Accuracy after additional sessions in % (number of additional sessions)	-	-	-	-	100 (3)	100 (5)	-	-	0(10)	66.70	57.70

Discussion

The overall control accuracy (68.1%) of the device was worse than in the work by Guger et al., (Guger et al., 2009). The device though is not intended to compete against visual P300 speller, but rather to be an alternative. Furthermore two of the three subjects who did additional training reached 100% accuracy after 3 and 5 session. For one of them (subjects 9) the accuracy decreased with every session, until he reached 0%. We suspect that this was due to a lack of motivation. Also the number of classes is lower compared to a visual P300-speller where one can use a bigger matrix of single characters. Some users reported that it was hard for them to discriminate neighboring fingers, but the users doing more sessions also reported that it got easier after some training.

Acknowledgements

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A 2D Cursor Control Based Brain-Computer Interface Speller

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Abstract. In this paper, we present a motor imagery based brain-computer interface speller that combines motor imagery based 2D cursor control with "Hex-o-spell" paradigm. The experimental results showed that the average spelling speed is 11.96 characters per minute and its average information transfer rate is 54.48 bits per minute.

Keywords: Speller, Motor Imagery, 2D Control

1. Introduction

Motor imagery based BCI speller generally can not use full size virtual keyboard on the screen due to their limited commands. Thus motor imagery based speller always work with the special designed paradigm. The Berlin BCI research group has proposed a excellent speller paradigm, called 'Hex-o-Spell' [Blankertz et al., 2006], in which the subject can spell a letter in two-step. This system is based on two-class motor imagery BCI and it's speed is between 4.6 and 7.6 characters per minute (CPM) for two subjects. Comparing spelling performance with ERP or SSVEP based speller, the speed of 'Hex-o-Spell ' speller is not comparable. In this paper, we present a novel BCI speller, which use BCI actuated 2D cursor to spell in 'Hex-o-Spell' paradigm. Five subjects achieve good performance in online experiments.

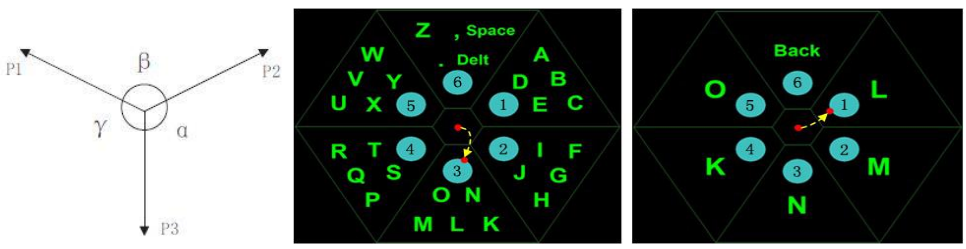
2. Material and Methods

2.1. 2D control

In our previous study [Xia et al., 2012], we presented a three-class (left hand, right hand and feet) motor imagery based BCI for 2D cursor control. The output probability $P1$, $P2$, $P3$, predicting probabilities of Support Vector Machine (SVM) classifier, are mapped to three vectors, as shown in Fig. 1(a). $P1$ is the probability of left hand imagery , $P2$ and $P3$ are the probabilities of right hand and foot imagery. The angle between two vectors is 120 degree and the value of vector is equal to the value of output probability. In order to move the cursor to a target, the subject should combine two motor imagery tasks simultaneous to generate a speed vector to drive the cursor to the target instead of considering horizontal and vertical movement.

2.2. Hex-o-Spell paradigm

We adopted a similar 'Hex-o-Spell' paradigm in [Blankertz et al., 2006], which consists of two-layer structure. Each layer includes six blocks. In the first layer, there are 5 letters or symbol and a blue circle in each block (Fig. 1 b). Only a letter/symbol and a blue circle in each block at second layer (Fig.1 c). There are 30 symbol in this paradigm (26 letters and four special symbols: comma, period, space and delete). A sample of spelling is shown in Fig.1(b,c). In the initial state, the cursor is at the center of the hexagon. In order to spell 'L', the user will move the cursor to choose the block with 'L'. When the blue circle of target block is hit, the paradigm will extend to second layer. At the same time, the cursor will be moved back to the center of the hexagon. Then the user will move the cursor to hit the blue circle of target block with 'L' and the procedure is finished.



(a) (b) (c)

Figure 1. *Speller paradigm (a).three-class MI based 2D control. (b) First layer (c). Second layer*

2.2. Experiment

The EEG signals are recorded with a 16 channel g.USBamp system using band-pass filtered between 5 and 30 Hz and sampled at 256 Hz. Electrodes are placed according to the international 10-20 system. Thirteen channels in motor cortex area were selected (FC3 FCz FC4 C5 C3 C1 Cz C2 C4 C6 CP3 CPz CP4), the ground and reference electrodes were fixed on Fz and the right earlobe respectively.

In our previous study, we recruited 10 naïve subjects for motor imagery based 2D control experiment [Xia et al., 2012]. Only six subjects finished the 2D control experiment and five of them are invited to attend current study (4 males; 1 female; all right handed; age 22-26 years; all got payments) .

In online spelling experiment, each subject is asked to spell English word in 3 runs (Run1 WOMEN_DESK_WATER_HAND_MEMORY; Run2 ZONE_BABY_FACE_TAXI_JUNE; Run3 QUICK _VIDEO_GOLF_HOUR_PENCIL). Subject repeated the experiment 3 times. We set the no error protocol in this experiment that means subject should correct spelling mistake.

Table 1. *Average Accuracy , CPM, ITR and Times*

Subject	*Accuracy(%)*	*CPM*	*ITR(bits)*	*D1(s)*	*D2(s)*	*D3(s)*	*D4(s)*	*D5(s)*	*D6(s)*
S1	92.04	9.82	36.71	1.78	5.17	4.32	2. 54	2.02	3.54
S2	98.48	14.87	72.33	1.55	2.33	2.20	2.49	1.56	3.24
S3	95.73	11.65	49.70	1.65	3.11	3.24	3.22	1.80	3.53
S4	95.39	8.84	37.68	2.91	3.78	4.42	3.52	1.90	4.91
S5	98.05	14.64	70.96	1.40	2.33	2.51	2.86	1.45	2.56
Mean	95.94	11.96	53.48	1.86	3.34	3.33	2.93	1.75	3.56

3. Results

To evaluate the performance of the proposed spelling system, we calculated the accuracy, the CPM , information transfer rate (ITR) and time of each direction. As shown in Table.1, the spelling accuracies are over 90% for all subjects. The CPM for three of five subjects is beyond 11. Even the Subject 4 can spell approximate 9 characters per minute. The average ITR of all subjects is 53.48. To move the cursor to target 1, 3, 5, the subject only uses one type of motor imagery . To hit the other three targets, the subject combined two type of motor imagery simultaneously. As shown in Table 1, the average times of target 1 and 5 are very short. But for some subjects, they can not control foot imagery well to hit the target 3 quickly.

4. Discussion

In general, Motor imagery based BCI spellers need special paradigm due to its limited commands. Even using well designed paradigm as Hex-o-spell, it can not achieve high speed performance. In this study, we combined Hex-o-Spell paradigm with 2d cursor control system to build a high speed speller. In online experiment, subjects can spell quickly and precisely. Comparing with other types speller system, such as P300 and SSVEP based speller[Speier et al., 2011;Hwang et al., 2012], our results are satisfactory and comparable.

Acknowledgements

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Hybrid Brain-Computer Interface based on Motor Imagery and Tactile Selective Attention

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Abstract. We propose a novel combination of two tasks to improve classification accuracy in Brain-Computer Interface (BCI): hybrid BCI using tactile selective attention and motor imagery. Subjects performed two different tasks: event-related desynchronization (ERD) using motor imagery, and steady-state somatosensory evoked potentials (SSSEP) using tactile selective attention. Subjects performed these two tasks individually, and then combined the two tasks simultaneously and sequentially in hybrid conditions. Ten healthy subjects participated in these four paradigms on the same day and off-line analysis showed that most subjects achieved improvement in classification accuracy in the sequential hybrid condition.

Keywords: Hybrid Brain-Computer Interface, event-related desynchronization (ERD), steady-state somatosensory evoked potentials (SSSEP)

1. Introduction

One of the biggest issues in motor imagery-based Brain-Computer Interface (BCI) technology is how to enable BCI-illiterate persons to control several machines with high reliability. Recently, hybrid BCI, which combines features acquired simultaneously from two different brain patterns, has been reported to facilitate this. Combining ERD and SSVEP yields better classification accuracy than each individual method alone and reduces the BCI-illiteracy. However, these results showed that classification accuracies were increased only for SSVEP-dominant subjects and that accuracies even decreased in the hybrid condition for ERD-dominant subjects. In addition, patients in the late stages of amyotrophic lateral sclerosis (ALS) cannot gaze at the flickering LED consistently when using SSVEP. To compensate for these disadvantages, we attempted to adapt SSSEP using tactile selective attention in motor imagery. For most subjects, this approach yielded better accuracy than each individual method alone, and it may be one solution for patients who cannot use their eyes to control BCI efficiently.

2. Methods

Ten healthy subjects (two females among them, 25 ± 2.78) participated in four BCI paradigms (ERD, SSSEP, Simultaneous hybrid, Sequential hybrid). Each subject performed these four paradigms randomly on the same day to avoid adaptation. Each paradigm consisted of two runs and each run collected 25 trials for each class. At the beginning of each trial, subjects focused on the center point of a computer screen. After 2 seconds, a left- or right-pointing arrow appeared on the screen and subjects imagined their hand moving for 3 seconds in ERD condition. Also, as in the ERD condition, in the SSSEP condition, subjects concentrated for 3 seconds on tactile stimulation of the thumb. Stimulation frequencies were selected by a screening procedure in order to apply resonance-like frequencies. Similar to the previous tasks, in the simultaneous hybrid condition, subjects imagined and concentrated simultaneously according to the direction of the arrow. In the sequential hybrid condition, the task period was 6 seconds. During the first 3 seconds, subjects concentrated on tactile stimulation, while for the last 3 seconds before the stimulations were removed, subjects imagined their hand movement. 64 EEG electrodes (Biosemi Active Two system) were attached on the scalp in the 10-20 international system and EEG signals were collected with 512 Hz sampling rates.

3. Results

For each paradigm, we estimated the BCI classification accuracy using Fisher's linear discriminant analysis (FLDA) after filtering by common spatial pattern (CSP). Five features that most related to each class were selected after CSP filtering. Datasets were separated into two groups (training: 70%, testing: 30%) and accuracy was calculated. This procedure was repeated 120 times to cross-validate performance thereby the mean accuracy from the estimates was adopted as a performance. Figure 1 depicts the average of the accuracies of all subjects corresponding to time and band power time courses. The classification results are tabulated in Table 1. In sequential hybrid condition, only imagination period was calculated to compare with ERD condition. ERD and SSSEP datasets were band-pass filtered with 8-15 and 16-25Hz, respectively.

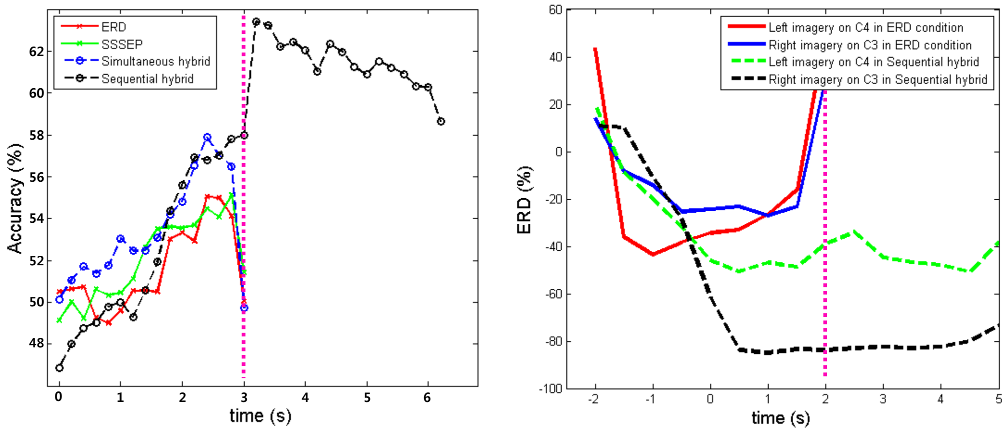

Figure 1. *__Left__:classification accuracy over ten subjects corresponding to time.__Right__:band power change with respect to pre-stimulus period of subject 5. Dashed vertical magenta line represents the end point of stimulations in the sequential hybrid condition.*

Table 1. *Results of the cross-validation procedure.The best condition for each subject is displayed in boldface.*

	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	***Mean***	***STD***
ERD	62.6	61.8	**82.4**	55.2	60.4	52.5	53.6	51.6	54.8	57.2	59.2	9.0
SSSEP	56.7	58.1	52.1	64.5	65.8	**66.2**	54.6	65.4	54.2	52.1	59.0	5.9
Simultaneous hybrid	58.6	66.3	61.4	56.6	58.8	57.6	63.5	62.9	52.3	58.1	59.6	4.0
Sequential hybrid	**81.1**	**67.2**	62.3	**74.9**	**95.1**	65.0	**67.1**	**68.8**	**60.8**	**65.8**	**70.8**	10.4

4. Discussion

In the simultaneous hybrid condition, no improvement in accuracy was evident that tactile stimulation could disturb motor imagination from the subject's questionnaire. On the other hand, the sequential hybrid condition yielded a remarkable improvement in accuracy and this is surprising since many of subjects showed around chance level in ERD condition. The reason why accuracies were improved in sequential condition is still under investigation.

Acknowledgements

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Evaluation of the Latency Jitter of P300 Evoked Potentials during (C)overt Attention BCI

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Abstract. Recently several reseachers proposed different P300-based Brain Computer Interfaces which can be controlled even with impaired eye movements (covert attention). However, in all the comparative studies, authors detected lower accuracy for the covert attention modality with respect to the overt one. This study aims to investigate if this decrement correlates with lower stability of the P300 potential evoked during the task. We evaluated the latency jitter of the P300 evoked potential with two BCI spellers exploiting overt and covert attention. We found that the P300 latency jitter is significantly higher and Written Simbol Rate is significanly lower for the covert-attention BCI speller. We conclude that the reduced performance of BCIs based on covert attention is only partially explained by the absence of discriminant short-latency Visual Evoked Potentials.

Keywords: Brain Computer-Interface; P300; Latency jitter; (C)overt attention; Wavelet analysis

1. Introduction

The Farwell and Donchin's P300 Speller interface is one of the most widely used BCI paradigm for text writing. Recently, some authors showed that the P300 Speller recognition accuracy significantly decreases when the eyes movements are impaired [Brunner et al., 2010]. User interfaces specifically designed to be operated in absence of eyes movements have been recently reported [Treder et al., 2010; Liu et al., 2010; Aloise et al., 2012]. In all the comparative studies, authors have shown a decrease in system performance using interfaces in covert attention condition with respect to the overt attention one, and they associated the spelling success with the overt tasks mainly on visually evoked potentials (VEPs) measured at occipital and parieto-occipital sites [Treder et al., 2010, Aloise et al., 2012]. Also, Thompson et al., [2013] demonstrated that accuracy achieved with P300 Speller, was strongly correlated with the P300 latency jitter. This study aims to investigate whether the decrease in system performance (i) is fully explained by the absence of VEPs, and (ii) correlates with a lower stability of the P300 evoked potential elicited in covert attention condition with respect to overt attention one.

2. Material and Methods

Nine healthy female subjects were involved in this study (mean age 27±5). Scalp EEG signals were recorded (g.USBamp, gTec, Austria, 256Hz) from 8 positions (Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8, referenced to the right earlobe and grounded to the left mastoid). The stimulation interfaces consisted in: i) the P300 Speller, a 6 by 6 matrix containing 36 alphanumeric characters; ii) the GeoSpell interface, in which characters are organized in 12 hexagonal groups of 6 characters each, following the same logic of a 6 by 6 matrix [Aloise et al., 2012]. Each subject performed 4 recording sessions in different days. A session consisted of 6 runs (3 runs for each interface) and 6 trials per run. Each trial (consisted of 8 stimulation sequences) corresponded to the selection of a single character displayed on the interface. Each stimulus was intensified for 125ms, with an Inter Stimulus Interval (ISI) of 125ms. For each participant, BCI performances were assessed offline, according to the number of stimulation sequences averaged during each trial. We used a Stepwise Linear Discriminant Analysis (SWLDA) to select the most relevant features that allowed to discriminate Target stimuli from Non-Target ones. In particular we performed a 3 fold cross-validation exploring all the possible combinations of training (2 runs) and testing (1 run) data set for each session and for each interface. The maximum Written Symbol Rate (WSR, symbols/minute [Liu et al., 2010]) was calculated for each iteration as a function of the number of stimuli repetitions in the trial. Furthermore, we excluded the contribution of the VEPs in the performance evaluation in order to take into account only the P300 event related potential. Only for the P300 Speller interface, we evaluated performances taking into account both VEPs and no-VEPs contribution. In this way, the EEG signal was reorganized in overlapping 600 ms long epochs starting 200ms (0 ms for the P300 Speller with the VEPs contribution) after the onset of each stimulus. Also, we evaluated the latency of the P300 evoked potential for each trial, in order to estimate the jitter of the latency for each interface. In this regard, we applied a method based on the Continuos Wavelet Transform (CWT) and the estimation of the empirical Cumulative Distribution Function (CDF), in order to enhance the signal (P300) to noise (spontaneous EEG) ratio [Hu et al., 2010]. At this point, we calculated the inverse CWT for each trial, and we estimated the latency of the P300 potential as the highest peak of the signal into the epoch. Therefore, we estimated the distribution of the P300 latency for each subject, for a total of 72 trials (4 sessions, 3 runs, 6 trials) for each interface. We evaluated the jitter of the latency subtracting the 3rd and the 1st quartile of the distribution.

3. Results

Results showed a significant decrease in the jitter of the P300 latencies during the P300 Speller task ($p < .05$), with respect to the GeoSpell interface one. Furthermore, performance achieved with P300 Speller in terms of WSR, were significantly higher ($p < .05$) with respect to the GeoSpell interface.

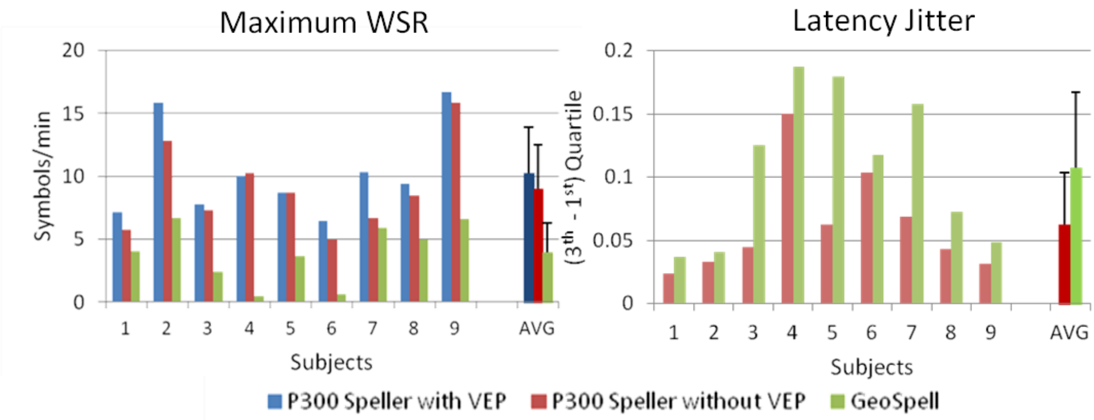

Figure 1. *Maximum value of WSR and P300 latency jitter over Cz channel for each subject, and the mean and stardard deviation over all the subjects for each interface. Also, WSR values with and without VEPs contribution have been represented for the P300 Speller interface.*

4. Discussion

The aim of this study was to investigate whether the decrease in system performance using GeoSpell interface in covert attention condition could be related to a low stability of the P300 potential evoked during the task. In this way, we evaluated the P300 latency jitter and the achieved performances of nine healthy subjects during the two tasks, excluding the VEPs contribution during the feature extraction stage. The results showed an increase in the P300 latency jitter, consistent with performances evaluation. Preliminary findings, indicated that even in the absence of VEPs, the P300 Speller interface used in overt attention modality, reaches greater accuracy with respect to the GeoSpell one used in covert attention. Furthermore, both the accuracy and the latency jitter significantly change comparing overt and covert tasks. This result could indicate that the low stability of the P300 evoked potential during the covert task would be one of the causes of the significant decrement of the system performances. Further investigations will be addressed to understand what are the neurophysiological causes of the high jitter detected during the covert task. A possible hypothesis would be that the covert attention modality induces an higher variability of the time needed for the perception and categorization processes of the stimuli. Also, a method capable to estimate the P300 latency at level of single epoch, could be used to decrease the P300 latency jitter online, improving the system performances.

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Offline Muscle Synergies Decoding from EEG

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Abstract. Muscle synergies are thought to be the building blocks used by the central nervous system to control the overdetermined problem of activation of muscles. Decoding these synergies from EEG could provide useful tools for BCI-controlled orthotic devices. In this paper, we assess the possibility of decoding muscle synergies offline from EEG slow cortical potentials in two healthy subjects performing a planar center-out reaching task.

Keywords: Offline decoding, Linear Decoding Model, EEG, Muscle Synergies, Kinematics

1. Introduction

When moving our limbs, our muscles are hypothesized to be controlled as group of muscles, or muscle synergies, instead of individual units. A lower dimensional descending neural signal is possibly integrated in the spinal cords before reaching the muscles. Decoding muscle synergies from EEG signals could be a useful tool to control a robotic arm in real-time. Indeed, muscle synergies contain information about the kinematics and dynamics of the arm.

3D hand kinematics have been shown to be relatively well decoded from EEG slow cortical potentials [Bradberry et al., 2010]. We hypothesize that the same slow cortical potentials might contain information on the synergies, as they also carry information on other motor parameters such as movement onset [Lew et al., 2012]. Therefore, we first extract muscle synergies from EMG data of two healthy subjects during a planar reaching task. We then decode the extracted muscle synergies from slow cortical potentials of EEG using a Linear Decoding Model. We finally compare the decoding performance of muscle synergies and kinematics.

2. Material and Methods

2.1. Experiments

Two healthy subjects were asked to perform center-out planar reaching movements to four targets, 10cm away from the center, while holding the PHANTOM robotic arm, which recorded the kinematics at 100Hz.

Scalp EEG were recorded for 64 electrodes (10/20 international system) at 2048Hz. 3 EOG channels were also recorded at 2048Hz. Raw EEG signals were low-pass filtered at 50Hz, resampled to 100Hz, high-pass filtered at 0.2Hz, low-pass filtered at 1Hz, and standardized to have zero-mean and unit standard deviation for each channel. Processed EEG signals were further corrected for processed EOG activity by linear regression.

EMG signals were recorded for 16 muscles of the arm, shoulder, upper back and chest (1KHz). Raw EMGs signals were high-pass filtered at 50Hz, rectified, low-pass filtered at 20Hz, down-sampled to 100Hz, baseline corrected using the processed rest EMG, and normalized to have unit variance on the whole EMG signal.

2.2. Time-invariant Synergies Extraction

Muscle activation can be represented in a lower dimensional space (i.e. muscle synergies) by the sum of K continuous positive activation coefficients multiplied by their fixed positive weight vector [Cheung et al., 2005].

We estimated the synergies using the Non-Negative Matrix Factorization algorithm [Lee and Seung, 1999]. The number of synergies was chosen so that the reconstruction R^2 of half of the trials – that were not used to estimate the synergies weights – was above 80%. With this criterion, seven synergies were sufficient. Once the number of synergies has been identified, the synergies weights and activation coefficients were extracted for all trials. The synergies activation coefficients were further low-pass filtered at 1Hz.

2.3. Decoding

To continuously decode muscle synergies and hand kinematics from EEG signals, we used a linear decoding model, similar to Bradberry et al. [2010]:

$$c_i[t] = a_i + \sum_{n=1}^{N} \sum_{k=0}^{L} b_{nki} EEG_n[t-k] \quad (1)$$

where c_i is the activation coefficient of the i^{th} synergy, a and b are weights obtained from multiple linear regression, L is the number of lags (L=10), and N is the number of EEG sensors (N=16). The EEG electrodes selected for decoding were located on the ipsilateral and contralateral motor cortex. The same model was used for decoding hand kinematics where c_i was replaced by the end-effector velocity.

Decoding performance was assessed by an 8-fold cross-validation. The performance measure is the

Pearson's correlation coefficient between the decoded synergies or kinematics and the actual signal. We computed the chance level by shuffling the input and output trials for training the decoder. We repeated the procedure 1000 times to get a distribution of decoding performance from random inputs and computed the one-sided 95% confidence interval as the chance level.

3. Results

The mean synergies weights for both arms of both subjects are shown in Figure 1A. The decoding performance for decoding the 3D end-effector velocities and 7 muscle synergies are given in Figure 1B.

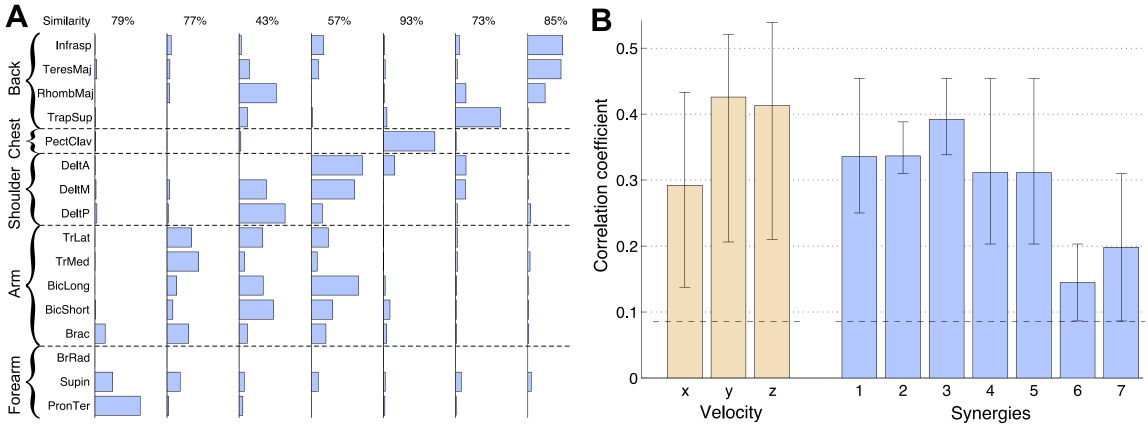

Figure 1. *(A) Mean synergies weights for the two arms of two subjects. 7 synergies were extracted with NNMF from EMG recordings of 16 muscles. Synergies were sorted by similarity across arms and subjects by maximizing the normalized dot product of the synergies weights. Mean similarity across subject is shown above each synergy. (B) Mean decoding performance (across two subjects, two arms) of the kinematics (velocity) and synergies activation coefficients from EEG slow cortical potentials. The dotted line indicates the one-sided 95% chance level. Error bars show the minimum and maximum decoding performance.*

4. Discussion

We showed that for two healthy subjects, it is possible to reconstruct some of the muscle synergies relatively well with two synergies being decoded with a performance close to that of the kinematics. However, other synergies were poorly decoded with a decoding performance close to the chance level. We note that our kinematics decoding performances were on average slightly higher (r_x=0.29, r_y=0.43, r_z=0.41) than those obtained in [Bradberry et al., 2010] (r_x=0.19, r_y=0.32, r_z=0.38).

One of the issues in decoding synergies is the definition of synergies itself. The number of synergies extracted is based on an arbitrary criterion and changing this number can affect the decoding performance of synergies that would be otherwise combined or separated with a different number of synergies. In addition, the algorithm used can also influence the extracted synergies, especially when using algorithms such as Factor Analysis that allows for negative synergies weights and activation coefficients.

In the near future, we will see if it is possible to decode kinematics from only the subset of the best decoded synergies which would indicate us which synergies are actually important to be decoded from EEG. In addition, we will test if similar synergies across subjects and limbs are systematically decoded with a similar accuracy. For example, we see from this two subjects analysis that the forearm, extensor, both shoulders and flexors, and chest synergies are relatively well decoded (r=0.34, 0.34, 0.39, 0.31, and 0.31 respectively) while the two synergies controlling the back muscles are not (r=0.14 and 0.2). If this is systematically true, we could decode only this highly decodable subset of synergies and use this as control input to a robotic device and, more importantly, to an exoskeleton or FES orthosis.

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Asking the Practioneers – Requirements Concerning a New EEG-based Diagnostic Battery

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Abstract. To overcome high rates of misdiagnosis in patients with disorders of consciousness (DOC) it has been discussed to develop diagnostic means based on imaging and electrophysiological techniques. Nine interviews have been conducted with representatives from acute care clinics and neurological rehabilitation centres to investigate their requirements concerning such new methods. It was found that the current diagnostic process still largely relies on clinical assessment. Interviewees criticised the dependence of the diagnostic outcome on skills and experience of the physician and the lack of measures to estimate the further development of patients. A new system is expected to provide reliable and valid results containing prognostic information.

Keywords: disorders of consciousness, detection of consciousness, diagnosis, EEG, event-related potentials

1. Introduction

Vegetative state (VS) is defined as 'wakefulness without awareness' meaning that these patients show signs of wakefulness like sleep-wake-cycles but are assumed to be unaware of themselves and their environment [Jennett & Plum, 1972]. In contrast, minimally conscious (MCS) patients do show inconsistent but reproducible behaviors associated with conscious awareness [Giacino et al., 2002]. Studies have repeatedly indicated a high proportion of misdiagnosis in patients in minimal conscious and vegetative state [Schnakers et al., 2009].
One aim of research with patients with DOC is to provide new diagnostic approaches to overcome this issue since only a correct diagnosis can be the starting point for an effective therapy. Making use of event-related potentials measured with EEG is one promising method [Kotchoubey et al., 2002]. However, in order to transfer research results into a ready-to-use product, it is essential to learn about requirements and expectations of physicians having to work with it in the future. This study presents first results from seven interviews conducted with representatives from different neurological institutions which deal with patients diagnosed with DOC.

2. Material and Methods

Semi structured interviews were conducted in nine different places across Germany – four in acute care clinics (ACC) and five in neurological rehabilitation centres (NRC). Interviewees were five medical directors, two chief physicians and two senior physicians. They were told about the development of a new EEG-based diagnostic battery based on event-related potentials. This system could support diagnostics by analysing brain reactions to different tones and semantic material. The interviews took approximately one hour and covered three main topics: current diagnostic procedures, weaknesses of the current process and expectations concerning a new diagnostic battery. All interviews were recorded and transcribed. Answers to each question were grouped into clusters and counted.

3. Results

For reasons of clarity, answers of ACCs and NRCs will be presented together unless a differentiation is of importance for the result.

3.1. Current Diagnostic Process

A diagnosis in ACCs is made rather quickly within few hours. NRCs acknowledge the diagnosis provided by the referring ACC but review it on admission of the patient. A diagnosis is regularly checked on an hourly (ACCs), daily or weekly (NRCs) basis depending on the status and medical history of the patient.

When making a diagnosis, physicians largely rely on the clinical assessment including observation of the reactions to speech, painful stimuli and visual stimuli. All institutions apply EEG, especially in comatose, VS and MCS patients. One institution (NRC) also applies event-correlated potentials. In some cases CT (n=6) or fMRI (n=4) are used additionally. The Glasgow Coma Scale is administered in six, the Barthel Index in five and the Coma Recovery Scale revised in two institutions.

Seven institutions consider their diagnosis to be of primary importance for treatment decisions and future therapeutic processes of the patients. Two institutions (NRC) consider the diagnosis to be important but put a greater focus on prognosis and treatment.

3.2. Weaknesses in the Current Procedures

Results in the current diagnostic process partially depend on experience and observational skills of the responsible physician (n=5). Therefore there is a wish for a stronger focus on different aspects of diagnostics already in the education of becoming neurologists (n=3).

Three interviewees also saw a weakness in the lack of methods to estimate the further development of a patient concerning regaining consciousness or rehabilitative progress. Furthermore, a lack of sufficient resources to apply imaging techniques was mentioned by three interviewees.

Two interviewees mentioned a lack of consideration for cognitive matters in diagnostics. A lack of measures to track the on-going development of a patient, the wish to become even quicker in the diagnostic process and a wish for a better transfer from science to practice was mentioned by one interviewee respectively. Furthermore, the wish for a clear differentiation of akinetic mutism and covered behavior was mentioned once.

3.3. Requirments and Expectations

Six interviewees stated a general interest in applying a new system in their institution (one ACC, three NRCs). The three remaining representatives from ACCs cannot imagine using it in their institutions but consider it to be interesting, especially for therapeutic institutions such as NRCs.

All interviewees named reliability and validity as absolutely mandatory. Additionally, a high immunity to disturbances and characteristics of a medical environment (n=6) and the practicability of the system regarding time, personnel, financing and the general design (n=7) are considered important. However, it was also mentioned four times that the amount of resources available to invest will largely depend on the benefit of the resulting output.

Following up on the weaknesses of the current diagnostics, the most decisive expectations are the prognostic value of the results (n=7) and a support in therapeutic decision-making (n=5). Thus, the output is expected to be accurate in terms of a selective differentiation between various diagnoses and prognoses.

4. Discussion

A correct diagnosis is vital not only because prospects for MCS patients are more favourable than for VS patients but also to avoid the situation of an aware patient being treated as being in VS [Healy, 2010]. The results shed light on two important aspects: Firstly, there are weaknesses in the current diagnostic process and practioneers are generally interested in new measures to overcome them. Secondly, practioneers have clear expectations concerning a potential new battery. Therefore, it will be necessary to create a validated system that works reliably, allows for prognostic statements and does not add to the burden of limited financial and personnel resources. Thus, further effort has to aim at providing an EEG based test battery for selective prognostic results for supporting and fostering diagnosis and therapy of DOC patients.

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A Pilot Study on Mental Workload Detection during Operation of a Self-paced ERD BCI

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Abstract. We explore whether it is possible to detect mental workload - based on established models described in literature - during self-paced event-related desynchronization (ERD) based brain-computer interface (BCI) operation. During 40 min. self-paced ERD BCI operation we found no detectable workload related changes in the electroencephalogram. We did, however, find changes in the heart rate that appear to be time-locked with patches of deteriorated self-paced ERD performance.

Keywords: Brain-Computer Interface (BCI), Electroencephalography (EEG), Event-Related Desynchronization (ERD)

1. Introduction

Self-paced event-related desynchronization (ERD) based brain-computer interfaces (BCI) are designed to grant users on-demand access to communication (e.g. [Millán and Mouriño, 2003]). The prospect of this natural, intuitive and non-muscular interaction renders such systems potentially valuable communication and control aids for individuals with severe functional disability.

Based on literature ([Hockey et al., 2003; Zander and Kothe, 2011]), we explore whether including awareness of the user's mental workload, could be used to counteract the inherent performance instability of asynchronous ERD BCI systems. According to established models, increased mental workload induces changes in the electroencephalogram (EEG; [Gevins and Smith, 2007]) and heart rate (HR; [Stuiver et al., 2012]). We evaluate, whether our implementation of these models - which we first validate using an N-Back paradigm - detects workload or other performance related changes during 40 min long online self-paced ERD operation.

2. Material and Methods

2.1. N-Back condition

Three male volunteers (S1-S3; age 28 ± 3.6 years) ran through 12 N-Back runs (50 x 3s trials) of different workload configurations (N=0-, 1-, 2- and 3; constant perceptual and motor demand, varied workload). Subjects were asked to press a button, whenever the current, visually presented letter matched the letter presented N steps before. For N=0, subjects were asked to press a button whenever the letter "H" was shown. After every run, participants rated their perceived level of workload between 0 and 10 (continuous scale). The 12 runs were configured to the N-Back levels 0, 1, 0, 3, 0, 2, 0, 3, 0, 1, 0 and 2. We recorded EEG using 12 sensors from frontal, central and parietal sites. ECG was recorded from a bipolar derivation on the thorax.

For offline analysis we band-filtered the EEG of channel Fz for the first 0-Back run between 4 and 8 Hz (theta-band), squared, logarithmized and averaged over the whole run to get a subject specific baseline [Gevins and Smith, 2007]. On the data from run 2 to 12 we continuously computed the logarithmic theta band power from Fz and averaged the resulting signal over 120 s. EEG segments, in which the computed time series exceeded 15% of the baseline value, were classified as time periods of high workload (binary EEG detector). For ECG the same procedure but a lower detection threshold of 8% was used.

2.2. Self-paced online ERD condition

Three non-novice male volunteers (S1, S4, S5; age 26.7 ± 5.5 years) participated in the self-paced online ERD experiment. The recording setup and offline simulation procedure were identical to Section 2.1. In addition, the system was configured to detect workload online based on the EEG. To avoid erroneous workload detections, the online, binary EEG detector output (0=no workload; 1=workload) was additionally averaged over 240 s. Online, high workload was detected only, when this additionally averaged signal exceeded the threshold of 0.5.

We set up the ERD classifier using a cue-guided, co-adaptive paradigm ([Faller et al. 2012]), where subjects performed right hand movement imagery vs. relax with eyes open. After calibration, users had to select a predefined sequence of menu entries by performing hand movement imagery within defined time periods using the Hex-o-Select ERD user interface (UI; [Faller et al. 2012] based on [Blankertz et al. 2006]) for 40 minutes.

3. Results

3.1. N-Back condition

Subjects reported the highest level of workload for the N-Back conditions N=2 and N=3. In two of the three subjects S2 and S3, both 3-Back and the last 2-Back condition were detected using the EEG based binary workload detector. Logarithmic theta band power in the different N-Back runs correlated statistically significant ($p \leq 0.05$) with the level of perceived workload for S2 ($r=0.86$; $p=0.0003$) and S3 ($r=0.72$; $p=0.0191$) but not for S1 ($r=0.54$; $p=0.067$). The HR based algorithm detected both 3-Back and one 2-Back condition in Subject S1 and one 3-Back condition in Subject S2. There were no detections for Subject S3. The averaged HR signals for the different N-Back runs correlated statistically significant ($p \leq 0.05$) with the levels of perceived workload for S1 ($r=0.80$; $p=0.002$), but did not for S2 ($r=-0.21$;$p=0.52$) or S3 ($r=-0.14$; $p=0.66$).

3.2. Self-paced online ERD condition

All participants were able to control the Hex-o-Select UI using the ERD input signal for the full 40 minutes, achieving positive predictive values of 40 to 63 %. The EEG-based workload detector, triggered in only one of three participants (at the same time point online and during offline simulation). In that case the detection onset coincided with very strong movement artifacts. During simulation, the HR-based workload detector triggered in two subjects (S1 and S5). These activations were time-locked to time-spans during Hex-o-Select operation, where the users made a high number of false positive selections or failed to trigger selections as instructed.

4. Discussion

For all participants in the N-Back condition, either the EEG or HR measure was sensitive to task difficulty and perceived mental workload. The self-paced ERD operation on the other side does not appear to induce workload at a high enough level to lead to detectable changes in the theta band of the EEG. Interestingly, the HR-based offline simulation led to detections that were time-locked with patches of low self-paced ERD Hex-o-Select performance. It is unclear, however, whether these HR changes might necessarily be related to workload. Alternatively they could appear in response to bad performance ("Fight-or-Flight" response) or maybe - although unlikely - even be indicative of a mental state that causes low self-paced ERD performance. In any case, results from this first pilot study suggest, that HR could be an adequate signal to detect phases where the ERD control output may be less reliable. Revealing the details of the apparent interrelations between ERD based Hex-o-Select performance and the changes in HR requires further, more detailed investigation.

Acknowledgements

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Connecting the Disabled to their Physical and Social World: The BrainAble Experience

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Abstract. Motor disabilities of people from any origin have a dramatic effect on their quality of life. The BrainAble project is about empowering them and pursues to mitigate the limitations of the everyday life to which they are confronted to due to innovative interfaces as BNCI and technologies of SmartHome, Social Networks and Virtual Reality. Now, at the end of the third and final year, when the development is finished and the cycles of user testing have been doing, it is time to summarize the project and propose new challenges.

Keywords: Brain Neural Computer Interface, Ambient Intelligence, Virtual Reality, SmartHome

1. Introduction

The aim of the BrainAble project is to offer an ICT-based HCI composed of BNCI system [Wolpaw, J.R. et al. 2002] combined with affective computing, virtual environments and the possibility to control heterogeneous devices like SmartHome (SH) environments, and Social Networks (SN), allowing the disable person to increase its level of autonomy and eInclusion. The paper summarizes the different techniques researched and developed to achieve this aim.

2. Material and Methods

As we have already introduced, the possibility to achieve the goal of BrainAble is only feasible by the combination of the last advances in BCNI, SH, Ambient Intelligence (AmI) [J.C. Augusto., 2007], and VR techniques. Figure 1 shows how the project establishes the key relationships between these technologies.

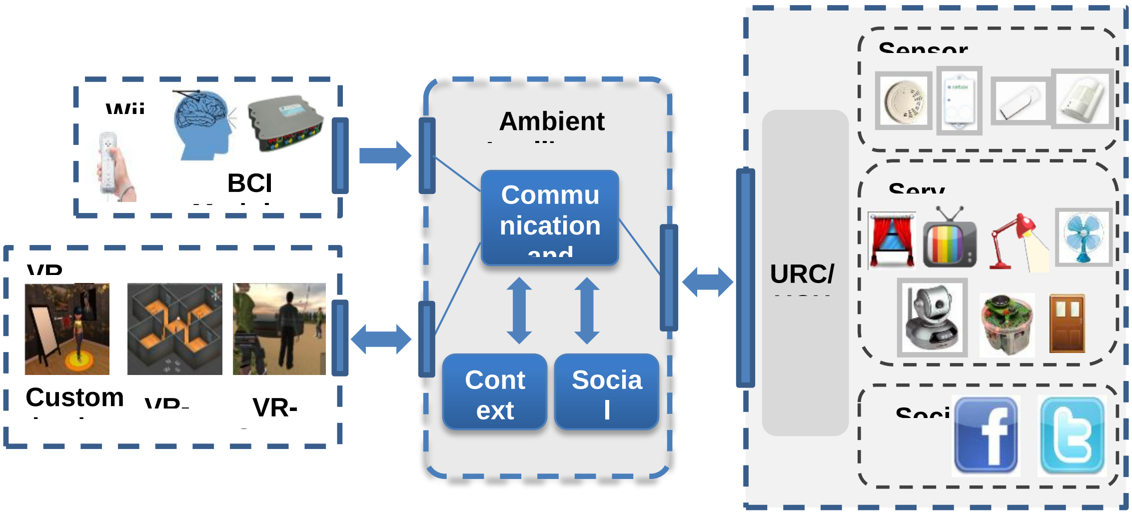

Figure 1. *System overview by modules related to technologies.*

2.1. BNCI

In Brainable, BCNI development is based on the non-invasive electroencephalogram (EEG). BCNIs have a very limited bandwidth and cannot compete with other means such as speaking, writing or traditional HCIs, but can be extremely useful for users who cannot speak, write or use traditional HCIs. Thus, by adding contextual information could increase the effectiveness of a BNCI by allowing users to accomplish their goals more quickly and effectively. The platform has been implemented with several BCNI GUIs, such as the P300 Matrix, and Hex-o-Select, SSVEP or ERD.

2.2. SmartHouse and Ambient Intelligence

The SH technologies allow the house resident to control different devices of the house as TV, lights or furniture, like curtains or doors. In conjunction with this set of devices, we can establish a network of sensors in order to known the current status of the environment. As an innovative point, the BrainAble system includes the SN as one more sensor of the platform understanding the social interaction and information as a part of the user's context.

With all the information collected, and thanks to the combination of different techniques of AmI, we can control the house based on the context and act according to it helping to the disabled to be independent in its own house. Another possibility is to use this information to increase the usability of the BNCI system suggesting the most suitable actions to the user in each moment [Casale P. et al., 2012].

2.3. Virtual Reality

BrainAble provides a virtual interactive environment for training a new user to the platform, and also for providing an enhanced experience. The user is represented by a customizable avatar and is able to navigate the virtual environment, which can represent, for instance, her/his home, with the smart devices allowing to interact with them directly from the VR. VR is also used as a way to reduce the isolation of the user, thanks to the inclusion of a virtual community where meeting other people and interacting with them directly.

3. Results

Currently, the project consortium has finished the third-year prototype that implements an operational system which allows a BNCI to interact with SH functionalities such as the controlling of a commercial television, lightning system, a surveillance camera, access to Twitter and Facebook and a telepresence service composed via a robot device to make the users feel as if they were somewhere else. The prototype also includes a customizable avatar in a virtual model of the user's home allowing to interact with the SH devices and also a virtual community. The consortium has generated two complete prototypes which are under the final revision cycle by the end users.

4. Discussion

After three years of development and research the BrainAble system is ready. The two prototypes, in United Kingdom and Spain, are showing the benefits of the system, the points to improve and they have opened the way to the evolution of the platform. Therefore, we can assure that the aims of the project have been accomplished. From the result of this project the BackHome project learns being a step forward in the research of the BCNI field. In fact, the next step is to move the system from the hospitals and rehabilitation centers to users' homes allowing them to follow the cognitive rehabilitation in a more comfortable and familiar environment. This evolution will be also able to evaluate the increase of the user's quality of life allowing the therapists to adapt the system to these parameters, thanks to telemonitoring capabilities, and the system to auto-evaluate itself.

Acknowledgements

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Spatio-temporal Discriminant Analysis for ERPs using Inverse Solution

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Abstract. In this paper, we present a method for spatio-temporal discriminant analysis of cortical sources corresponding to the EEG signals recorded for Event-Related Potentials (ERP). We use cortical current density inverse method to localise the sources from the surface EEG and then find discriminant sources corresponding to the task at different time instances. We show the results for two different ERP experiments which are based on error-related potentials (ErrP) and evoked potentials in rapid serial visual presentation (RSVP). The spatio-temporal discriminant sources provide essential information about the brain dynamics for different experiments performed.

Keywords: Inverse solution, EEG, discriminant sources, event-related potentials

1. Introduction

The spatio-temporal discriminant analysis for event related potentials (ERPs) is conventionally performed on the sensor space, i.e. at the level of scalp EEG. In this paper, we are presenting a method to perform the same analysis on the source space with the use of distributed inverse solution. The method finds spatial sources across time that best discriminate two class-conditions for error-related potentials (ErrP) and rapid serial visual presentation (RSVP) based ERP experiments. For a given experiment, the analysis is performed across all subjects. When compared to discriminant analysis on sensor space, our method provides functional information of localization of discriminant sources over time. The localization results obtained with ERP experiments show that the discriminant activity of a signal is originating from a focalized source that varies spatially in different regions across time.

2. Experimental Setup

The protocol and experimental setup for measuring ErrPs is similar to the procedure presented in [Chavarriaga and Millán, 2010]. Ten healthy subjects (3 females) took part in the experiment. The subjects were asked to monitor movement of a cursor which was moving in discrete steps towards a fixed target on the screen. The cursor movement is termed erroneous whenever it moves away from the target. For discriminant analysis, data from six offline runs was used totaling 600 single trials (about 20% were erroneous).

For the RSVP experiment, 12 subjects (7 females) were instructed to count images of a specific object while natural images were presented to them at a rate of 4Hz. There were four different search tasks corresponding to four different animals. The images were selected from the Corel natural image database. A total of 1600 images were shown, among which 10% of images were target images.

3. Discriminant Analysis

The experiments were performed with 64-channel Biosemi EEG system using 10/10 international configuration of electrode positions at sampling frequency of 2 KHz. The EEG data was common average referenced and filtered in the frequency range [1 10] Hz. The intra-cranial source activity is estimated from surface EEG using cortical current density (CCD) based distributed inverse method [Cincotti et al., 2008]. The discriminant power (DP) for each estimated source was computed using Fisher score $((mean_1 - mean_2)/(var_1 + var_2))$ and at each time instance in the period [0 1]s after stimulus onset [Goel et al., 2011]. We selected top 100 discriminant sources at each time instance and equated their score to 1 and others to 0. Subsequently, we averaged the new scores across subjects for each experiment. The cumulative score obtained in the time interval was normalized by the highest score obtained among the sources.

4. Results

Fig. 1 (top) shows the mean and variance over subjects on the grand averages of all the trials belonging to two classes error-correct and target-distractor for both experiments. Channel FCz is selected for ErrP experiment and channel Pz is selected for RSVP experiment, since these channels are known to capture the error activity and P3b evoked activity, respectively. These plots also give insight of the temporal activity for two experiments. The

ErrP has prominent peaks around 300, 400 and 500 ms; whereas the P3b has prominent peak around 500 ms after stimulus onset.

As shown in Fig. 1 (bottom), the spatial localization of discriminant sources for ErrP is quite prominent in the fronto-central region of the cortex. The intensity of localization is high at time instances when the difference waveform in grand average plot peaks while the localization is sparse when the difference waveform crosses zero. Overall, the discriminant sources remain strongly focalized in the same region.

For the evoked activity in RSVP experiment, we find a clear cluster of discriminant sources only at a specific point in time that corresponds with the peak of the grand average that fits neurophysiological evidence of P3b. This cluster is present over parietal cortex at time instance 0.48s.

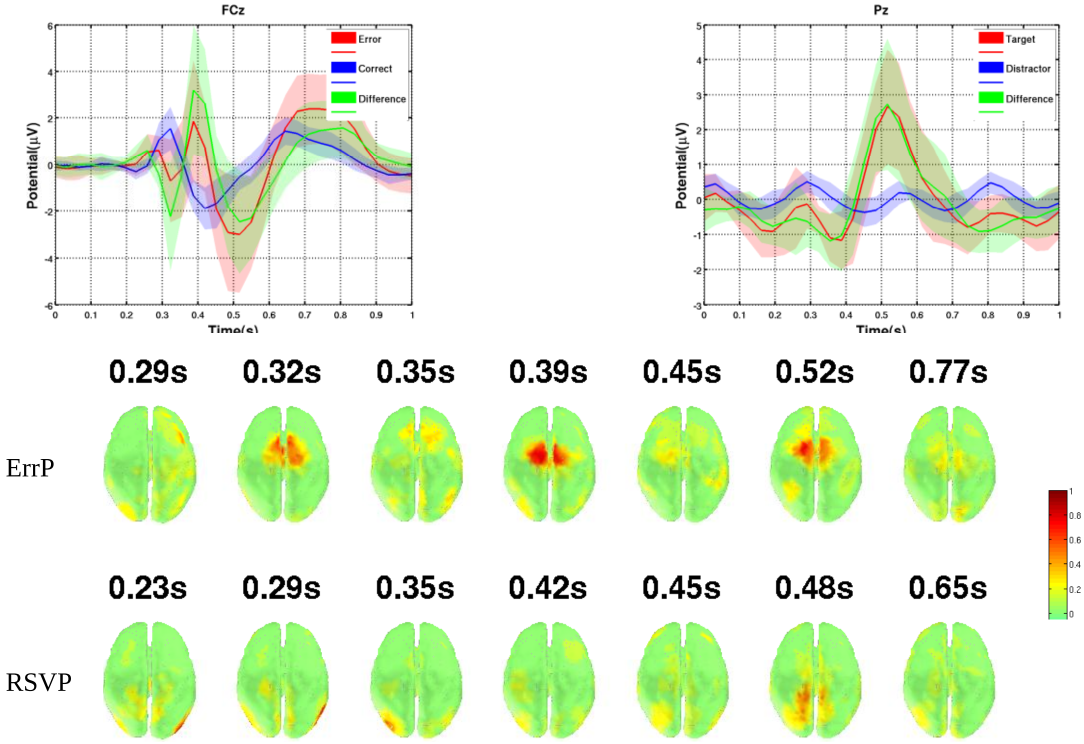

Figure 1. *(Top Row) Grand average across trials of one class and their difference for ErrP (CPz) and RSVP(Pz) again averaged over subjects. (Bottom Row) Source localization of selected discriminant sources at various time instances shown on head model (dorsal view).*

5. Discussion

In this paper we presented a method for spatio-temporal discriminant analysis of cortical sources obtained by the use of inverse solution. It provides direct correlation between task discrimination and the related functional anatomy at cortical source level. The extra step for inverse computation is not that demanding and makes it possible for real time use. The relevant discriminant sources identified by this method have been further selected for the purpose of classification in a brain-computer interface task that commonly uses these ERP signals. The process yields comparable performance to scalp EEG, while providing information about spatial distribution of cortical sources (i.e. finer-grain resolution than EEG).

Acknowledgements

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Freeing the Visual Channel – Feeling the BCI Vibe!

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Abstract. Controlling a device by the brain requires the user to pay visual attention to it, which is partly in conflict with the visual BCI feedback. Therefore, a tactile stimulator is developed, which provides a tactile illusion as BCI feedback. The stimulation system consists of six coin motors and a single-board microcontroller. Several psychophysical experiments are conducted to optimize the parameters that generate the illusion. Two protocols that convert the BCI feedback into spatiotemporal patterns of the stimulator are tested online.

Keywords: BCI, EEG, Tactile Feedback, Motor Imagery

1. Introduction

When controlling brain-actuated devices a split attention between the application and the brain-computer interface (BCI) feedback is needed, which is sometimes demanding for the participants [Leeb 2012]. Imagine controlling a wheelchair with the BCI: on the one hand you have to look where you want to drive your wheelchair, since you want to find the way and avoid obstacles, on the other hand you have to be aware of the BCI feedback, which shows your current brain status and gives information about how close you are to delivering commands with the BCI. Therefore, both visual feedback loops are important for a successful application control, but are competing for the same resource: our visual channel. Is there a chance to reduce the load or to free the visual channel from one of the components? Auditory or somatosensory modalities have already been used in BCI research. Since, we are interested in controlling our applications in a self-paced way without any external cues, evoked activities like auditory BCIs or steady-state-somatosensory potentials are not in our focus. Therefore, we transferred the position of the normal feedback bar in case of the visual BCI feedback, into a tactile feedback with stimulators on the neck of the participant. A similar approach was already presented in [Cincotti 2007], but their magnetic actuators interfered slightly with the electroencephalogram (EEG). Here we: present some new tactile stimulation hardware; investigate different stimulation patterns to optimize the subject's sensations; and analyze the influences of the tactile stimulation into the EEG.

2. Material and Methods

2.1. Hardware and Software Setup

Six coin motors (Precision Microdrives, UK) with a diameter of 10mm and a typical vibrational amplitude range of 0.5g to 1.8g are utilized for delivering tactile BCI feedback. The motors are attached in a horizontal line on lower neck with a center point at the spine and about 2.5cm of inter-motor-spacing (Fig. 1a). The spatiotemporal vibration pattern of the stimulator is controlled by the laptop through a single-board microcontroller (Arduino, Italy) to indicate the BCI performance of a subject in a 2-class BCI (Fig. 1b).

Two types of protocols, point-based and movement-based, that convert the current BCI feedback to spatiotemporal vibration patterns were tested. The point-based type places illusory tactile sensation at one point corresponding to the visual BCI performance. For example, for a classifier probability of 0.75, the virtual sensation point is placed at the mid-point between the spine and the rightmost motor. In the movement-based protocol, the speed of illusory tactile feeling of movement via all motors from one side to the other is altered based on the BCI performance. For example, a probability of -0.75 generates continuous left direction movements and that of 1 produces continuous right movements with a higher speed than that of 0.75. In addition, for both protocols, the amplitude of the vibration increases as the probability approaches to the extreme values.

2.2. Characterisation of the tactile illusion

The tactile illusion that places the virtual tactile sensation point in between the two real stimulation points [Alles 1970] is employed in both protocols to increase the spatial resolution (only 6 motors). This illusion point varies the position depending on the amplitude ratio of the real stimuli. For example, when two motors vibrate with the equal amplitude, tactile illusion is located at the center, whereas when the amplitudes are unbalanced it moves closer towards the larger stimulation amplitude. Hence, if the amplitudes of two motors are properly varied over time, a smooth movement between the two motors appears. To determine the appropriate shape of this amplitude variation, two types of preliminary experiments (i) between two motors and (ii) over all motors are conducted. Three subjects were asked to rank (1=low–4=high) four stimuli that have different shapes of amplitude variation (linear and three logarithmic) based on the characteristics of illusory movement: consistency of perceived strength, position of the illusion, and direction of the movement. In addition, to provide a constant increment of the perceived amplitude, the just-noticeable difference (JND) was measured for each subject.

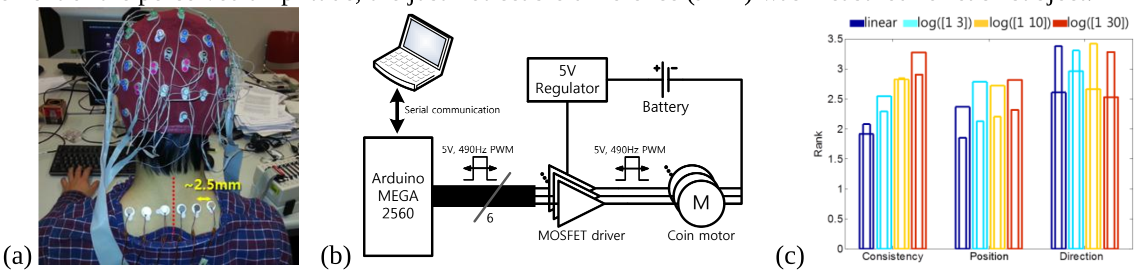

Figure 1. *(a) Picture of a typical setup and (b) block diagram of the developed tactile BCI feedback system with six motors. (c) Reported average ranks after normalization over each subject. Wide and narrow bars represent the results of virtual movements between two motors and over all motors, respectively.*

3. Results

3.1. Parameters for apparent tactile illusion and constant increase of perceived strengh

Fig. 1c shows the results of experiments to determine the shape of the amplitude variation. It shows that consistency increases in both cases, between two motors (wider bar) and over all motors (narrower bar), as the shape becomes more logarithmic over time [Alles 1970]. However, there is a certain preference to the shape of log([1 3]) in direction when the tactile illusion moves between two motors. For position, subjects preferred logarithmic shape. This results suggest that it is better to use the shape of log([1 3]) for the point-based protocol and the shape of log([1 10]) is appropriate for the movement-based protocol. In the JND experiments, JNDs lie in the range of 5% to 20% for different locations and base amplitudes. As a result, Weber fraction is set to 0.2, such that the vibration amplitude varies depending on the BCI performance. Note that, over a wide range of Weber fraction values, the shape of the exponential function remains almost unaffected when the function is scaled to the available ranges of the amplitude of the motors and that of the BCI performance.

3.2. Influence of vibrotactile stimulation on the EEG

The EEG was recorded from 64 channels (active BioSemi amplifier, fs=2048Hz, filter: DC–417Hz) while different tactile stimulation patterns (all motors / just left side / just right side / movement-based) were tested 30 times each. Every trial consisted of 5 seconds stimulation and 15 seconds rest. The spectrum was calculated for 1-second epochs (5 per stimulation period and 5 per rest (second 6-11)) and averaged over the repetitions for each condition. No influence of the various stimulation patterns could be found in the EEG spectra while comparing stimulation to rest and over the conditions.

Furthermore, to see the influence of the tactile stimulation on the online performance of a motor-imagery based BCI (g.USBamp, 16 channels, 512Hz, filter: 0.5–100Hz), two subjects compared the different feedback modalities. Two runs with 15 left and 15 right cues were performed for the following conditions: normal visual feedback, visual and tactile feedback, only tactile feedback and again visual feedback. No difference in the performances (99.2%, 98.3%, 99.2% and 90.8%, respectively) could be identified.

4. Discussion

In this work we presented the setup of a tactile stimulator which can be used to provide tactile BCI feedback to the user without interfering with the EEG. It seems that the subjects are able to perceive this type of tactile feedback well and no performance degradation could be identified. The next step would be to test this directly with an application, to add the visual part of it and to investigate the split attention with more subjects.

Acknowledgements

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A Portable Auditory P300 BCI using Directional Cues and Natural Stimuli

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Abstract. Currently many brain-computer interface systems require intact gaze control. This excludes all users who have lost such control. One possible alternative is the application of non-visual stimuli. We propose a P300 speller system using auditory stimuli based on natural sounds with additional spatial cues. Eleven healthy participants peformed two sessions with the proposed system. Average offline accuracies of 90% and bit rates of 5.45 bits/min were achieved in the second session of training.

Keywords: EEG; auditory P300; spelling

1. Introduction

Brain-computer interfaces (BCIs) provide a communication channel for severely paralyzed people. P300-BCIs can be controlled without functional gaze if auditory stimuli are used. Different systems have been proposed including spoken words [Furdea et al., 2009], tones augmented by physical spatial cues [Schreuder et al., 2010] or systems using tones with simulated spatial cues [Käthner et al., 2012]. We propose a new design combining spatial cues with natural sounds as stimuli.

2. Material and Methods

2.1. Participants

Eleven healthy participants took part in the study (eight female, mean age 24.27 years, *SD* = 7.14 years). Participants were compensated with 8€/hour or course credits.

2.2. Data acquisition

The electroencephalogram (EEG) was recorded with 32 active Ag/AgCl electrodes. These were located at positions F3, Fz, F4, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3, P1, Pz, P2, P4, PO7, PO3, POz, PO4, PO8, Oz and four EOG channels. Channels were referenced to the left and grounded to the right mastoid. The EEG was sampled at 500 Hz with a BrainAmp amplifier (Brainproducts, Germany).

2.3. Auditory ERP speller

Every participant used the auditory P300 BCI on two consecutive days. Online feedback was provided using a stepwise line discriminant analysis (SWLDA) classifier trained on the first three runs of the first session. After analyzing the data offline it was found that performance significantly increases if the classifier is retrained using the first three runs of the second session before classifying the remaining data of the second session. Every participant spelled nine words with five or six letters totaling 48 letters per session. In the first session an additional three words with five letters were recorded to train the classifier (consisting only of letters from the diagonal of the matrix: AGMSY).

Five different animal sounds augmented with spatial cues as described by [Käthner et al., 2012] were used as stimuli (Figure 1). The stimulus for row/column one (“duck”) was presented from the left, for the second (“bird”) from diagonal left, the third (“frog”) from the central position, the fourth (“gull”) from diagonal right and the fifth (“pigeon”) from the right. The user would first select a row and then after a short pause of 1920 ms a column of the matrix. Stimuli were presented with a duration of 150 ms followed by a pause of 250 ms (400 ms total inter-stimulus interval (ISI)) and repeated a total of 10 times per row and column. The BCI2000 software in combination with BrainVisionRecorder handled all aspects of stimulus presentation, data recording and online classification.

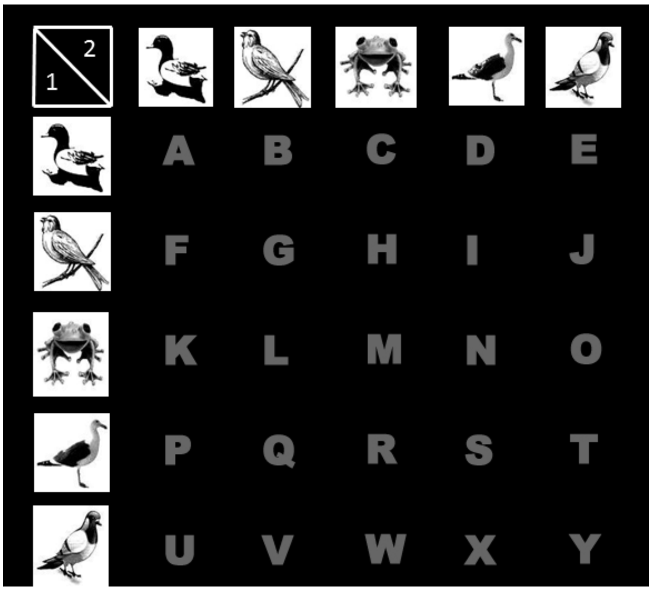

Figure 1. *Visual support matrix. The animal icons indicate which of five different sounds coded for a particular row or column. For example, to select K the user would attend to the frog to select the third row and then attend to the duck to select the first column.*

3. Results

Participants achieved mean accuracies of 76.73% in the first session and 69.64% in the second session. After retraining the classifier on the first three runs of the second session an accuracy of 90.18% was achieved when classifying the remaining six runs (with a total of 32 letters). The online information transfer rate (ITR) of the first session was 4.23 bits/min. This increased to 5.45 bits/min after retraining the classifier offline (using the same procedure and parameters as online) with the data from the second session.

4. Discussion

With 70% online accuracy subjects performed sufficiently well to possible operate a spelling system. The substantial increase in classification accuracy after retraining in the second session suggests that training effects can be expected if the participants perform more sessions. Event-related potentials are not affected by the training. Therefore, we assume a training effect on the task of focusing on the target stimuli. An increase from 2.76 bits/min in [Käthner et al., 2012] to a minimum of 4.23 bits/min was achieved through the use of natural sounds as stimuli. Thus, this design is a promising path for increasing ITRs in auditory P300 BCIs that will lead to a communication method for people in the complete locked in state.

Acknowledgements

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Increasing Tactile ERP-BCI Performance using Generic Models

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Abstract. Tactile ERP-BCIs may provide unique advantages over visual and auditive BCIs but often suffer from lower user performances. Herein we thus, evaluated the use of generic models for increasing BCI performance of low performing subjects. Such models create a generalized classifier from a pool of calibration sessions. Data of N=15 healthy participants was used to evaluate different generic models. Preliminary results display the potential of generic models for increasing the performance of those users who do not achieve sufficient accuracy from their own calibration run. Further research will be required to evaluate the effectiveness of different generic models in an online setting with larger sample size.

Keywords: Brain Computer Interface (BCI), event-related potentials (ERP), Generic model, tactile ERP-BCI,

1. Introduction

ERP-BCIs offer a high amount of control without the need for long-lasting training sessions. Tactile stimulation allows users to retain visual and auditory senses for non-BCI tasks and can easily be hidden underneath the cloths to reduce visibility of the system. Tactile stimulation was found to be a viable modality for ERP-BCIs [Brouwer and van Erp, 2010]. Although it may yield unique advantages in terms of user-friendliness it was found to achieve lower performance compared to visual or auditory stimulation [Aloise et al., 2007]. It has been shown for the visual modality that some users can use generic model classifiers instead of personalized classifiers to achieve acceptable performances [Jing et al., 2012]. Such models incorporate data from a pool of participants to create a generalized classifier independent from participants´ own data. Herein, we evaluated the potential of generic models in tactile ERP-BCIs for increasing accuracy of low performing participants.

2. Material and Methods

N=15 healthy participants (12 female, mean age 22.5 years, SD=3.2) participated in the study. Tactile stimulation was applied to participants' left leg, right leg, belly and neck with 4 pairs of vibrate transducers (C2 tactors; Engineering Acoustic Inc., USA; stimulus duration: 220 ms; inter-stimulus interval: 400 ms). EEG signals were recorded from 16 passive Ag/AgCl electrodes and amplified using a g.USBamp amplifier (g.tec Engineering GmbH, Austria). Two data sets per person were included into this offline analysis, i.e. one calibration run and one run for testing of classifier performance. The reported accuracies are based on classification of 48 single sequences.

Offline classification was performed in MATLAB 2010b (The Mathworks Inc., USA) using stepwise linear discriminant analysis. Participants who achieved performances below the required level for communication of 70% [Kübler et al., 2001] were regarded as low performance participants (N=6). For each participant four different classifiers were generated:

1. Base model: Base performances were gained using only participants' own calibration data for classification.
2. Generic model: A generic model was computed based on data from the full sample except for the participant on which the model was tested, i.e. the model was different for each participant but comprised data from the remaining N=14 participants.
3. Optimized generic model: Additionally, we created an 'optimized' generic model using only the calibration data of the N=8 participants who achieved more than 70% performance with their reference classifier. To maintain generic property of the model for those high performance participants, we created classifiers excluding their own calibration data from the optimized model.
4. Mixed model: Finally for each participant we created a mixed classifier using the weights from the *generic model* classifier and the participant's personal classifier (*base model*).

3. Results

Different classifiers were used to calculate offline performances for 6 low performance participants (see Fig. 1a). Three of six low performance participants (P2, P3, and P15) could achieve higher performances using the optimized generic model classifier. Importantly, optimized generic models boosted performance of P3 by 65% and of P15 by 36% of the performance achieved with their own model. However, not all low performers could benefit from generic models. One participant achieved almost the same level of performance and the remainder displayed decreased performances (P8: -4%, P5: -20%; P6: -12% of performance with their own models).

Additionally offline performances were also calculated for the 9 high performance participants. ERPs of some participants well matched the features underlying the generic model, while others displayed great difference. For example participant 1 scored the best performance using the optimized generic model, due to broad similarities between spatio-temporal features (Fig. 1b). On the other hand, participant 9 achieved the lowest performance as his individual pattern did not match the generic model. Our results thus suggest that different models may be needed to account for inter-individual differences.

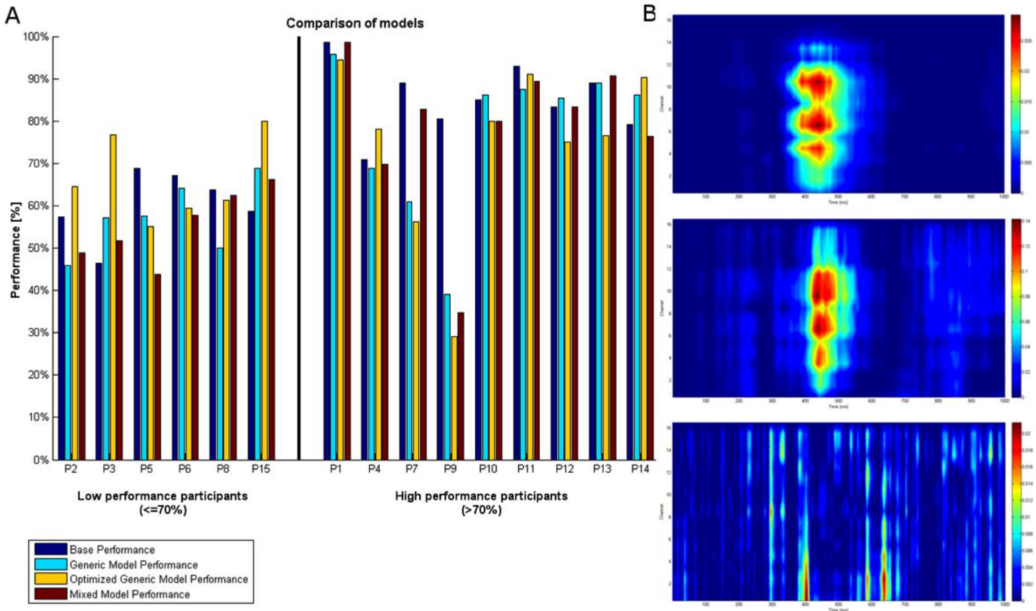

Figure 1. (A) *Average single trial performance, using 4 different classifiers. (B) Determination coefficients for data from generic model (top) vs. data from exemplary participants 1 (middle) and 9 (bottom). Channels are shown on the y-, time on the x-axis and R^2-values are color coded. Please note that color scales are different.*

4. Discussion

Preliminary results show that some low performance users can achieve higher performance using a generic model classifier and particularly display the potential of the optimized model. Some low performance users, however, do not improve using a generic model. From data of high performers it can be seen that not all users may display EEG patterns in line with the generic model, e.g. in P9 generic model classifiers did reduce the performance drastically. Despite using features that strongly differed from the generic model, he achieved high performance using his own classifier. Therefore our generic classifier is not generic for all tested participants. Additional participant data is required to evaluate whether there might be different generic models which could account for users not compatible to this generic model. Additional data may also further contribute to a better generalization of the generic model. Finally, use of generic models for tactile ERP-BCIs has to proof its validity in an online setting. However, our results are promising in that three participants, who achieved only low performances using their personal classifiers, could benefit strongly from using an optimized generic model classifier

Acknowledgements

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Extraction of Oscillatory EEG during Palm and Finger Movements

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Abstract. As a preliminary study of the EEG-based BCI to detect motor imagery of fingers, the EEG responses to the movements of palm, index and little finger of the right hand were investigated. The 63-channel EEG responses of four healthy human subjects were measured and the spatial distributions of the sensory motor rhythm (SMR) components on mu, beta and gamma bands were evaluated. It was shown that the mu band ERD during movements and beta band rebound ERS were observed in the contralateral hand area on sensorimotor cortex of three subjects, and the high gamma band ERS responses during movements were observed in the contralateral hand area of one subject. It was also shown that a clear high gamma band component could be extracted from the responses of one subject to the three tasks by using ICA.

Keywords: EEG, motor execution, sensory motor rhythm (SMR), high gamma band, ICA

1. Introduction

The BCI (brain-computer interface) based on motor imagery using EEG can be realized by focusing on the sensory motor rhythm (SMR) components from sensorimotor cortex, in which the ERS/ERD (event-related synchronization/desynchronization) of mu and beta band EEG were extracted and detected [Pfurtscheller and Lopes da Silva, 1999].

Recently the possibility to detect high gamma (HG) band EEG during motor tasks was shown [Darvas et al., 2010]. The HG frequency is higher than typical artifacts (e.g. EOG) or hum noise. The oscillatory EEG with higher frequency is hypothesized to be detected faster than that with lower frequency. These features indicate that the BCI to detect HG SMR might improve the current BCI based on motor imagery.

In this study, the SMR responses on mu, beta and gamma band frequency to the grasping of palm, tapping of index finger and little finger were investigated for further possible improvement of BCI based on motor imagery.

2. Material and Methods

Four right-handed able-bodied male subjects (22-24 years old) took part in the experiments. The study was reviewed and approved by the Ethics Committee on Clinical Investigation, Graduate School of Engineering, Tohoku University.

Subjects sitting on an armchair in an electromagnetically shielded room were requested to execute one of the tasks which were self-paced movements of palm (grasping), index or little finger (tapping) of right hand. On each trial, subjects were instructed to grasp or tap rapidly three times with a self-paced interval which was longer than 4 seconds. A session consisted of 25 trials and the task was fixed on each session. For each subject, the experiments were conducted for two days, and the number of sessions for each day was 12 (4 sessions for each task in a randomized order).

During experiments, EEG was recorded from 63 Ag/AgCl electrodes placed over the whole head based on the extended international 10-20 system (reference and ground were right and left earlobe, respectively). Additionally, a bipolar EMG was recorded from extensor digitorum muscle. The measured signals were bandpass-filtered between 1 and 500 Hz and sampled at 2500 Hz. No notch filter was applied.

After applying the CAR (common average reference) filter, the time-frequency ERS/ERD maps were computed. The onset time of the motor execution was detected from the envelope of the EMG data by applying the Hilbert transform.

The recorded data was also analyzed after applying ICA (independent component analysis). The FastICA algorithm [Hyvärien and Oja, 1997] was used in this study.

3. Results

In three subjects, mu band ERD during movements and beta band rebound ERS were observed in the hand area of sensorimotor cortex. The activations in contralateral area were larger than in ipsilateral area. The responses to finger movements were smaller than those to palm movements (Fig.1(a), left), and the spatial

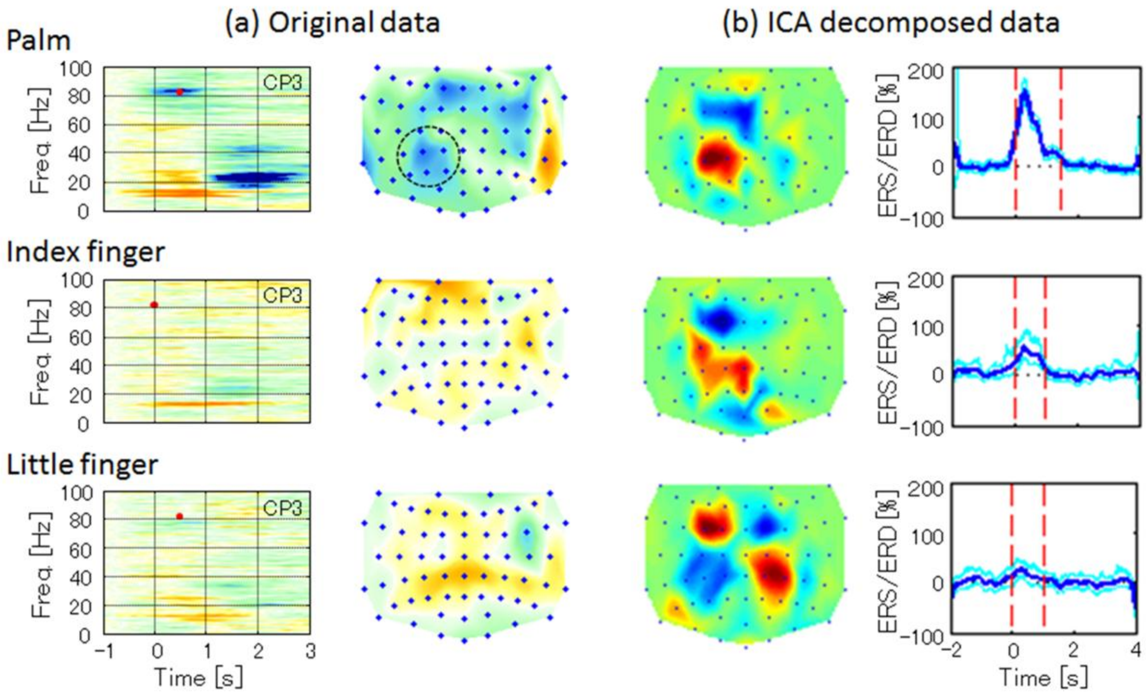

Figure 1. Responses to the movements of palm, index finger and little finger on one of the subjects. (a) ERS (blue) and ERD (orange) responses of the original EEG. Time-frequency map of ERS/ERD of the measured EEG taken from CP3 (left), and the spatial distribution of the HG response at time and frequency shown on the map by red point, on which the maximum ERS was observed during movement at 80-100 Hz (right). (b) A selected unmixing matrix obtained by ICA (left), and the ERS/ERD of the corresponding HG independent component at the same frequency shown in the right figure in (a). The Bootstrap confidence intervals (99%) were displayed by cyan lines (right).

distributions of these responses were similar. A HG ERS (82 Hz) during palm movements was observed from one of the three subjects (Fig.1(a), right).

The ICA was applied to the EEG data taken from the same subject as in Fig.1(a). All the obtained independent components were analyzed to find significant HG responses. The unmixing matrix selected on each task (left) and the ERS/ERD on HG band of the decomposed data (right) were shown in Fig.1(b). It was shown that the HG components elicited by the movements of palm, index finger and little finger could be extracted by ICA. The weight values of the unmixing matrixes were localized near to the contralateral (and ipsilateral on little finger) hand area on sensorimotor cortex.

4. Discussion

Although the mu and beta band ERS/ERD responses were found from three subjects, the HG responses could be observed from one subject. In this subject, it was shown that the ICA could decompose the measured EEG signal to the clear HG components related to palm, index finger and little finger, as well as the mu and beta band components. The ICA might be useful for designing spatial filters with local spatial distribution for decomposing the target responses to classify motor tasks [c.f. Kanoh et al., 2012].

The spatial distributions of the ERS/ERD responses to the movements of index finger and little finger were quite similar on these frequency bands. The cortical mapping of the SMR could be effective for classification of precise hand movements or motor imagery.

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A BCI using Electrocorticographic VEPs

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Abstract. Many brain-computer interface applications rely on visual stimulation causing steady-state visual evoked potentials. Most of them are non-invasive and based on scalp recordings. Therefore, performance for non-invasive methods is well known. However, there are no results for invasive, sub-dural recordings available. In this work one epileptic patient was tested in using a BCI relying on code based VEPs.

Keywords: ECoG, c-VEP, BCI, SSVEP

1. Introduction

A brain-computer-interface (BCI) allows the user to control a device like e.g. a neuroprosthesis with brain activity (Wolpaw et al., 2002). Usually, BCIs use brain activity extracted from electroencephalography (EEG) or electrocorticography (ECoG) (Leuthardt et al., 2004). Some of them rely on visual stimuli that elicit steady-state visual evoked potential (SSVEP) (Wang et al., 2008) or code-based VEPs (Bin et al., 2011). The code based approach promises better accuracy and higher ITR than the frequency coded SSVEP (Bin et al., 2009). This work investigates the comparison of code-based VEPs in the EEG and ECoG, as well as the online classification performance of a corresponding BCI system.

2. Material and Methods

The BCI system is based on MATLAB/Simulink and performs online and offline signal processing. Online classification results can be sent an arbitrary device. For visual stimulation a 63 bit pseudo-random m-sequence (Sutter, 2001) was presented on a standard 60 Hz LCD monitor. One subject suffering from epilepsy was not photosensitive and therefore participated at the experiment. Six intracranial electrode grids across the left hemisphere (Figure 1, left) were placed for ECoG recordings, because of a scheduled resective brain surgery. Data was recorded using a g.USBamp bio-signal amplifier (g.tec, Graz, Austria) with a sampling rate of 256 Hz and band-pass filtered between 0.5 and 30 Hz. As the visual cortex was not covered by all electrodes, only electrodes that were closest to the visual cortex were used for the analysis. The first task (i) was to gaze at a reference target over 200 cycles, to extract an average template signal from the ECoG for each electrode, with respect to the sequence. In a second task (ii), four target sequences were presented on the screen simultaneously. Each sequence is a phase shifted version of the reference sequence from (i). The subject had to gaze at each target three times for 10 s (3 s of rest and 7 s flickering), which led to 12 trials in total. For online target identification, a 2.1 s (two sequence cycles) long signal buffer is compared with the previously calculated templates using a canonical correlation analysis (CCA). Therefore, the canonical vector based on the templates and the raw data, is calculated offline and then used as a spatial filter, to combine the signal channels in the online experiment. The correlation coefficients between the spatial filtered signal and the phase shifted templates are the features in a linear discriminant analysis (LDA). The LDA classifier is computed offline, based on the comparison of the raw data from (i) and four phase shifted versions of the templates and then applied for online classification.

3. Results

Figure 2 shows the VEPs of eight electrodes after task (i), whereas the response of electrode E1 is highest (up to 50 µV). In the second task (ii), the ECoG experiment showed a maximum online classification accuracy of 83 % (Figure 1, right).

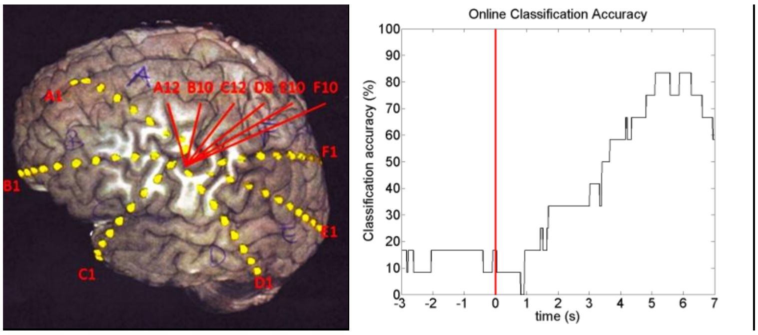

Figure 1: *Electrode montage with 6 strips (A1-A12, B1-B10, C1-C12, D1-D8, E1-E10, and F1-F10) across the left hemisphere (left). Online classification error of code-based VEPs, based on four phase shifted visual stimulation sequences (right).*

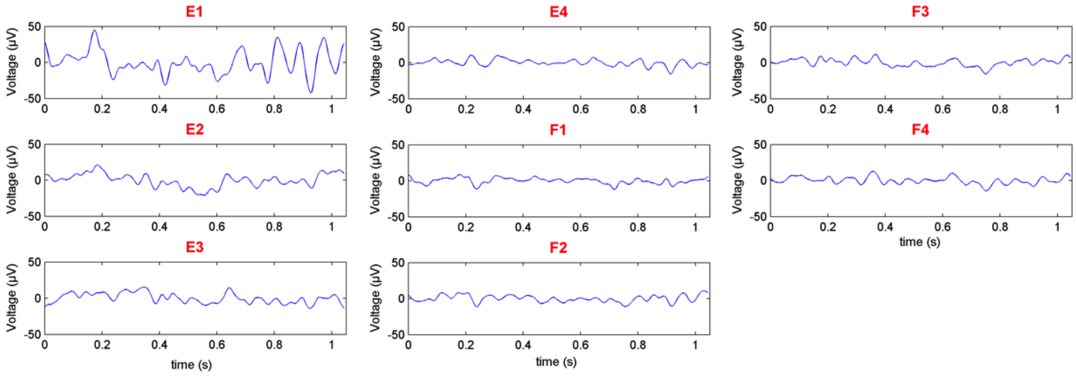

Figure 2: *Templates of the individual electrode positions according to the ECoG grid E and F of the subject. Only the first four electrodes of the grids were used, as they cover best the visual cortex. Electrode E1 shows the highest amplitudes in the VEPs.*

4. Discussion

Studies using code based VEP response and EEG achieve grand average accuracies of 92 % (Bin et al., 2011). Nevertheless, the coverage of the visual cortex was much better in the EEG experiments compared to the ECoG subject. A visual inspection of the ECoG templates shows that only electrode E1 has a good response to the visual stimulation. The presented system can be used for continuous control of a device, as well as trial based control for high-level commands. The current implementation contains a latency of about 2-3 s, which influences the reaction time, especially in the continuous mode. As ECoG provides higher temporal resolution compared to EEG, higher stimulation frequencies in combination with smaller signal buffer might be useful, to reduce latency.

Acknowledgements

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Face Stimuli Prevent ERP-BCI Inefficiency in Users with Neurodegenerative Disease

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Abstract. Recent advances in brain computer interfaces (BCI) based on event related potentials (ERP) proved that face stimuli can increase spelling performance due to an improved signal-to-noise ratio of the recorded ERPs. This study investigated its effect on BCI inefficiency in users with neurodegenerative disease who often display decreased spelling performance as compared to healthy participants. Performance achieved with the commonly used BCI (P300-BCI) was compared to BCIs using face stimuli in several online sessions with different number of stimulation sequences. Herein we report on data from N=9 participants with neurodegenerative disease. Online performance was significantly increased when using face stimuli as compared to classic stimulation. Importantly, two users who were highly inefficient with the commonly used BCI (performance $\leq$ 40%) spelled with high accuracy levels when using face stimuli. Our results thus display particular benefits of face stimuli in the target user group.

Keywords: brain computer interface (BCI), P300, event related potentials (ERP), face stimuli, neurodegenerative disease

1. Introduction

Recently we proposed a paradigm for Brain Computer Interfaces (BCI) based on event-related potentials (ERP) in which faces are used as stimulus material for elicitation of ERPs [Kaufmann et al., 2011]. Instead of highlighting characters in a visually displayed character matrix (as done in the commonly used ERP-BCI paradigm), faces were used as character overlay. Participants focused their attention on the intended character and counted the number of face flashings instead of counting the number of character highlighting. It was found in healthy participants that such face stimuli significantly improve spelling accuracy due to an improved signal to noise ratio of the recorded EEG post stimulus [Kaufmann et al., 2011; Zhang et al., 2011; Jin et al., 2012].

Herein we further investigated this benefit by (1) targeting users with neurodegenerative disease and (2) by systematically validating its effect on online performance when spelling speed was increased step-by-step (i.e. decreasing the number of stimulation cycles). In particular, we were interested in the potential effect of stimulus material on BCI inefficiency as such decreased performance is an issue often raised when bringing BCI technology to potential end-users (e.g., [Nijboer et al., 2008]).

2. Material and Methods

Users with neurodegenerative diseases (N=9; eight men; mean age 50.00 years, SD = 15.21, range 26-72) participated in the study. They were diagnosed with ALS (N=4), SMA (N=2), SBMA (N=2) and MD (N=1). EEG was obtained from 12 passive Ag/AgCl electrodes at positions Fz, FC1, FC2, C3, Cz, C4, P3, Pz, P4, O1, Oz, O2 and sampled at 512 Hz (BCI2000 software, g.USBamp amplifier).

2.1. Paradigms

Three different paradigms were validated by these users. First, the commonly used character flash (CF) paradigm in which characters of the visually displayed matrix are light flashed in random order. Second, the face flashing (FF) paradigm as introduced by Kaufmann and colleagues [2011]. Instead of light flashing, characters are overlaid by the famous face of Albert Einstein. Third, we introduced personalized stimuli to the FF paradigm, i.e. characters were flashed with faces of personally well-known and liked persons (friends, family members). We assessed if personal familiarity with the stimulus material may further increase BCI performance as compared to famous face stimuli.

2.2. Experimental Design

Each of the speller paradigms described in 2.1 was calibrated once with 15 stimulation sequences (one sequence comprised each row and column flashed once) on a ten-character word. Thereafter, users participated in 5 online sessions (a session comprised one run per paradigm) starting with 10 stimulation sequences and gradually decreasing the number to 6, 3, 2 and finally 1 sequence. Consequently, spelling speed was increased from run to run, thereby increasing error probability by limiting the amount of ERPs that entered classification.

3. Results

Users 1 and 2 skipped the last online session due to strain. Classification accuracy obtained offline was in line with previous report for healthy participants [Kaufmann et al., 2011], i.e. FF paradigms were superior to CF.

3.1. Online Spelling Performance

The effect of stimulus material on spelling performance appeared particularly pronounced when exposed to an online setting with decreased number of stimulation sequences. Difference in spelling accuracy between paradigms was significant in all scheduled online sessions (Kruskal-Wallis tests; all $H(2) > 8.85$, all $p \leq .012$; Bonferroni adjusted alpha level: $\alpha = .0167$). Post-hoc Mann-Whitney-U tests revealed no significant difference between FF paradigms (all $p>.317$) but high superiority of both FFs over CF (all $p \leq .0033$).

3.2. Effect on BCI Inefficiency

Two users (6 and 7, see Fig. 1) were not able to communicate with an online accuracy above 40% when exposed to the commonly used CF paradigm. To investigate if this high inefficiency was due to a bad calibration run (e.g. due to lack of attention), we recalibrated the system based on data from online session 1 (10 sequences) and recomputed performance in session 2-5 offline based on this recalibrated classifier. However, accuracy remained low. In contrast, when exposed to FF paradigms, these users spelled at high accuracy levels. User 7 did not even perform any error with any of the FF paradigms.

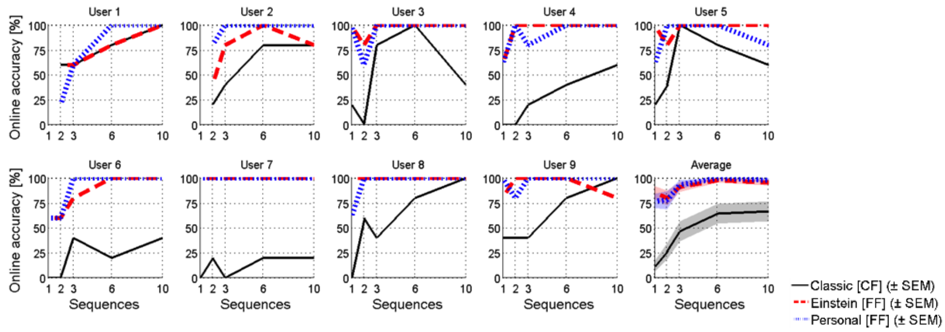

Figure 1: *Accuracy achieved online by N=9 users with neurodegenerative disease*

4. Discussion

These results manifest the importance of improving stimulus material for overcoming BCI inefficiency in users with neurodegenerative disease. By increasing the signal-to-noise ratio of the EEG post stimulus with face stimuli, classification of ERPs was facilitated. No indication was found that personal familiarity with the presented face further increases performance, yet users verbally reported that they preferred those stimuli. Jin and colleagues recently reported no effect of face motion and emotion [Jin et al., 2012]. Future research should further investigate improvements to the stimulus material, as its strong benefit is apparent [Kaufmann et al., 2011; Zhang et al., 2012; Jin et al., 2012].

Acknowledgements

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Empathy and Motivation in BCI Performance

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Abstract. Motivation was shown to have an effect on P300 BCI performance and P300 amplitude. Usually monetary reward has been used for motivation manipulation. In this study we not only investigated a non-monetary reward method (an information presentation about BCI research), but also included empathy as a possible psychological factor influencing BCI performance.

Keywords: Empathy, motivation, Brain-Computer Interface (BCI), P300.

1. Introduction

Motivation was found to influence Brain-Computer Interface (BCI) performance in healthy subjects (Kleih et al., 2010). However, one might criticize that monetary reward was used to manipulate motivation as the motivation to use a BCI in patients in need is, by no doubt, of a much more internal and therefore different nature (Nijboer et al., 2010). There might also be healthy subjects who participate in BCI studies because they wish to contribute to research development and for whom monetary reward is less important than the content of the study. Motivation then could be defined as "motivation-to-help". Those who have a higher motivation to help may also be more empathetic which might result in a higher ability to take other peoples' perspective. We hypothesized in this work that participants who are highly motivated to help and empathetic perform better in a P300 BCI spelling task as compared to participants who are motivated only by monetary reward they receive for participating in the BCI study. We further hypothesized that P300 amplitudes in motivated participants would be higher compared to unmotivated participants.

2. Material and Methods

2.1. Subjects

Our sample of N=20 participants was on average M=23.35 (SD=3.87, range 18-35) years of age and N=14 participants were female. Participants were reimbursed with 8 Euros per hour and all were naïve with regard to BCI training.

2.2. Design

A univariate between-subjects design with two levels in the variable *group* was used. Participants were divided into two groups (N=9 motivated and N=11 unmotivated) by sending a questionnaire via e-mail and evaluating the results before inviting participants for an information presentation for additional motivation manipulation one week before the BCI measurement. In this information session, first motivation and empathy were assessed using questionnaires (Visual Analogue Scale motivation, Questionnaire for Current Motivation-BCI, Saarbrücker Persönlichkeits Fragebogen and NEO-FFI agreeableness scale). Then the existing motivation (high versus low) was further manipulated by the content and the way the information presentation was designed. In the motivated group, the information presentation about BCI use was designed to be very vivid and enthusiastic. Patient examples were used to illustrate the rationale behind BCI research and diverse media were used for content presentation (Power Point, Video, Interview material). In the unmotivated group, only black and white slides and no other media than Power Point were used. The content of the presentation was an introduction to the procedures and material necessary for an EEG measurement such as the size and shape of electrodes. While in the motivating presentation, participants were encouraged to ask questions and discuss the contents interactively, the non-motivated group was taught ex-cathedra. Within one week after the information session, appointments for the BCI measurement were scheduled with participants.

2.3. Procedure and Data Analysis

Prior to the BCI measurement, participants received a written reminder which summarized the contents of the information session to reactivate the motivation manipulation. Motivation questionnaires were applied again and participants spelled two five letter words, each word four times. For data acquisition, we used BCI2000 Software, 12 Ag/AgCl electrodes, and a g.USB amplifier. Data were classified with stepwise linear discriminant analysis (SWLDA). We used Brain Vision Analyzer for peak detection within 200 and 600 ms after stimulus onset. The level of significance was set to α = .05.

3. Results

3.1. Motivation Manipulation and its Effect on P300 and Accuracy

We found significantly higher motivation as measured with the VAS in the motivated compared to the unmotivated group ($F_{(1,18)} = 5.34$, $p < .05$). Therefore, motivation manipulation was successful. However, we neither found higher P300 amplitudes in the motivated compared to the unmotivated group ($F_{(1,18)} = 1.54$, $p = .23$), nor was BCI performance as measured by accuracy higher in the motivated group ($F_{(1,18)} = .46$, $p = .51$).

3.2. Empathy and its Effect on P300 and Accuracy

After regrouping participants depending on their ability for perspective taking as measured with the SPF, we found significantly higher P300 amplitudes on electrodes P3, Pz and P4 in participants with a low ability for perspective taking (LAPT) and therefore, lower empathy, compared to participants who are highly able to take others' perspective (HAPT) ($F_{(1,18)} = 6.64$, $p < .05$, see Fig. 1).

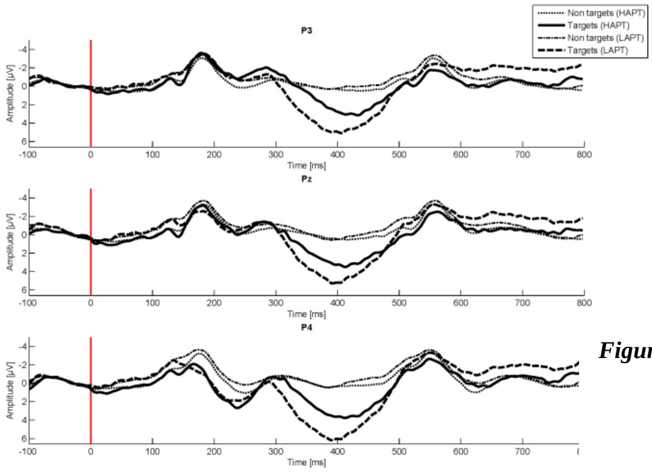

Figure 1. *P300 amplitudes in the groups with high ability for perspective taking (HAPT) and low ability for perspective taking (LAPT).*

4. Discussion

Contrary to our hypotheses, we found no effect of motivation on BCI performance and P300 amplitude when further increasing the existing motivation level (motivated versus unmotivated) in participants before the BCI measurement. However, when redistributing participants according to their empathy as measured with the subscale 'perspective taking' in the SPF, we found higher P300 amplitudes in the less empathetic participants. We speculate that subjects with higher empathy values were less able to focus attention allocation. Participants who are highly able to take the perspective of a patient who is in need of assistive technology, might be more emotionally involved and therefore, less able to focus on the BCI task at hand. Future research should aim at further elucidating the psychological factors influencing attention allocation in BCI tasks as personality traits seem to influence BCI performance and might need to be considered for explanation of variance in BCI performance.

Acknowledgements

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Sensitivity and Specificity of the Studentized Continuous Wavelet Transform for ERP Detection – A Simulation Study

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Abstract. *For clinical assessment in patients with brain injuries, it is crucial to detect the presence and absence of ERP components at the single subject level. One sensitive but so far rarely tested method seems to be the Studentized continuous wavelet transformation. Here, we evaluated a new implementation of this method using 800 simulated EEG datasets.*

Keywords: EEG, t-CWT, wavelet, multiscale analysis, P300, simulated data, sensitivity, specificity

1. Introduction

Event-related potentials (ERP) promise to become an essential tool in assessing conscious processes in patients with severe brain damage. In healthy participants, EEG signal-to-noise ratios (SNR) vary from -10 to -5 dB [Coppola et al., 1988]. While we know of no direct SNR estimates in patients, reports on, e.g. reduced ERP amplitudes [Duncan et al., 2005] suggest reduced signal strengths.

The Studentized continuous wavelet transform *[t-CWT; Bostanov et al, 2006]* has been suggested as a particularly sensitive method for ERP detection. However, an application of this procedure for diagnostic purposes does not only require information about sensitivity (true positive rate), but also about specificity (1-false positive rate). Sensitivity can be estimated from EEG recorded from healthy participants using reliable paradigms, since all participants can be reasonably expected to show ERPs, the paradigms were designed to elicit [e.g. Bostanov et al., 2006]. For exactly the same reasons, specificity cannot be ascertained this way, but requires data from which it is known that no signal exists. Sensitivity and specificity of the t-CWT were ascertained using simulated EEG data with low SNRs and compared to a peak detection procedure (MAX). Sensitivity of the t-CWT was hypothesized to be higher than for the alternative.

2. Material and Methods

Calculation of the t-CWT First, the continuous wavelet transform [Mallat, 1999] is calculated for each trial and channel using the modified Mexican hat wavelet [Bostanov et al., 2006]. Second, student t-values are calculated from the resulting wavelet coefficients, either across all experimental conditions – if one is interested in detecting activity different from baseline – or between experimental conditions – if the focus is on differences between experimental conditions. Third, local extremes are detected using a 2d-peak detection procedure. Fourth, significance of extremes is ascertained via t-max randomization tests [Blair et al., 1993].

Calculation of peak detection (MAX) First, the EEG signal is averaged, either across all experimental conditions or as the difference between experimental conditions. Second, local extremes are detected using a 1d peak detection procedure. Third, significance of identified peaks is ascertained via t-max randomization tests.

Sensitivity was assessed by creating 400 datasets simulating EEG recordings as might be obtained during a simple auditory oddball paradigm (60 "odd" and 60 "frequent" trials). Odd trials showed a deflection (+5µV) at 350ms, thus simulating a P300 ERP. Signal-to-noise ratio (SNR) was varied in four steps from -18 to -13 dB by adding the required amount of noise to the generated signals.

Specificity was assessed by creating another 400 datasets (as above), in which odd and frequent trials did not differ.

Statistical analysis was based on the F1 score. If no false negatives/positives exist, this measure reaches its theoretical maximum of 1, if no true positives exist, the measure reaches zero. Thus, higher F1-scores indicate better overall performance. Monte-Carlo simulations [Goute et al., 2005] were used to test whether t-CWT was associated with higher F1 scores than the MAX procedure. Type 1 error was controlled at $\alpha = .05$ for all analyses.

3. Results

Figure 1 shows the results of the simulation studies. For the two methods, the true positive rate is plotted against the false positive rate for four SNRs. The true positive rate for the t-CWT is consistently higher than for the MAX procedure, while achieving the essentially same false positive rate (t-CWT: mean $\alpha = .0675$, MAX:

mean α = .05). F1-scores were significantly higher for the t-CWT than for the MAX procedure at all four SNRs (-13 dB: 0.92 > 0.87, $p < .05$; -15 dB: 0.93 > 0.84, $p < .01$; -16 dB: 0.86 > 0.78, $p < .05$; -18 dB: 0.76 > 0.60, $p < .01$), indicating higher overall performance of the t-CWT procedure.

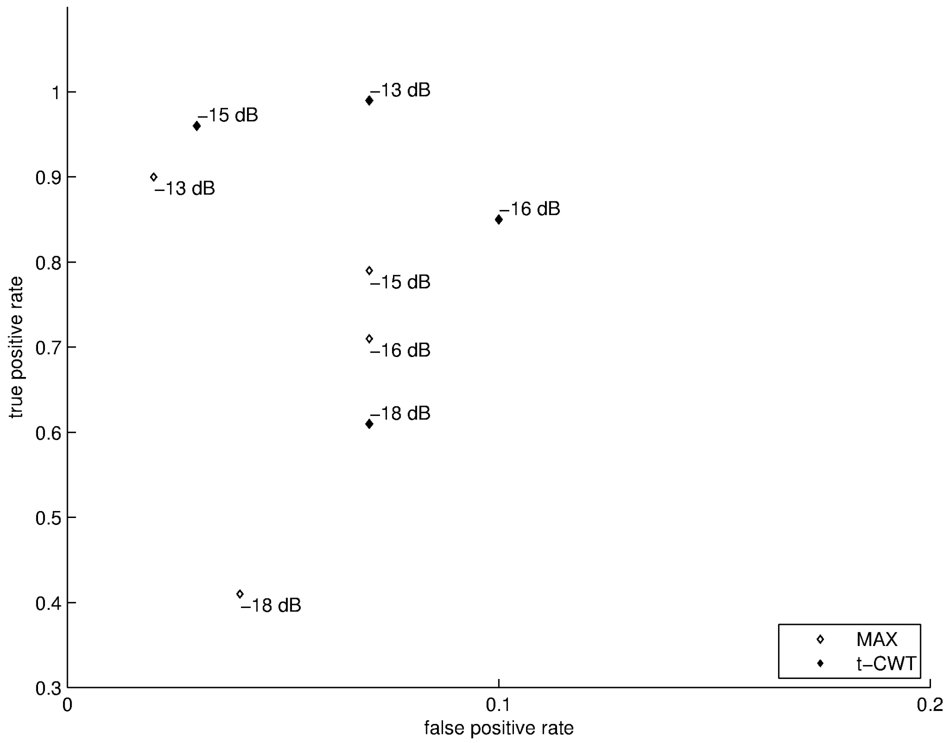

Figure 1. *Results of the simulation studies. True positive rate vs. false positive rate for four signal-to-noise ratios.*

4. Discussion

Results indicate that the performance of the t-CWT is superior in comparison to a peak detection procedure across a range of signal-to-noise ratios. The t-CWT, thus, combines high sensitivity with high specificity. Given the low signal-to-noise ratio in brain-damaged patients, these properties suggest a useful role of the t-CWT in the analysis of such patients' data.

Acknowledgements

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Detection of Anomalies in EEG Signal: An Information Theoretic Approach

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Abstract. The use of BCI protocols relies on the stationarity of the signals. This assumption may not be hold in the real-life situations, where the electrodes may be misplaced, get noisy, or disfunctioned during any experiment. Monitoring the EEG signals and quantifying the reliability of the electrodes in order to notify the operator could help him to take a counteraction and to improve the BCI performance. In this work, we propose a method which monitors changes in the mutual information between the signals of the electrodes, and it is counted as the deviation from the expected behaviour.

Keywords: Anomaly detection, EEG, Mutual Information

1. Introduction

Bringing BCI outside laboratory needs more care since lay experimenters may not be familiar of using devices correctly and on the other hand many factors may affect the EEG signals, such as environmental noise, electrode failure and etc [Leeb et al., 2011]. This could degrade the performance of BCI system dramatically. To avoid it, there is a need for a systematic approach which monitors signals at run-time and quantifies how much the signals deviate from the expected behavior (as observed in a training set). [Sagha et al., 2012] proposed a method to monitor data based on the distance of samples to the mean of its conditional distribution giving the values of other electrodes. This approach is complex and time consuming which affects the latency of detection. Here, we have used another measure based on an information theoretic approach to monitor signals with a faster response.

2. Material and Methods

We define the deviation of the signal as the difference between the mutual information of a pair of electrodes on the test and on the train set. High differences mean the signals do not behave as before. To extract mutual information, I, first we filter the signal with a band-pass [4 24] Hz, because this band is usually common between most of BCI protocols and experimentally we found that the information in this band is enough for anomaly detection. Then the filtered signals are quantized into some predefined bins which could be automatically defined [Wand, 1997]. Mutual information between electrodes n and m is computed as:

$$I_{nm} = \sum_{x \in bin_n} \sum_{y \in bin_m} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \tag{1}$$

At runtime, to compute the deviation, we subtract the I in a window of the data of length L with the I we obtained on the training set.

$$Diff_{nm} = I_{nm}^{test} - I_{nm}^{train} \tag{2}$$

To remove the effect of common changes which affects the whole electrodes, the deviation will be computed as the distance to the average value of the all differences, $\overline{Diff}$, and summed over all the electrodes.

$$Deviation_n = \sum_{m \neq n} (Diff_{nm} - \overline{Diff})^2 \tag{3}$$

A moving average window can be used to smooth the values, giving more reliable estimates. The computational cost is $O(LN^2)$ which is quite less than $O(NN_{n_e}^4)$ as the cost of the method proposed in [Sagha et al., 2012], where N is the number of electrodes and N_{n_e} is the average number of neighbor electrodes of all electrodes in the montage.

3. Results

3.1. Swapping Electrodes

In this experiment we simulate an anomaly by swapping two neighbor electrodes. This is to show that although the nature of signals is not changing, still the method is able to give a high deviation value for the swapped electrodes. The experiment is done for 13 subjects and for each we used two recording sessions, one for training and one for testing, then we swapped five times randomly two topographically neighbor electrodes. The neighborhood could be one of the closest electrodes (radius 1) or with an electrode in between (radius 2). The used setup is 16-electrode g-Tec system with the universal 10/20 EEG cap model. I^{train} is computed using the whole data in the training session.

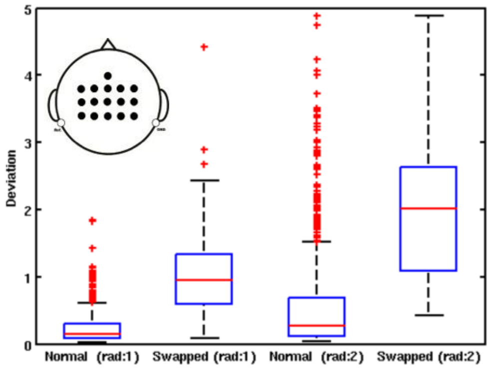

Figure 1- *Deviation value for swapped and normally situated electrodes.The topological distances of the swapped electrodes are provided in parentheses.* Top-left: *Electrode montage*

The deviation values for the not-swapped (Normal) and swapped electrodes are shown in Fig. 1. Sampling rate is 256Hz and we set L as 200 samples. The values are the average over the whole session. The deviation values are significantly different for the swapped ones are higher than the others.

3.2. Imposing Electrodes

In this experiment, we used 64 electrode Biosemi system and down-sampled data from 2048Hz to 256Hz. After having a 5 minute training data for computing I^{train}, we recorded another 5-minute of data and we imposed anomalies as follow:

1) Normal situation (no anomaly) [30 sec]
2) Press C4 [30 sec]
3) Press Cz [30 sec]
4) Detach FC2 [60 sec]
5) Detach FCz [60 sec]
6) Replace FC2 and FCz [60 sec]
7) Press F5 [30 sec]

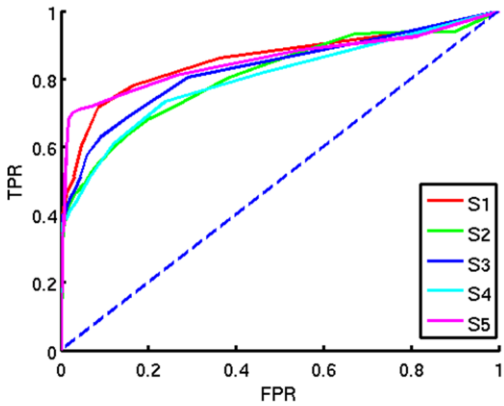

Figure 2- *ROC for the second experiment.*

The goal of Pressing electrodes is to change the conductivity, and for Detaching we are aiming to simulate online disconnectivity.

By counting each of these manipulations as anomalies and setting different thresholds on $Deviation$ we extract the ROC curves. The evaluation is done on all 64 electrodes. The ROC curves for detection of these anomalies are shown in Figure 2, for 5 subjects. The skew of the curves toward left shows the low false positive rate using any threshold.

4. Discussion

Online detection of anomalies in EEG recording is an important issue when BCI goes to clinics and out of research labs. The proposed method brings the ability to monitor the signals online and it quantifies the amount of abnormality of the EEG streams. This could be counted as reliability of each electrode, and can be combined with BCI protocol to improve the performance. We are going to extend this study and investigate the power of this method while imposing other kind of noises, such as environmental noise.

Acknowledgements

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Non-invasive Decoding of Hand Movements from Brain Signals - Influence of Execution Velocity

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Abstract. Recently published results of a center-out experiment showed the basic feasibility of the offline-decoding of hand movements from continuous Electroencephalogram (EEG) recordings. However, the decoding accuracy is limited and it is still unclear which conditions may lead to an improved estimation of movement parameter. Thus, in the presented work the influence of velocity on the decoding accuracy was investigated. The analysis of center-out tasks with different execution velocities performed in 5 healthy subjects shows that velocities of the hand are better decodeable, if movements are executed with higher velocities. It may be concluded that users of Brain-Computer Interfaces (BCIs) based on movement decoding for control of upper extremity neuroprostheses should be instructed to use fast movements to improve the decoding accuracy.

Keywords: Electroencephalogram (EEG), execution velocity, movement decoding, accuracy

Introduction

In [Bradberry et al., 2010] it was first shown that offline-decoding of three-dimensional hand movements during center-out tasks is basically possible from EEG signals. In the meantime these results were confirmed [Antelis et al., 2011; Ofner et al., 2012]. However, accuracy of the decoding of movement parameters is limited (range: 0.2 - 0.7) and the influences of the type of feedback or the movement execution velocity are unknown. This work aimed at the quantification of the influence of execution velocity on the decoding performance.

Material and Methods

Five right-handed healthy subjects (3 females and 2 males) participated in the study (age 29 ± 8, range 22-42). EEG was recorded with 61 electrodes on standard positions of the 10/10 system. The reference electrode was placed on the left mastoid, ground on the right. Five synchronized amplifier (g.USBamp, g.tec, Graz, Austria) sampled the EEG with 512 Hz. Signals were bandpass (0.01-100 Hz) and notch filtered (50 Hz). Upper extremity kinematics were measured with a motion analysis system (Motion Analysis Corporation, Santa Rosa, CA, USA). Eight infrared cameras recorded the position of reflective markers on the index finger and 32 markers on other anatomical landmarks of the torso/head with a sample rate of 64 Hz. The EEG and motion measurements were synchronized with a hardware clock signal. Processing of the EEG and motion data was similar to the methods of [Bradberry et al., 2010].

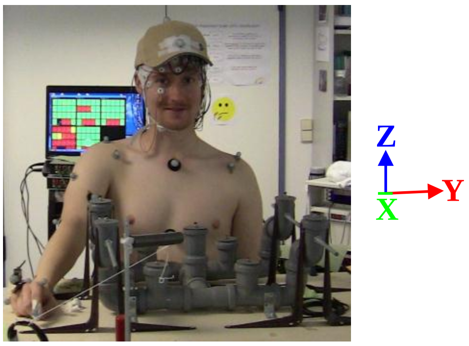

Figure 1. *Experimental setup, X, Y and Z indicate the directions of the axis of the coordinate system.*

The task was to perform a movement with the fingertip of the index finger from a starting position in the center to one of 8 fixed targets and to return to the initial position (Fig. 1). Range of motion was in X direction 35 cm in Y 41 cm and in Z 11 cm. Targets were self-selected and movements were self-initiated. Subjects were carefully instructed to gaze at a fixed central point and try to avoid eye movements and blinking. For every subject 6 runs (5 min. each) were recorded in a fixed order: three runs at a low velocity (4 sec. for each completed center-out task), two runs at medium velocity (2 sec. each task) followed by one run as fast as possible.

Post processing of the EEG data included (1) low-pass filtering (cut-off frequency 30 Hz) (4^{th} order butterworth), (2) down sampling to 64 Hz and (3) bandpass filtering from 0.1 to 4 Hz. Post processing of the Motion data was low-pass filtering (cut-off frequency 4 Hz) (4^{th} order butterworth). Next, the derivations of EEG and motion data were computed and each EEG channel was normalized to a mean of 0 and a standard deviation of 1. A linear regression was computed for velocities in X, Y and Z direction for the index finger marker in a 8x8 cross-validation using the normalized standardized data of all EEG-electrodes of the current sample and the last 7 time lags (~100 ms).

Results

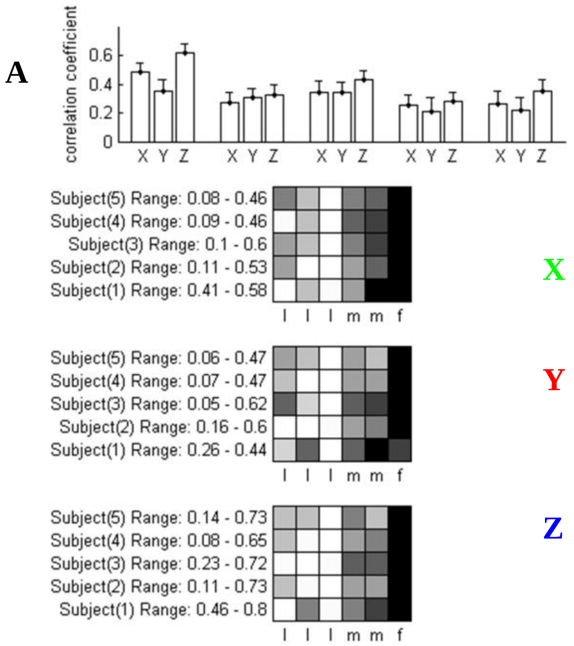

Figure 2. *A: mean correlation coefficient (CC) and standard deviation for X, Y and Z velocity components for all runs, X: CC for X-direction, Y: CC for Y-direction, Z: CC for Z-direction. Low velocity (l), medium velocity (m), fast velocity (f). Colour coding is normalized for each subject and velocity component. Normalized colour coding was preferred over absolute coding for better comparability among subjects. White squares indicate a low mean CC, black squares a high mean.*

Figure 2 shows the correlation coefficient (CC) between the computed and the real index finger velocity. Mean and standard deviation of the CCs for all subjects and runs in X-direction is 0.32±0.08, Y 0.28±0.08 and Z 0.40±0.7 (Fig. 2 A).
CC increase in every direction with higher velocities(Table 1).

Table 1. *Correlation coefficient (mean ± standard deviation) of real and estimated velocity grouped by velocity level and direction.*

	low (l)	medium (m)	fast
X	0.22±0.07	0.37±0.08	0.53±0.08
Y	0.18±0.08	0.33±0.08	0.51±0.07
Z	0.26±0.06	0.44±0.07	0.73±0.08

Discussion and Further Steps

In conclusion, our results confirm those of previous studies, that the mean CCs of EEG and motion data are in an interval of 0.2-0.7. In addition, the patterns in Fig. 2 implies that the velocity components in X, Y, Z direction of faster movements are better decodeable than slower movements. In an additional analysis we reassigned EEG data of the subjects to different center-out tasks and obtained CCs below 0.01. Therefore, a bias resulting from the intrinsic properties of the decoding algorithm can be excluded. In future applications using movement decoding based on BCIs for arm neuroprosthesis control users should be the instructed to use fast movements.
The combination of multi channel EEG and a sophisticated biomechanical model of the upper extremity will allow a much more detailed analysis of EEG movement decoding strategies than pure end-effector based approaches The next steps in the analysis of the available data will be (1) to investigate the correlation between Electrooculogram (EOG) and EEG parameters, (2) to include additional features (frequency bands, time windows) and (3) to investigate the accuracy of the decoding of other parameters e.g. joint angles, absolute coordinates of body segments or joint moments.

Acknowledgments

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Comparison of Vibro-tactile ERPs Classification Methods

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Abstract. Vibro-tactile ERPs were recorded using whole hand stimulation in a classical odd-ball paradigm. Five different classification methods applied to single brain responses were compared off-line to perform a sub-optimal selection of the algorithm for future on-line implementation of a brain-computer interface.
Keywords: ERPs, vibro-tactile, classification, comparison, odd-ball.

1. Introduction

Event-related potentials (ERPs) are currently used to assess clinical/cognitive status of paralyzed and non-responsive patients [Kotchoubey et al., 2003] and to restore basic yes/no communication in severely paralyzed patients [Kübler and Birbaumer, 2008]. Recently, the tactile stimulation has been used with stimulator placements such as waist, fingertips, foot big toe tip and lip [Brouwer and van Erp, 2010; van der Waal et al., 2012; Murguialday et al., 2011] because of compromised vision. Restoring basic yes/no communication, detection of tactile ERPs was usually performed by arbitrarily selecting the classification algorithm. In this pilot study we placed the stimulator for ERPs recording on the palm of one hand (high density of sensory receptors) and we investigated the possibility to make a sub-optimal selection of the classification method to be applied to single-trial non-target and target brain responses (odd-ball paradigm, [Sutton et al., 1965]). At this aim we compared five classifiers for future on-line implementation with feedback: least-squares regression (LS), stepwise regression (SWLDA), logistic regression (LG), genetic algorithm (GA) and support vector machine (SVM) methods were employed.

2. Material and Methods

2.1. Participants

ERPs measurements were carried out on a group of six healthy volunteers (four females and two males, mean age of 33 years, range 27-50 years) and one Amyotrophic Lateral Sclerosis (ALS) patient (33 years old female, ALS-functional rating score 26, [Cedarbaum et al., 1999]). Informed consent was obtained for each participant according with the Declaration of Helsinki.

2.2. Recording Setup and ERP Paradigm

EEG was recorded using 4 Ag/AgCl scalp electrodes (Cz, Pz, P3, P4) according to the International 10–20 System, sampled at 512 Hz (band-pass pre-conditioning filter from 0.1 up to 30 Hz; gUSBAmp, g.tec) by BCI2000 platform [Schalk et al., 2004]. Vibro-tactile stimulation of the hand was provided by the end-effector of a haptic device (Phantom, Sensable). A single stimulus consisted of a sinusoidal force field along the x-axis of the end-effector lasting for 600ms. The force field frequency was set to 20Hz for non-target stimuli and 100Hz for target stimuli, its magnitude was set to 1.5N for both cases. EEG epochs of 1.25s length synchronized with each stimulus (.25s before and 1s after stimulus onset, error smaller than 5ms) were grouped in two classes (non-target and target). Exploiting the classical odd-ball paradigm, a pseudo-random sequence of non-target (probability .7) and target (probability .3) stimuli was presented to each participant with an inter-stimulus interval of 2s. Each participant was asked to grasp the end-effector, close his/her eyes and count target stimuli. Four sequences of 40 stimuli were presented to each participant (i.e. 160 epochs).

2.3. Off-line ERPs Analysis

Off-line classification of brain responses to target and non-target stimuli were performed using the following algorithms: LS, SWLDA and LG methods as implemented in BCI2000; GA as described in Dal Seno et al. (2008); radial-basis function kernel SVM as described in Joachims (1999). To compare the five classification methods, the same set of 32 features was extracted from each single epoch applying the following procedure to every single channel separately: low-pass filtering at 8Hz (order 4, zero-phase), direct current adjustment using pre-epoch interval (.25s) and down-sampling of the post-stimulus interval (1s) with a factor of 16. For each participant a randomly chosen half of the ERPs dataset (i.e. 80 epochs) was used to train the five classifiers, the remaining half to test them. The cross-validation procedure was repeated 50 times for each classifier and for each recorded channel separately. The mean error was estimated by the averaging of the classification errors considering all epochs and repetitions. A two-way ANOVA for repeated measures was performed only on healthy subjects' results considering *channels* and *classifiers* as factors. ALS patient's ERPs classification results were compared to the healthy subjects' results by means of single-case test [Crawford and Garthwaite, 2002]. Averaged ERPs and mean classification errors evaluated at channel Pz are illustrated in Fig.1.

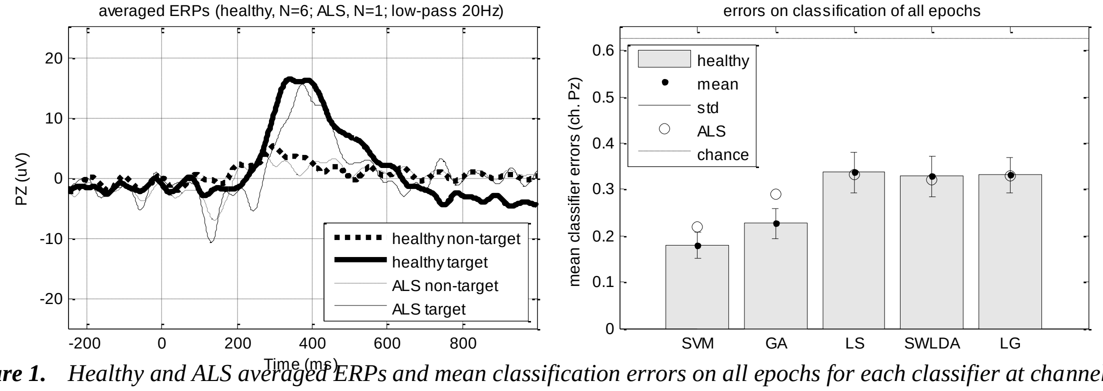

Figure 1. *Healthy and ALS averaged ERPs and mean classification errors on all epochs for each classifier at channel Pz.*

3. Results

ANOVA of mean errors showed a significant main effect of *classifier* (*F(4,100)=73.6; p<.001*), but no significant main effect of *channels* (*F(3,100)=.49; p=.69*). Contrasts revealed that SVM error estimates were significantly lower than the other four classifiers error estimates (always *p<.001*). Repeated t-test between error estimates of each couple of channels and for each classifier showed non-significant results (Pz was used in later comparisons). Concerning ALS patient ERPs classification results we found no significant differences between error estimates at channel Pz and those of healthy participants (considering each classifier separately).

4. Discussion

The first result indicates that a sub-optimal selection of the classifier is possible. The SVM classification outperformed all others methods. The second evidence indicates that there is no difference concerning the channel selected for feature extraction among the channels used in this experiment since the classification was performed for each channel separately with the same procedure. Hence a single channel could be used to record and classify this type of ERPs. The third evidence is that ALS patient's ERPs can be classified with errors similar to those of healthy subjects.

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Monitoring Sustained Visual Attention

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Abstract. Modeling electroencephalographic (**EEG**) correlates of mental states of brain-computer interface (**BCI**) users' can be used to adapt BCI's operation. It can also serve to develop BCIs not targeted at providing a control signal to operate a device, but rather whose main goal is only to monitor users' mental states, e.g. attention levels. In this off-line study we test the feasibility of real-time recognition of subject's sustained attention to the visual feedback used in our BCI applications. Cross-validation results indicate usable accuracy.

Keywords: Brain–Computer Interface (BCI), Electroencephalography (EEG), Attention, Visual System

1. Introduction

EEG-based BCIs rely on identifying signals that can be intentionally modulated by the user to control a device. However, such control signals are superimposed on the fluctuating background of EEG correlates of myriad other cortical processes. A way to deal with this issue is to develop algorithms automatically adapting to the resulting non-stationarities, regardless of their neurophysiological underpinnings. However, for a **well-defined subset** of "background mental processes" it should be more beneficial to explicitly model their EEG correlates. This way additional data is gathered on the user's state, which can provide a more informative explanation of a degradation of the control signal. It is debatable, what such subset of modelable "mental states" should be. Attention, however, seems to be a good candidate as it is reasonably well developed conceptually and experimentally [Knudsen, 2007]. Here we take a pragmatic approach. Since most of our BCI applications rely on motor imagery with visual feedback, this makes them a special instance of a visuomotor task. Thus sustained visual attention is required to operate them. Lapses in such kind of attention, should therefore be recognized and influence BCI's operation.

2. Methods

We recorded 64-channel EEG while subjects (n=8) performed visual and auditory reaction-time tasks. In the center of a computer screen we displayed a rectangular bar (identical to the visual feedback used in our BCI applications), which moved horizontally changing direction every 3~6 s (random intervals). Subjects were also wearing pneumatic earphones through which we played alternating epochs of white and pink noise, switching also every 3~6 s, independently of visual stimuli. Visual and auditory streams were played continuously, while subjects' attention was cued to one of them by an icon of an eye or a loudspeaker in a fixed location over the bar; the icon also served as eye fixation point. Every 40~60 s the subject heard a tone and the cue changed. The subjects' task was to respond as quickly as possible to visual (bar direction changes) or auditory (changes in the noise) stimuli by pressing the left mouse button. After every cue change, a mean response time from the completed block was displayed on the screen directly above the cue for 2 s to keep the subject engaged in the task. If fatigued, the subjects could pause the experiment at any time by pressing the right mouse button; they pressed it again to resume. The experiment lasted 30 minutes, excluding breaks taken by the subjects.

3. Results

Average results of our experimental manipulations largely confirm the effects of visual attention known from basic neuroscience: attenuation of the occipital ("visual") alpha (8-12 Hz) rhythm (e.g. [Foxe et al, 1998]), that is reversed once the attention is disengaged from the visual domain (**Fig. 1A**). Two of out of eight subjects do not demonstrate this effect, and, tellingly, they are the subjects in whose case single-trial classification fails (see below). For single-trial classification we used spectra from 10 s non-overlapping epochs of data. Discriminant power of the features across subjects was located in alpha and lower beta (13-20 Hz) bands, over occipital and parietal cortices (**Fig. 1 A, B**). We estimated the performance of a two-class LDA classifier on the data with leave-one-out cross validation. In every fold the LDA classifier was based on two most discriminant spectro-spatial features, based on their Fisher score from the training data (using specifically two features generalized well across subjects). Results are presented in **Fig. 1C**. For six out of eight subjects over 70% of samples were correctly classified; for the remaining two subjects classification was unreliably low.

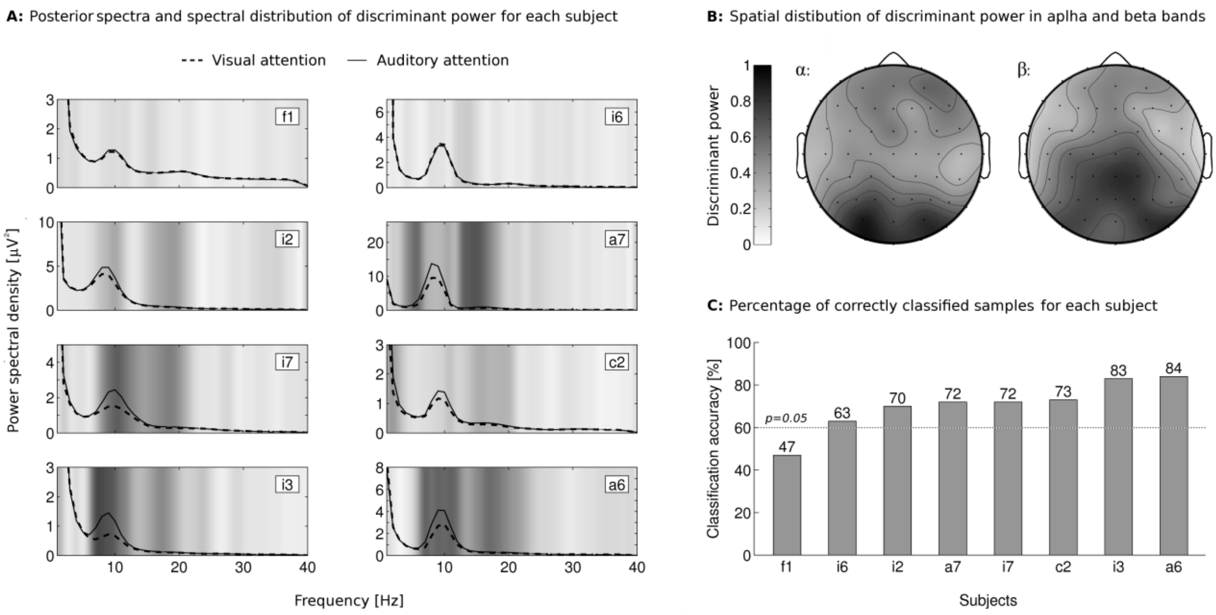

Figure 1. *(A) Averaged spectra from parietal and occipital electrodes for visual (broken line) and auditory (solid line) attention conditions for each subject. Shadings indicate discriminant power (Fisher score) for particular frequencies (see bar on the right for scale). Labels in upper-right corner of each plot are subject IDs. (B) Scalp distribution of discriminant power in alpha (8-12 Hz) and lower beta (13-20) bands. Plots show grand averages across subjects; data from each subject was rescaled to unit scale prior to averaging. (C) Accuracy of classification of visual vs. auditory attention (two-class LDA), estimated with cross-validation. Broken line indicates empirically estimated chance level of p=0.05.*

4. Discussion

In this study we tested the feasibility of recognizing subject's sustained visual attention, contrasting it with auditory attention. We chose auditory attention for the contrast task, instead of rest, to discern processes specifically related to visual attention. We do not confound them with other variables, such as cognitive workload, motor activity, etc.: they were constant across the conditions. Moreover, due to the neuroanatomy of auditory cortices [Weisz et al, 2011], in EEG we expected mostly to see correlates of visual attention – or lack thereof – and our results confirm this. The spatial distribution of discriminant features clearly relates to visual, but not auditory processes (**Fig 1B**). Our results suggest there may be two separate EEG carriers of sustained visual attention accessible to BCI, with distinct distributions: the occipital ("visual") alpha and more anterior (parietal) beta activity. The first process (i) seems to best lend itself to single-trial recognition presumably because of EEG alpha's broadest dynamic range (best signal-to-noise ratio), and (ii) has relatively clear neurophysiological underpinnings (e.g. [Foxe et al, 1998]). Moreover, it should be regarded as fundamental, since the absence of alpha modulation seems to exclude any reliable classification (see subjects "f1" and "i6" in **Fig. 1**). The significance of lower beta is less elucidated. If more observed more anteriorly, it is related to motor processes [Pfurtscheller et al., 1999], if co-registered with alpha oscillations, it can simply be a harmonic of the latter. Its involvement in visual attention in human EEG is controversial, but rarely has been reported as opposite to what we observe [Kamiński et al., 2012]. However, theoretical neurophysiological explanation is beyond the scope of this communication. Here we specifically used visual stimuli employed in our motor imagery-based BCI applications for the purpose of developing these applications to include monitoring of an operationally defined, but presumably generalizable attentive state – and in this respect the results seem promising.

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Using Random Forests for Classifying Motor Imagery EEG

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Abstract. We applied Random Forest (RF) classifiers on electroencephalographic (EEG) data of right hand vs. feet motor imagery (MI) and achieved a cross-validation classification accuracy of 79% on average over 10 participants. Furthermore, we used the intrinsic Gini Index (GI) based feature rating mechanism of the RF classifiers to find most discriminative features and compared them to the differences in the event related desynchronization/synchronization (ERD/S) maps between the classes. We found mu and beta band measured at position C3 most important for classification, which is in line with current state of knowledge.

Keywords: BCI, EEG, ERD/S, Motor Imagery, Random Forests, Feature ranking

1. Introduction

One crucial issue to achieve good on-line performance in sensory motor rhythm (SMR) Brain-Computer Interfaces (BCI) is the selection of the most discriminative oscillatory components. In this work we study the usefulness of the Random Forests (RF) ensemble classifier for classifying electroencephalographic (EEG) motor imagery (MI) data. RF classifiers are interesting because in other areas they achieve high classification accuracies and they have a built in feature rating mechanism, which can be useful for checking the validity of the selected features. Furthermore, RF are robust against outliers and can handle high dimensional input variables. In this work, we perform offline analysis of right hand vs. feet MI data and compare the feature rating results with event related desynchronization /synchronization (ERD/S) maps.

2. Material and Methods

2.1. Random Forests Classifier and Feature Rating with Gini Index

A RF classifier is an ensemble of many decision trees. Each decision tree contributes a vote for a majority decision about the class membership of an ensemble classifier's input. An ensemble classifier's accuracy depends on two things: High accuracy of the individual tree, and low correlation between the trees [Breiman, 2001]. For RF classifiers, the correlation can be decreased by using randomness during the training of the classifier. The randomness is introduced through an individual bootstrap sample of the training data for each tree and through an individual random feature subset for each split in each tree. Decision trees split up the training trials into subsets which should be as pure as possible. The purity is measured with the Gini Index (GI) [Breiman, 1983]. The GI is a measure of statistical dispersion and is zero if all class labels in a subset are the same and one if all class labels in a subset are uniformly distributed. The ratio between GI before and after the split is calculated and that feature is chosen which decreases that ratio at most. As there are many different decision trees in a RF classifier the average decrease in GI among all trees caused by a feature can be calculated. High average decrease means that this feature is often found to be the best selection to produce pure subsets, which is equivalent to the statement that this feature contains information about the class membership and is therefore important [Breiman, 2001].

2.2. Paradigm and Data Processing

EEG recorded by a standard cue-based paradigm with 4 s time periods of right hand and feet MI was analyzed [Müller-Putz, 2010]. Laplacian derivations of the positions C3, Cz and C4, according to the international 10-20 system, were divided into overlapping (0.5 s) windows with a length of 1 s. A fast Fourier transform (FFT) was applied to each window. We limited the frequency range from 5 to 40 Hz at a frequency resolution of 1 Hz. Absolute values of the 108 frequency bins (36 freq. at 3 channels) were used as features for the RF classifiers. Classifier's settings: 1000 trees, the bootstrap sample's size was equal to the number of training trials, 10 random features for each split in each tree. We used artifact free trials (up to 80 per class; visual inspection) of a participant, to calculate 10x10 fold cross-validation (CV) accuracies for each time window and each participant independently. Further, we calculated the GI based feature ratings, and the ERD/S time/frequency maps for each class [Pfurtscheller, 2001]. To validate whether features GI ratings and differences in ERD/S maps relate, we computed the correlation coefficients between the GI ratings and the significant differences of ERD/S maps. Significant means where the 99% confidence intervals of the ERD/S maps values did not overlap.

3. Results

The CV results and the correlation coefficients of each participant are presented in Table 1. Figure 1 shows one example of the calculated maps and the average GI feature rating over all participants.

Table 1. *Peak cross-validation accuracies of RF classifiers and correlation coefficients between RF classifiers feature rating and significant (99% confidence interval) differences of ERD/S time/frequency maps of the classes right hand vs. feet (n.s. not significant).*

Participant	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	*Mean*
RF	94%	70%	75%	86%	91%	64%	70%	85%	74%	80%	79%
Corr. coeff. (p<0.001)	0.45	n.s.	n.s.	0.34	0.16	0.44	n.s.	0.17	0.12	0.71	0.34

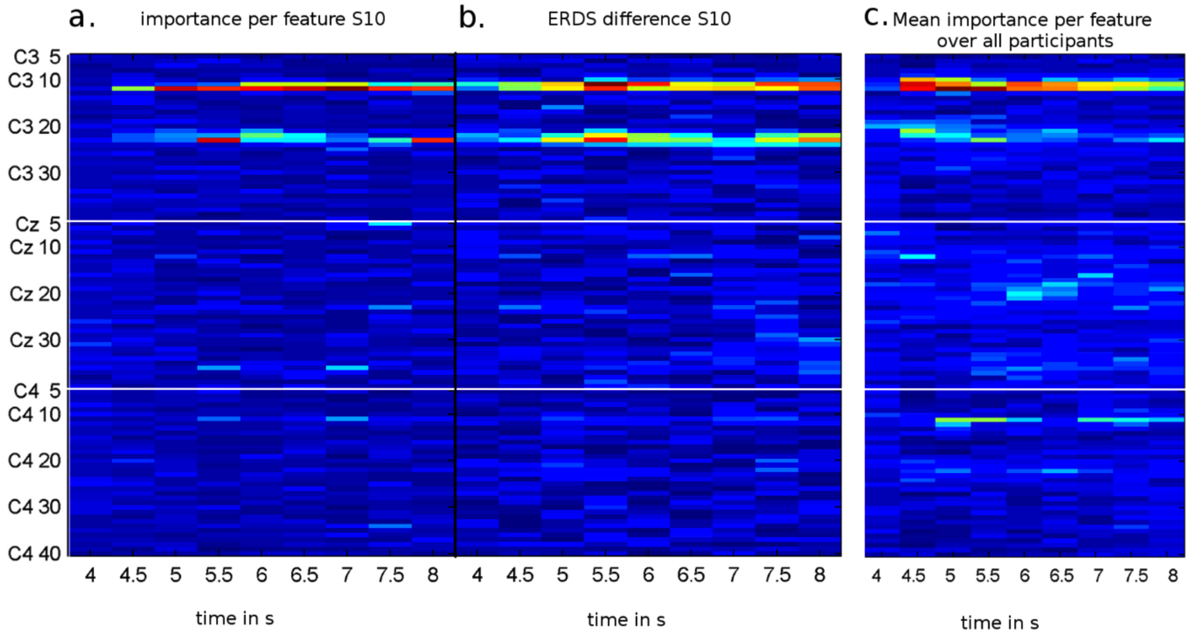

Figure 1. *1a) GI rating map for right hand vs. feet MI of participant S10. Each time segment was individually analysed. 1b) difference of ERD/S time/frequency maps between right hand and feet MI for participant S10. 1c) average GI ranking average over all participants. Note: Color coding of the maps is not compareable, because the color was normalized to the maximum value of the respective map.*

4. Discussion

RFs were successfully applied to EEG data for single trial classification of MI. We computed an average peak accuracy of 79%. For comparison DSLVQ achieved 81% [Müller-Putz, 2010]. The training of the classifier and the calculation of the ratings was reasonable fast with about 1 s per classifier. The time for classifying one sample was less than 0.05 s. The top rated features for MI were in average the frequencies in the mu and in the beta band of channel C3 (Fig. 1c). Moreover, in average there were important features on the ipsilateral side (C4), which is in line with literature [Pfurtscheller, 1997, 2001]. Although there is a noticeable similarity between the GI rankings (Fig. 1a) and the differences of ERD/S maps (Fig. 1b), the computed correlation coefficients (Tab. 1) were low. A possible cause is that significant differences of ERD/S maps were rather spots than sustained due to the low resolution of the maps and the assessment of ERD/S differences to certain frequencies can slight vary between ranking and difference maps due to the dissimilar calculation methods (FFT vs. band passing).

Summing up, Random Forests classify motor imageries in EEG and are able to find neurophysiological reasonable features. We are currently working on an online study using RFs and first results are promising.

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TOP-DOWN BNCI based Rehabilitation Approach: Kinematic and Electromyographic Visual Biofeedback Training by means of a New Ankle-Foot Orthosis for Stroke Subjects

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*Abstract***:** Among classical rehabilitation techniques for patients with stroke, there is insufficient evidence to state that a specific approach is more effective in promoting recovery than other. Only combination of different rehabilitation strategies seems to be more effective than conventional therapy alone. Currently robotic devices for nurorehabilitation are based on a Bottom-Up approach. We have developed a new tool based on a Top-Down Approach, in terms of kinematic and electromiographic (EMG) feedback for the recovery of ankle mobility and the treatment of ankle muscle spasticity. Positive results were found in terms of spasticity reduction and increment of agonist vs. antagonist activity. This feasibility study supports the idea that a Top-Down approach can be effective in neurorehabilitation, for reducing spasticity and improving EMG activation pattern in stroke subjects.

*Keywords:*Stroke, ankle, rehabilitation, EMG, kinematics

1.Introduction

The key point of TOP-DOWN (TD) rehabilitation approach is to control and enhance patient collaboration and attention [Langhorne, 2011] during physiotherapy (PT) in order to enhance TD control and improve motor function and brain reorganization. This approach represents a significant change from the traditional bottom-up (BU) approach that relays more on peripheral intervention over peripheral reflexes and proprioceptive stimulation [Belda-Lois et al, 2011] . We applied TD concept by means of kinematic and electromyographic visual biofeedback training using a new Ankle-Foot Orthosis (AFO) for ankle rehabilitation in stroke subjects.

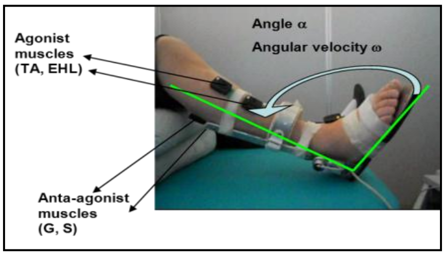

Figure 1: AFO tool and EMG sensors

2. Material and Methods

The AFO, showed in Figure 1, was formed by a specifically designed exoskeleton for the ankle, allowing for dorsi-plantar flexion movements, containing a set of sensors for on-line and off-line analyses of ankle joint range of motion (ROM - °) and ankle joint angular velocity (SPEED - °/sec.) in sagittal plane. AFO also contained 4 electromyographic electrodes record EMG activities of dorsiflexor (Tibialis Anterior - TA, Extensor hallucis longus - EHL) and plantarflexor (Gastrocnemious - G, Soleus - S) ankle muscles. Five sub-acute stroke subjects were enrolled into experimental group (EXP) and matched according to clinical and epidemiological features with other 5 subjects enrolled into CTRL group (CTRL). For EXP and CTRL group mean (sd) age, time from lesion and aetiology were respectively: 60.8 (15.96) – 66.2 (14.60) years; 64.8 (35.73) – 88.2 (30.16) days; 80% ischemic - 20 % aemorragich aetiology. Both groups underwent 6 weeks treatments, 5 times a week, 60 minutes each day in a lying down position with knee and hip flexed and with AFO tool and EMG sensors applied (Figure 1). For CTRL group whole treatment was devoted to conventional rehab training (i.e. proprioceptive exercises, passive and active tasks of dorsiflexion/plantarflexion movements) but without vBFB. EXP patients underwent 40 minutes of the same CTRL group treatment, followed by 20 minutes of vBFB training. 2 PC monitors were placed in front of EXP patients for real time vBFB monitoring (ankle angle and angular velocity on the first screen, and EMG patterns of TA, EHL, S and G on the other screen). vBFB training: 8 minutes of passive movements performed by physical therapist in which patients had to maximize proprioception and maintain muscles relaxed, 2 minutes of pause, 10 minutes of active movements in which we asked patient to gradually increase angular velocity. When EMG signals showed characteristic EMG patterns of spasticity the exercise was interrupted, and subsequently restarted. For both groups assessment was performed at beginning of the study (T0), after 15 (T1) and 30 rehabilitation days (Tend). Clinical evaluation: active and passive ankle dorsiflexion and plantarflexion ROM, Modified Asworth Scale (MAS). Instrumental assessment: ankle SPEED, EMG activities recorded during 5 tasks of active and passive dorsiflexion movements. Instruction gave to subjects for passive movements were to stay relaxed without helping physical therapist, while for active movements were to try to move as fast as possible the ankle. Data provided by the AFO tool were adequately processes, in order to obtain for each subject mean values of 5 active/passive peaks of SPEED used for dorsiflexion movements. We evaluated EMG activity by using a Coactivation index CI= (TA+EHL)/(S+G) defined as ratio between sum of flexor muscles and sum of extensor muscles. A CI equal to 0 represents a co-contraction of agonist and antagonist muscles. Rehab target is to achieve positive CI values. For each patient we analyzed and averaged 5 maximum peaks of CI corresponding to the 5 EMG activity peaks during dorsiflexion movements of T0, T1 and Tend assessments.

3. Results

Clinical and instrumental assessment results are reported in Table1. Statistical differences between groups at T0, T1 and Tend, reported as grey cells in Table1, were assessed in order to point out outstanding results by means of Independent t test. At T0 clinical features were comparable between groups ($p>0.05$). In order to stress progressive improvements due to training, an ANOVA analysis was performed for each group between T0, T1 and Tend. Significant results among training steps were obtained only for EXP group: at Tend, in comparison to T0, it was observed a significant reduction in MAS and increments in Active Velocity and CI ($p<0.05$ for all indexes).

	MAS			DorsiFLexAct			DorsiFLexPax			PlantiFlexAct			PlantiFlexPax			Passive Velocity			Active Velocity			Coactivation Index		
	T0	T1	Tend	T0	T1	Tend	T0	T1	Tend	T0	T1	Tend	T0	T1	Tend	T0	T1	Tend	T0	T1	Tend	T0	T1	Tend
EXP1	3,0	2,0	1,0	80,0	90,0	95,0	90,0	95,0	95,0	135,0	135,0	135,0	135,0	135,0	135,0	29,1	26,8	18,0	25,7	25,9	18,9	43,5	30,8	37,9
EXP2	3,0	2,0	0,0	90,0	95,0	95,0	90,0	95,0	97,0	90,0	95,0	140,0	140,0	140,0	140,0	16,9	11,2	13,7	0,0	0,0	0,0	2,1	1,3	2,2
EXP3	4,0	3,0	1,0	80,0	90,0	95,0	95,0	95,0	95,0	135,0	135,0	140,0	135,0	135,0	140,0	19,8	5,3	27,4	17,5	6,1	34,1	3,2	5,3	5,1
EXP4	3,0	1,0	0,0	95,0	90,0	95,0	95,0	95,0	95,0	95,0	95,0	135,0	135,0	135,0	135,0	9,5	12,2	10,5	0,0	6,1	4,2	1,3	5,8	8,3
EXP5	4,0	2,0	4,0	80,0	92,0	90,0	85,0	88,0	85,0	100,0	110,0	115,0	120,0	120,0	120,0	10,4	15,8	21,1	3,5	3,8	5,7	2,2	1,8	14,3
MeanEXP	***3,4***	***2,0***	***1,2***	***85,0***	***91,4***	***94,0***	***91,0***	***93,6***	***93,4***	***111,0***	***114,0***	***133,0***	***133,0***	***133,0***	***134,0***	***17,1***	***14,3***	***18,1***	***9,3***	***8,4***	***12,6***	***10,5***	***9,0***	***13,6***
SDEXP	***0,5***	***0,6***	***1,5***	***7,1***	***2,2***	***2,2***	***4,2***	***3,1***	***4,8***	***22,2***	***20,1***	***10,4***	***7,6***	***7,6***	***8,2***	***7,1***	***7,1***	***5,9***	***10,4***	***9,0***	***12,5***	***16,5***	***11,1***	***12,8***
CTRL1	2,0	2,0	1,0	70,0	70,0	95,0	95,0	70,0	80,0	120,0	120,0	120,0	120,0	120,0	120,0	14,2	14,2	16,8	12,3	3,5	4,7	2,4	2,6	1,8
CTRL2	4,0	4,0	4,0	115,0	115,0	100,0	85,0	85,0	90,0	120,0	120,0	110,0	120,0	120,0	120,0	22,1	18,9	19,7	11,6	0,9	2,6	13,5	1,4	1,7
CTRL3	3,0	3,0	3,0	80,0	95,0	105,0	80,0	80,0	80,0	120,0	120,0	110,0	120,0	120,0	120,0	17,9	15,0	17,3	0,4	0,0	0,3	2,6	3,3	3,1
CTRL4	4,0	3,0	3,0	110,0	85,0	100,0	85,0	85,0	85,0	110,0	105,0	120,0	120,0	120,0	120,0	24,7	30,5	17,0	0,5	16,4	6,7	0,6	6,8	18,2
CTRL5	2,0	1,0	1,0	75,0	80,0	80,0	60,0	75,0	80,0	110,0	110,0	125,0	110,0	110,0	125,0	24,6	26,2	32,0	11,8	15,6	26,5	7,1	9,5	8,4
MeanCTRL	***3,0***	***2,6***	***2,4***	***90,0***	***89,0***	***96,0***	***81,0***	***79,0***	***83,0***	***116,0***	***115,0***	***117,0***	***118,0***	***118,0***	***121,0***	***20,7***	***20,9***	***20,6***	***7,3***	***7,3***	***8,2***	***5,2***	***4,7***	***6,6***
SDCTRL	***0,9***	***1,0***	***1,2***	***20,9***	***17,1***	***9,6***	***12,9***	***6,5***	***4,5***	***5,5***	***7,1***	***6,7***	***4,5***	***4,5***	***2,2***	***4,1***	***6,4***	***5,8***	***5,6***	***7,2***	***9,4***	***4,6***	***3,0***	***6,3***

Table1: Results of clinical and instrumental assessments. Grey cells indicate significant comparisons between EXP and CTRL groups at T0, T1 and Tend ($p<0.05$)

EMG % of improvement obtained by means of trainings were also assessed for each group, and reported in Table 2. Statistical comparison between groups underlined statistical differences for TA, G and S (*: $p<0.05$).

Overall subjects: Tend vs T0 % of Improvement				
	EXP		**CTRL**	
	Mean	**sd**	**Mean**	**sd**
TA *	151,77	404,90	106,35	285,38
EHL	206,32	393,17	287,25	746,75
G *	-26,15	63,75	-11,25	72,12
S *	-56,19	43,16	0,34	51,73

Table 2: EMG muscles improvements, indicated as Tend vs To improvements (%); "-" represents a reduction in EMG activity

4. Discussion

The use of AFO tool in association with vBFB suggests the idea of the efficacy of a tool based on a TD Approach in neurorehabilitation. These preliminary data on TD approaches supports the implement of BCI based rehab tools. Present results seem to indicate the AFO as a valuable tool to exploit efficacy of BCI integrated robotic rehab devices. Kinematic and electromyographic vBFB addition to the conventional rehabilitation protocols seems to be more effective than rehabilitation alone for improving ankle spasticity, angular velocity and EMG activation in stroke subjects. These results are in line with the EMG % of improvements, obtained especially in EXP group.

Acknowledgments

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Should Proficient Subjects Use More Complex BCIs?

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Abstract. This study presents results of an offline experiment comparing brain computer interfaces of varying complexity over a sample of 10 subjects. The aim of this experiment is to determine the optimal number of intentional control tasks that can be used by subjects to maximise the usability of the interface. Despite various levels of proficiency from the remaining users, the 3-class problem (2 intentional control tasks and a no-control state) led to the highest bit-rates for all non-illiterate users.

Keywords: Motor-Imagery, Brain-switch, System-paced BCI.

1. Introduction

Brain switches based on the event related (de)synchronisation (ERD/ERS) complex have been investigated recently due to their simplicity in terms of setup, calibration and usage [Pfurtscheller and Solis-Escalante, 2009]. However, these interfaces suffer from low information transfer rate (ITR), as only a single bit is transmitted per trial and each trial has a minimum duration of 3-4s, due to the time required to perform motor imagery (MI) and the manifestation of the ERS following MI. As such, their application has been predominantly relegated to an on/off switch to enable the user to engage with a more effective BCI [Pfurtscheller et al., 2010].

One application which is often linked to MI based BCI is the navigation of a space. Indeed, a control interface has been proposed to allow a BCI with a single intentional task (IC) to navigate a space [Velasco-Alvarez et al., 2010]. However, such an system requires an intermediary interface to translate the basic control signal (is the subject performing MI) into the desired action in the 2-dimensional space (turn left, turn right and walk). As such, utilizing more IC tasks would be beneficial to reduce the need for an intermediary interface and render the navigation more seamless to the user, such as in Scherer et al. [2008] where rotation direction was controlled by each hand and forward movement was controlled by foot or tongue MI. The drawback of using multiple IC tasks with an ERD based BCI is that the subjects typically require numerous calibration and training sessions in order to achieve acceptable control of the interface.

Here, we investigate an ERD/ERS based BCI which is based on similar principles as brain-switches, but can discriminate between multiple IC tasks as well as the no-control (NC) state. The performance of the BCI as a function of the number of IC tasks discriminated is evaluated over 10 subjects to determine the optimal number of tasks to maximise the usability of the system, measured here by the ITR rate.

2. Material and Methods

2.1. Experimental setup and data acquisition

A total of 10 subjects were recruited to perform MI without feedback. Subjects watched a monitor showing a fixation cross, and at random intervals one of three cues appeared corresponding to right hand, left hand or foot MI. The duration of the cue was 2s, and the subjects were instructed to perform MI only while the cue was on-screen. For each subject, a total of 100 presentations were obtained for each IC task, and longer inter-cue breaks were used to obtain NC data (150 trials).

2.2. Transducer design

The BCI transducer investigated here is based on ERD/ERS features [Thomas et al., 2012]. Only 3 channels are used: C3, Cz and C4. The EEG is bandpass filtered between 4-40Hz, and decimated from 512Hz to 128Hz. Each trial is represented by the spectrograms of each channel based upon the short time Fourier transform with non-overlapping windows of 0.25s. Thus, each coefficient represents activity in a particular channel spanning over 0.25s and 4Hz. The original feature vector is composed of all the coefficients corresponding to 8-30Hz and 0-4s with respect to the cue onset.

Three different systems are compared corresponding to the different number of IC tasks classified. For a single IC task vs NC, the optimal IC task is determined in training, feature selection is performed via paired t-tests of all spectrogram coefficients and a linear support vector machine (SVM) is used for classification. For the 2 IC tasks and NC case, a similar pipeline is used: the optimal pair of IC tasks is computed in training via t-tests, and 2 optimised feature sets are used with 2 SVMs (NC vs both tasks, and task1 vs task2). For the 3 IC tasks and NC problem, a genetic algorithm is used to determine a single optimal feature set for the 4-class problem and a multiclass linear discriminant is employed for classification.

3. Results

The results presented here were calculated via nested cross-validation using 5 contiguous blocks for the testing folds, and 5 randomised nested blocks for the validation stage in which the parameters were selected. Table 1 shows the results obtained in terms of information transfer rate (ITR), as this metric allows for comparison between BCIs with different numbers of classes. We note that all but one subject achieve the highest ITR in the 3 class problem. It can also be seen that 2 of the subjects (S7 and S9) appear to be BCI illiterate, as even the simplest BCI paradigm yields extremely low ITR. The mean values are presented for both the entire subject set and the for only the subjects considered non-illiterate.

Table 1. *Results in terms on ITR (bit/min). Subjects considered BCI illiterate have been marked by an asterisk.*

Subjects	*1 IC vs NC*	*2 ICs and NC*	*3 ICs and NC*
S1	9.9	**12.6**	10.6
S2	6.8	**10.1**	7.9
S3	4.3	**5.5**	2.1
S4	3.5	**9.6**	7.2
S5	4.5	**5.9**	4.1
S6	7.2	**10.4**	9.5
S7*	0.3	0.8	**1.1**
S8	7.6	**7.8**	4.3
S9*	1.1	**1.5**	0.8
S10	10.7	**12.2**	11.4
Mean	5.6	**7.6**	5.9
Mean non-illiterate	6.8	**9.3**	7.1

The specificity of the NC class for the non-illiterate subjects was 81% for the 2 class problem, 80% for the 3 class problem and 69% for the 4 class problem. The mean task specificity was 91% for the 2 class problem, 73% for the 3 class problem and 52% for the 4 class problem

4. Discussion

Several conclusions can be drawn for the results presented in table 1. First, it can be seen that certain subjects (S7 and S9), deemed BCI-illiterate, achieve ITR rates too low for useful control of the interface, regardless of the simplicity of the task. However, for the remaining subjects 2 IC tasks and a NC state result in the largest ITR values. This is particularly interesting as the non-illiterate group is comprised of both high performers (S1, S2, S4, S6 and S10) and average performers (S3, S5, S8).

One noteworthy aspect of the results is that the specificity of the NC state remains high for both the 2-class problem (81% specificity) and the 3-class problem (80% specificity). Thus, the addition of a second IC task does not decrease the ability of the BCI to identify the NC state, and the reduction in task specificity (91% to 73%) is acceptable due to the overall increase in ITR.

In conclusion, for the presented processing scheme, 2 IC tasks and a NC state can be discriminated to give the largest ITR. This suggests that for all subjects in which the ERD/ERS is observable and can thus be classified, employing 2 motor effectors rather than a brain-switch will lead to higher ITR, and thus more useful, and natural BCI paradigms.

It should be noted that the results here represent the performance of the offline transducer rather than that of the overall BCI in an online self-paced scenario. Furthermore, the inclusion of subject training and the availability of more data could result in higher ITR for more complex paradigms.

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Robust User Interfaces for Motor Imagery Channels

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Abstract. We present a novel selection mechanism for binary input channels such as motor imagery EEG, which is robust to very high noise levels and biased inputs. This technique makes otherwise weak channels usable for interaction, and closely approaches theoretical optimal performance, while retaining a simple, clear interface.

Keywords: Motor imagery, error correction, bias, spatial selection

1. Introduction

Motor imagery based EEG is a widely-used paradigm for BCI control, which is distinctive in that is not externally evoked. However, it is slow, supports few output classes and noise levels tend to be very high. Although some individuals may perform reliably, even sophisticated binary motor imagery BCIs often have reliabilities <80% for many users [Blankertz et. al. 2008]. Conventional user interfaces (e.g. backspace or undo) cannot cope with error rates at this level. We show how a simple user interface can be built around probabilistic feedback error-correcting codes, which facilitates interaction at very close to the theoretical optimum.

2. Method

Our approach uses posterior-matching feedback error-correction codes to facilitate input. Because BCI is highly asymmetric, with a very low bandwidth input channel and a high-capacity feedback channel [Williamson et al, 2006], we can take advantage of effectively instantaneous and noise-free feedback (such as a visual display) to perform efficient error-correction with very short code lengths. In our system, the decoding algorithm maintains a probability density over the unit interval [0,1], which is initially uniform. The input the user is trying to communicate is mapped onto this interval as a value x_t (e.g. by arithmetic coding). Interaction proceeds by repeated bisection, where the median value m of the distribution is displayed to the user, and the user communicates whether $x_t>m$ or $x_t<m$ at each time t. This is displayed spatially so that each step the user makes a left/right choice on a number line.

If this were trivial binary bisection, there would be no tolerance for errors. By maintaining a complete probability density over the interval throughout selection, and distorting this density appropriately after each input, any level of error tolerance can be achieved [Shayevitz and Feder 2007]. Moreover, this tolerance is very close to the theoretical capacity of the input channel. By adjusting the distortion function, the decoder is also near-optimal for asymmetric channels (i.e. where there is bias – which is often the case with motor imagery). This decoder requires accurate knowledge of the channel statistics of an input channel – the true noise level and bias distribution - but we have constructed an adaptive variant of the algorithm which can track these statistics continuously without additional input overhead.

We have built a user interface around this algorithm, in which users zoom in upon a two-dimensional target. Selection is performed by alternating between two of these robust decoders, one for each spatial dimension. The result is a target reticule which gradually contracts around the intended target; errors automatically result in the reticule backing off. The interaction is carefully tuned to minimize visual disturbance, by intelligently rendering a selection reticule of constrained minimum size and zooming only as required, and by rotating the unit square by 45^o, such that dimension alternation can still be mapped to direct left/right input (see Fig. 1a).

3. Results

We have performed detailed offline simulation to evaluate the performance of the algorithm, along with proof-of-concept tests with online simulators and live motor-imagery BCI. The performance of the decoder is determined by two main factors: the length of a message before decoding is finalized, and the matching of the true channel statistics to estimated channel statistics. Longer messages are more efficient but are more difficult for humans to deal with, as they require “bundling” input into longer chunks. While this makes sense for tasks such as selecting a word from a dictionary or indicating a region on a map, it is unsuitable for real-time interaction as would be required to control a robot. We have found that good performance can be achieved for message lengths as short as 16 bits. Fig 1b shows the empirical performance of the decoder in simulated trials for 16 bit blocks.

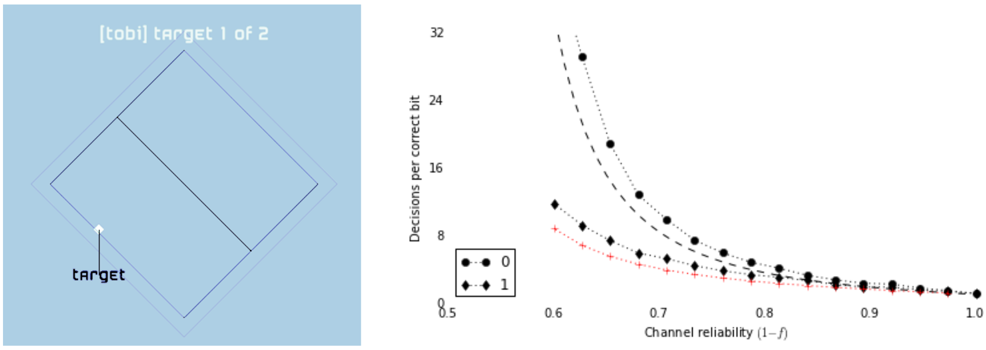

Figure 1. *(a) The selection interface for selecting 2D regions with minimal visual disturbance. In this case, the user would try and execute a "left" command for the next input (b) The performance of the decoder, shown as inputs per correct bit communicated, against channel reliability. ● simulated performance for a symmetric noisy channel; ♦ completely biased noisy channel (i.e. Z-channel – bit flips can only occur from 0->1). The Shannon symmetric channel bound is shown as --, and the Z-channel bound as +.*

Tests with online simulation, where a user interactively controls an input with BCI-like signal properties using a simple keyboard interface, have very similar performance to that seen in the offline automated simulation. We have also performed a single-subject 1 hour-long BCI trial with the interface as part of an on-going study, and the performance, although obviously inconclusive from such a small test, suggests that the simulation models are an accurate model of true performance. Table 1 shows results for various block lengths averaged over channel reliabilities from 60% to 90%.

Table 1. *Performance in simulated trials, with known channels statistics. Results are the average of 500 symbol selections for 20 channel reliabilities in the range [0.6, 1.0]. Performance is given as a multiple of the Shannon bound.*

Symbol length (bits)	*Relative performance*
24	1.182
16	1.254
8	1.421
4	1.491

4. Discussion

Existing user interfaces for BCIs are often frustrating and break down completely with reliability <80%. But this is often the level of performance which is achieved for a broad range of subjects. Our results show that the transparent encapsulation of robust probabilistic error-correcting codes in an visually simple user interface can provide reliable and efficient input for these low-reliability channels. It still remains to be seen how well the adaptive algorithm can cope with real BCI variability in channel statistics.

Acknowledgements

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Automated Assessment of Pathologic EMG Synergies for BCI-based Neuro-rehabilitation after Stroke

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Abstract. BCI systems may be employed in stroke rehabilitation to monitor and reinforce EEG patterns generated by motor imagery (MI). In the rehabilitative path of a stroke patient, therapists would encourage and reinforce any residual (or recovered) execution of the MI trained hand movements. For this reason, a hybrid BCI-driven rehabilitative device was proposed in order to boost motor recovery of the upper limb in stroke patients. This system would employ brain signals generated from motor attempt and reinforce voluntary contraction reflecting correct muscles activation as recorded by surface electromyography (EMG). The aim of the present work is to provide an EMG classification method that would be compliant with the current rehabilitation principles.

Keywords: BCI, EEG, EMG, FES, Post-stroke rehabilitation

1. Introduction

In BCI applications for stroke rehabilitation, sensorimotor (SMR) based BCI systems are used in order to provide patients with an instrument that is able to monitor and reinforce EEG patterns generated by motor imagery (MI). This task-specific training is meant to improve motor recovery by exploiting the activity-dependent brain plasticity phenomena [Pichiorri et al., 2011]. A further implementation of rehabilitative protocols can be achieved by employing motor-related brain activity to supplement impaired muscular control. In the rehabilitative path of a stroke patient, therapists encourage and reinforce any residual (or recovered) execution of the MI trained hand movements, yet ensuring that this does not induce unwanted contractions and spasticity. In this regard, a hybrid BCI-driven rehabilitative device was proposed in order to boost motor recovery of the upper limb in stroke patients (Fig. 1a). The communication between system modules was realized using the Tobi interfaces [Breitwieser et al., 2012]. In this hybrid approach, the patient's motor intent is recognized (EEG patterns) and the muscle contraction is produced via FES only if his/her specific EMG features of the patient's voluntary motor attempt are recognized as "correct" [Aricò et al., 2012].

Here, we performed a feasibility study over two subject, with the aim of identify and classify the specific muscular patterns which must be reinforced (and/or suppressed) depending to the specific required movement, according to the current rehabilitation principles.

2. Material and Methods

Two post-stroke patients were involved in this study; residual strength in distal segments of the stroke affected upper limb was 4 according to the Medical Research Council scale for muscle strength. EMG signals were recorded (8ch g.USBamp, gTec, Austria, 256Hz) from 4 positions (finger flexor and finger extensor, biceps and triceps). Subjects were asked to perform two simple hand movements (grasping and finger extension) with the affected hand. The experiment was carried out in the presence of rehabilitation experts who were asked to label each motor task as "correct" or "incorrect" according to current rehabilitation principles. For each type of movement, patient had to perform the movement, until there were at least 10 correct trials labeled as good by the expert (in this study, ~20 trials were performed for each task). In an offline stage, we evaluated and tested a classification method that would reflect the "human decision". In this regard, we used different rules (in agreement with the neurorehabilitation experts and compliant with the current rehabilitation principles), which could provide information on the quality of the movement, according to the required task and the patient's clinical state (spasticity, residual strength, etc.). In this regard, for the finger extension, the EMG patterns were considered as correct when the signal amplitude of the target muscles (finger extensor and triceps) was higher than the amplitude of their antagonist (finger flexor and biceps). As for the grasping movement, the attempt to grasp may cause unwanted (involuntary) recruitment of the biceps muscle, due to an increase in flexion spasticity. Therefore, classification patterns were considered successful when the signal amplitude on the finger flexor was higher than the biceps. These principles were translated into mathematical expressions, and used to classify the required movement using the EMG patterns. In order to obtain a signal directly correlated with the contraction strength, we evaluated the EMG (filtered between [20-80] Hz and rectified) linear envelope.

Furthermore, maximum voluntary contractions (MVCs) for each muscle and the rest EMG value (extracted at the beginning of the experiment) were included in the classifier, in order to normalize the EMG scores between 0 and 1. We evaluated the Area Under Curve (AUC) of the Receiver Operating Characteristic (ROC) curves calculated over the classified trials, in order to estimate the correspondence of our method results to the neurorehabilitation expert labeling procedure. Additionally, we introduced an automatic procedure to update the rest values of the EMG score for each trial during the experiment (continuous recalibration), in order to make the classification process more robust to the patient's posture changes during the experiment.

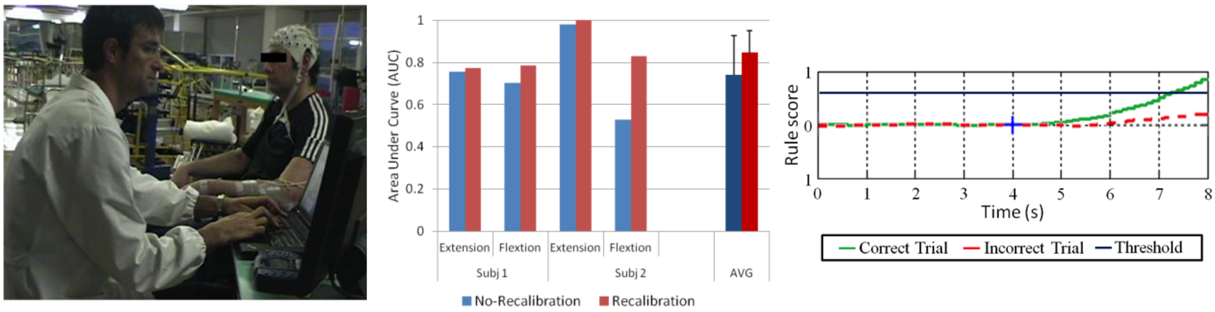

Figure 1. *(a) Hybrid BCI controled FES application for post-stroke motor rehabilitation; (b) AUC of the classifier for each patient and task, with and without recalibration;(c) example of "correct" and "incorrect" trial and threshold chose through ROC curves evaluation.*

3. Results

AUC values reveal that automated classification of EMG patterns show a good match with the experts' evaluation. Moreover the adaptive classification method allows to achieve higher (but not significant, p>.05) AUC values with respect to the classification method which does not provide a continuous recalibration of the EMG value related to resting state. Considering continuous recalibration the accuracy of the system reached on average 80%.

4. Discussion

The aim of the proposed study was: i) to evaluate a classification method for EMG signals that would be in agreement with the neurorehabilitation experts and compliant with the current rehabilitation principles (accuracy of the system); ii) to evaluate the accuracy of the system applying an adaptation of the resting value trial by trial, in order to make the system more robust to the changes of the patient posture over time. Preliminary results, showed that the proposed classifier reflects with an high accuracy (~ 80%) the judgment criteria of the neurorehabilitation experts. Furthermore, continuous recalibration of some system parameters (e.g. rest values), improves the accuracy of the classifier. The proposed system has been installed in a rehabilitation hospital ward and is currently under testing with the participation of post-stroke patients and rehabilitation experts. We expect to generate a generalized model of EMG classifiers (based on the algorithmic implementation of rehabilitation expert knowledge), empowering the physiotherapist's ability to evaluate the correctness of the patient's residual motor activity and thus, improving the patient's functional motor recovery.

Acknowledgements

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Brains of Proficient and Less than Proficient BCI Users: Is there a Difference?

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Abstract Motor imagery-based brain machine interfaces (BMIs) have been shown to be a promising substitute when the body's own peripheral motor system fails. However, not all users are able to achieve a sufficient degree of control of such systems and there is an open debate on the underlying causes of this phenomenon. In this study we use ultra-high-field magnetic resonance imaging (MRI) to investigate whether anatomical and functional characteristics of the brain explain proficiency of BMI control.

Keywords: BCI performance, Functional Magnetic Resonance, Kinesthetic motor imagery

1. Introduction

Principal non-invasive BMI approaches utilize various signals registered with scalp electroencephalography (EEG), particularly desynchronization and synchronization of cortical oscillations accompanying imagined movement. Many users have successfully used such systems for controlling devices like wheelchairs [Carlson and Millán, 2012] or telepresence robots [Tonin et al., 2011]. The development in the field over the last decades has progressively contributed to transfer the technology from controlled laboratory conditions to real-life environments. Nevertheless, there is evidence that a significant percentage of the population is not able to attain proficient control of a typical BMI system. To explain the reason behind proficiency, several studies attempted to identify psychological and neurophysiologic features as predictors of BCI performance [Blankertz et. al., 2010; Halder et al., 2011; Hammer et al., 2012]. In this preliminary study we investigated whether, and to what extent, the inter-subject variability in the control of motor imagery-based BMI systems is explained by functional and anatomical characteristics of the brain. We used ultra-high-field MRI to measure differences in brain activation during imagery of movements in trained BMI users.

2. Material and Methods

Three subjects took part in this pilot study (p1, p2, p3). Participants were selected from a sample of BMI users within our laboratory. All of them had previous experience with motor imagery-based BMI.

Subjects were visually cued to imagine – performing kinesthetically – three motor tasks: repetitive flexion/extension of the (i) right hand (RH), (ii) left hand (LH), and (iii) simultaneously both feet (FT) with a control condition of – similarly visually cued – No-Imagery (No-IM). The experimental protocol consisted of three imagery runs, each containing five 10-second trials of each of the above tasks in random order.

Imaging was performed on a 7T Magnetom Siemens scanner, and all images were acquired using a 32 channel head coil. Three-dimensional anatomical scans were acquired with high-resolution 1 mm (3D MP2RAGE sequence (Marques et al., 2010), repetition time (TR) 5500 ms, echo time (TE) 2.84 ms). Functional T2*- weighted images using echo planar imaging sequence (EPI) were acquired using the following parameters: TR 2500ms, TE 26 ms, flip angle 75 degree from Anterior Commissure-posterior Commissure (ACPC), 46 oblique slices with 1.5mm gap,1.5×1.5×1.5 mm^3 voxel size, covering the whole motor strip.

SPM8 (http//:www.fil.ion.ucl.ac.uk/spm) software package was used to preprocess and analyze the functional data. Images were realigned to correct for head movements, whereupon they were co-registered with each subject's anatomical MRI and subsequently normalized to the Montreal Neurological Institute's (MNI) reference brain. The voxels were spatially smoothed with an isotropic Gaussian filter of 3 mm full width at half-maximum. A linear regression model (General Linear Model - GLM) was fitted to the fMRI data to obtain the brain regions more correlated to each motor imagery task (height threshold T=3.10, p<0.001 uncorrected).

3. Results

To find functional brain areas activated during kinesthetic motor imagery that reflect the EEG features in BMI control, we contrasted the activity of imagery tasks to No-IM. As shown in Fig. 1.a, p1 had activations in multiple sensorimotor areas in all the three conditions. This subject achieves 100% accuracy by modulating EEG features of left hand versus feet, or hands versus feet. Subject p2 had less activity in sensorimotor areas (Fig. 1.b). This subject has BMI session accuracy on average 80% modulating right hand and feet. Subject p3 had the smallest activation in primary sensorimotor areas (Fig. 1.c). Specifically, the spatial location of the Precentral Gyrus activation (z=25) might explain the p3's poor BMI performance (less than 60%) since it is anatomically less readily accessible by EEG.

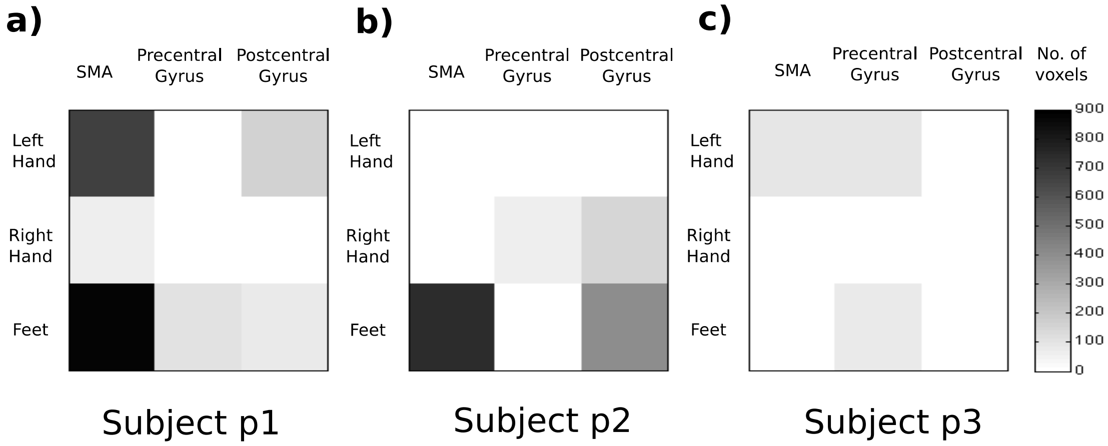

Figure 1. *a) High proficiency in all the BMI classes; b) Reasonable proficency in one class (i.e right hand versus feet imagery); c) No profiency in any of the BMI classes.*

As shown in Table 1 other non-primary motor regions within the motor imagery network [Decety, 1996] were activated in at least one imagery condition.

Table 1. *Specific activation during foot and left hand motor imagery*

Contrast	*Anatomical Region*	*Subject*	*Cluster size (T=3.10, p<0.001, uncorrected)*
FT > No-IM	Middle Frontal Gyrus_L	p2, p3	369,70
	Superior Frontal Gyrus_L	p2, p3	64,164
	Middle Frontal Gyrus_R	p2	101
	Inferior Frontal Gyrus_R	p2	369
	Inferior Parietal Lobule_L	p1,p2	203,591
	Medial Frontal Gyrus_L	p2	322
LH > No-IM	Inferior Frontal Gyrus_R	p1	271

4. Discussion

Our preliminary study reveals a direction to pursue in explaining a long-standing question of the causes of failures in BMI control. Although this pilot's small sample does not allow us to statistically compare the results with previous literature, they suggest that the brains of proficient motor imagery-based BMI users have functional and spatial features that predispose them to such proficiency. An upcoming full-scope study will verify this claim on a larger sample. In addition, an ongoing brain morphometry analysis is also testing the hypothesis that brain structure is a factor affecting BMI performance.

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Wavelet Tools for the Detection of Error-related Potentials

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Abstract. Non-invasive brain-computer interfaces (BCIs) are limited by a low signal-to-noise ratio and a consequent high error rate. Error correction mechanisms based on Error-related Potentials (ErrPs) have been studied extensively but reliably detecting such potentials in single trials has proven to be a challenge. We propose a new detection strategy based on the extraction of time- and frequency-domain information with a dual-tree complex wavelet transform (DT-CWT). Different classification techniques are evaluated and the stability of DT-CWT features is demonstrated, thus advancing toward reliable and efficient error-corretion mechanisms in BCI.

Keywords: EEG, Error-related Potential, Single-trial analysis, Complex Wavelet Transform

1. Introduction

Over the years, non-invasive brain computer interfaces have become increasingly accurate, yet errors are still frequent and bound to occur. The implementation of error correction mechanisms in general, and via the detection of error-related EEG potentials in particular, has the potential to provide significant improvements in both the usability and reliability of BCI systems. This requires accurate recognition of ErrPs in single trials. In particular, care should be taken to avoid false positives as they dramatically reduce the BCI bitrate by introducing spurious error correction.

In the current paper we present a novel approach to the detection of ErrPs by exploiting the frequency-domain information obtained with the Dual-Tree Complex Wavelet Transform [Kingsbury et al., 2005] in addition to time-domain values. This transform, notable for being computationally efficient (similar to the discrete wavelet transform) and shift-invariant, yields stable features for ErrP patterns as detailed below. Several classification strategies based on these features are evaluated and compared, notably with regard to the overall decrease in errors across the BCI communication channel.

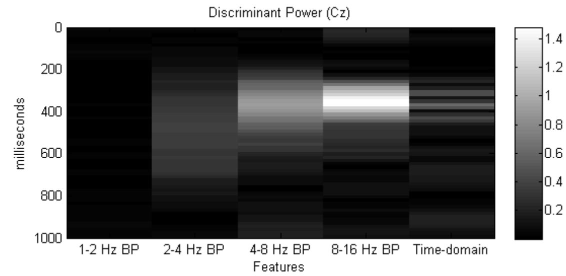
2. Material and Methods

2.1. Datasets

The approach to ErrP detection presented in this paper has been evaluated on two datasets. Both datasets are based on the 'Dancing Robot' protocol [Ferrez and Millán, 2008; Chavarriaga and Millán, 2010]. Each dataset contains recordings of six subjects on two separate days (several weeks or months apart). The two datasets have five subjects in common. In the 'Interaction' dataset, the user is led to believe he's controlling a square displayed on the screen through motor imagery. The square moves in discrete steps toward a 'target' position but 20% of the steps go in the opposite direction, thereby eliciting an error-related potential. In the 'Monitoring' dataset, the same events take place on the screen but the subject is only instructed to monitor the movement of the square, he doesn't feel responsible for its behavior.

2.2. Methods

All processing on the datasets was carried out offline but the processing architecture is designed for real-time execution and the results thus reflect the expected online performance. The EEG signal is acquired over 64 electrodes (10/20 configuration) at 512 Hz. It is re-referenced to common average reference, low-pass-filtered below 17 Hz (Chebyshev II, order 6), down-sampled to 64 Hz and high-pass-filtered above 2 Hz (Chebyshev II, order 4). The dual-tree complex wavelet transform is then applied to the signal and the band power computed over the following frequency bands is kept: 1-2 Hz, 2-4 Hz, 4-8 Hz, 8-16 Hz. In parallel, time-domain features are obtained by further filtering the signal below 12 Hz (FIR, order 20). Fisher's discriminant is then computed for a one-second window, over all channels and features (both time and frequency domain). The 100 most discriminant features are retained. The classifier is then trained on the data from one day of recording and tested on the other. Two classification algorithms, noteworthy for their simplicity and speed, have been evaluated: LDA and k-NN (k=15, obtained by cross-validation). Two 'reference' classifier performance indices were used: LDA-T (i.e. LDA over time-domain features only) and LDA-F (DT-CWT features only). The LDA decision boundary was chosen in all cases so as to minimize the number of errors along the communication channel, knowing *a priori* the 20% error rate in the protocol. This favors high specificity at the expense of sensitivity.



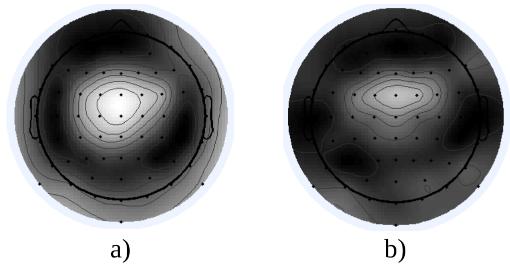


Figure 1. *Left: discriminant power (Fisher's criterion) on data for electrode Cz. Right: Topography of the discriminant areas for bands 8-16 Hz (a) and 4-8 Hz (b), 390ms after stimulus. Few channels provide most of the information.*

3. Results

The frequency-domain information extracted by the complex wavelet transform provides consistent and stable features, with high discriminative power in compact sets of features (see Fig. 1). These features enable the classifiers to perform moderately well in terms of sensitivity whilst achieving very high specificity.

The 'Interaction ErrP' dataset benefited most from the error-correction methods proposed herein. With respect to the initial 20% error rate of the dataset, the BCI errors were decreased by 28.3% by using the LDA classifier and by 38.6% with the k-NN classifier, as opposed to a mere 12.7% decrease with LDA-T and 15.8% with LDA-F. It should also be noted that none of the subjects experienced an increase in error rate because of the error-correction mechanism we implemented, whereas one did with LDA-F (+24.2%) and three of them did with LDA-T (up to +20.7%).

Results are, however, less conclusive with the 'Monitoring ErrP' dataset. Its very low signal-to-noise ratio makes the detection of ErrPs less reliable. In particular, the features for two subjects have low discriminability both in time and frequency domain. In this dataset, the reference LDA-T classifier increases the error rate on the BCI channel by 2.2% on average. Nonetheless, LDA-F manages to reduce errors by 6% and the LDA exploiting both time- and frequency-domain features reaches a decrease of 9% on the number of errors (25% excluding the two low-performance subjects). On the other hand, the k-NN demonstrates high variability in performance between subjects (from -45.8% errors to +53.4%) which results in no statistically significant effect.

Table 1. *Average classifier performance over the two datasets. 'Interaction ErrP' is left, 'Monitoring ErrP' is on the right.*

Classifier	*Sensitivity*	*Specificity*	*AUC*	*ΔError*	*Sensitivity*	*Specificity*	*AUC*	*ΔError*
LDA-T	63.1%	87.4%	75.3%	-12.7%	40.3%	89.4%	64.8%	2.2%
LDA-F	53.8%	90.5%	72.2%	-15.8%	34.8%	92.8%	63.8%	-6.0%
LDA	67.8%	90.1%	79.0%	-28.3%	38.0%	92.8%	65.4%	-9.0%
kNN	52.5%	96.5%	74.5%	-38.6%	41.4%	89.7%	65.5%	-0.1%

4. Discussion

We have presented the use of the Dual-Tree Complex Wavelet Transform for the detection of Error-related Potentials. The results are encouraging and these features could be considered for other kinds of evoked potentials. Whilst complex wavelet transform cannot substitute the use of time-domain information in ErrP classification, it does provide complementary information that may lead to higher accuracy. Further work would be aimed at leveraging the statistical relations between features for classification purposes as well as evaluating and extending these tools to Error-related Potentials generated in asynchronous protocols, where time-domain features aren't sufficient to achieve reliable detection.

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Relaxation Exercise improves SMR-BCI Performance

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Abstract. Psychological factors such as users' ability to concentrate on a task and their visuo-motor coordination ability have been identified to predict performance in sensorimotor rhythm based Brain Computer Interfaces (SMR BCI). The present study investigated if performance can be enhanced by active intervention prior to BCI usage. N=59 healthy, naive subjects took part in one of three different interventions (two-hand coordination training, Jacobsen's progressive muscle relaxation training and BCI-related book chapter reading) before performing an SMR BCI session. Preliminary results indicate that relaxation exercise has a positive effect on performance, and relaxation level of the user could be a predictor of SMR-BCI performance.

Keywords: Brain Computer Interfaces (BCI), Sensorimotor rythms (SMR), Relaxation

1. Introduction

Sensorimotor-based Brain-Computer Interfaces (SMR BCI) allow a user to control a device by modulation of motor cortex signals resulting from imagined localised body movements. Current systems are constantly improving thanks to hardware and software development. However, we are still facing a phenomenon called "BCI inefficiency" stating that 10% to 50% of users do not achieve accurate control over the interface [Kübler et al., 2011].

Psychological variables have been found to correlate with SMR-BCI performance [Hammer et al., 2012]. (1) The score achieved in a visuomotor coordination task (guiding a visually displayed point in a two-dimensional track utilizing a controller with separate horizontal and vertical controls). (2) The "attentional impulsivity" value from the Barrat Impulsiveness Scale (BIS), and (3) Attitude Towards Work (AHA). Visuomotor task (1) depicts a person's motor related ability whereas questionnaires (2) and (3) display a person's ability to concentrate on a task. Guided by these results, the current study investigated if BCI performance could be increased by a prior (non-BCI) training intervention. Subjects participated in a relaxation exercise, or a visuomotor coordination training. The control group did not participate in such trainings but was reading BCI related literature instead.

2. Material and Methods

The preliminary results presented in this abstract are from N=59 healthy, BCI-naïve participants (17 male, aged 23.3, SD=4.7). The intended sample size of this study will be N=162 participants. EEG was recorded from 64 active electrodes (BRAIN PRODUCTS ActiCAP system, 10-20 system) with dense electrode coverage of motor areas.

2.1. Pre-BCI Intervention

Subjects were randomly assigned to one of the three groups. (1) in the "Relax" group, subjects were instructed to listen and follow a 23 min audio recording of Jacobson Progressive Muscle relaxation, which consists of an alternation between maintained contraction of groups of muscles and relaxation. (2) The "2Hand" group was given a knob controller for each hand. The left knob controlled vertical movement and the right knob horizontal movement of a point that had to be accurately steered on several narrow paths displayed on the screen. (3) The "Information" (control) group read a text about current BCI Technology for the same amount of time.

2.2. BCI Session

The BerlinBCI software system with co-adaptative calibration was used in this study [Vidaurre et al., 2011]. The session started with a three minute "eye open, eye closed" recording. Then, each run followed the same scheme : At 0s, a fixation cross appeared in the middle of the screen, at 1s a directional arrow appeared, instructing subjects about the target movement (left hand, right hand or feet movement) they had to kinesthetically imagine. As a feedback, the fixation cross changed color and moved in the direction interpreted by the classifier during 3s, then a 2s break followed. During calibration runs, independent adaptive LDA classifiers indicated "positive-only" feedback for each movement imagery. After 120 trials, frequency bands were chosen and subject-specific LDA classifiers were trained with extracted features using Common Spatial

Filters. The two imageries that were best discriminated were chosen for the online runs, which comprised 80 trials each. Performance depended on the subject's ability to move the cross in the correct direction.

2.2. Psychological Tests

Several psychological tests were administered, but only results of a visual analog scale (VAS) to coarsely assess relaxation are reported here. The VAS ranged from 0 (not at all relaxed) to 10 (maximally relaxed) and was filled out by the subjects immediately after the intervention.

3. Results

Average level of correct SMR modulation was M=72.6%. The Relax group had a higher mean M=78.1%, compared to 2Hand group M=71.9% and Information control group M=68.0%, as detailed in Table 1.

A 3 (group) by 4 (run) repeated measures ANOVA yielded significant interaction between group and time, $F_{(5.26,\ 147.22)}=2.61$, $p\leq .025$. Post-hoc pairwise comparisons revealed that in runs 1 and 2 the Relax group performed significantly better than the Information group (both $p\leq .05$). Correlation between performance and relaxation VAS score was significant for all runs, $r(57)=.289$, $p\leq .014$.

Table 1. *Performance means for all run and all intervention groups (1). Correlation between relaxation Visual Analog Scale value after intervention and performance across all intervention groups for each online run (2).*

Online run	*(1) Feedback performance[%]*								*(2) Correlation*	
	Relaxation N=19		*2Hand N=20*		*Information N=20*		*Total N=59*		*performance and relaxation VAS value*	
	Mean	*STD*	*Mean*	*STD*	*Mean*	*STD*	*Mean*	*STD*	*r*	*Sig(1-tailed)*
1	79.3	15.5	72.5	19.8	63.8	14.5	71.8	17.7	.256	.026
2	76.2	14.4	71.2	16.9	66.0	10.2	71.0	14.5	.232	.040
3	79.4	13.1	72.3	16.9	71.1	13.0	74.2	14.7	.295	.012
4	77.5	16.5	71.6	16.4	71.1	13.7	73.3	15.6	.299	.011
All	78.1	14.9	71.9	17.5	68.0	12.9	72.6	15.6	.289	.014

4. Discussion

Relaxation exercise seems to positively influence performance in an SMR controlled BCI, however, its effect decreases with time. The Progressive Muscle relaxation technique centers subject's thoughts on body sensations and might help them to concentrate, thus possibly allowing them to better kinesthetically imagine the movement. The relaxation level of the subject could thus possibly serve as a performance predictor for SMR-BCIs. Visuomotor coordination training did not show any significant effect on performance. Visuomotor coordination, however, is a skill that may develop with longer training. Short-term intervention may only have a negligible effect on this predictor. More data will be acquired, to further corroborate our results or reject our hypotheses.

Acknowledgements

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P300-speller Adaptivity to Change with a Backspace Key

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Abstract. We develop a simple algorithm that uses the backspace key to recalibrate a standard P300 speller during use. We show it to be efficient in a series of computer simulations mimicking an electrode breakdown, where the spelling accuracy is shown to recover in about 50 trials.

Keywords: grid-based P300-speller, adaptive BCI's, failure detection, online recovery

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1. Introduction

The "Backspace" key of the standard computer keyboards is interesting to consider from the perspective of adaptive BCI P300-spellers. It may indeed provide an information (or a guess) about the correctness of the previous spelling, and thus allow to decipher between valid letters and invalid letters in the current series of spelled characters. We developed a specific algorithm where *(i)* a training set, containing only the most *recent* examples, is maintained during use and (*ii*) the device recalibration is allowed only when the rate of correct spelling is too low (typically 3 successive failures).

2. Material and Methods

2.1 Algorithm: Online Recalibration using the "Backspace" key

In principle, it is possible to recalibrate the device every time a letter is not followed by a backspace, which is obviously too resource-consuming. Here we propose to recalibrate the system only when a significant performance drop is observed. Our algorithm relies on a very simple (and quite coarse) online estimation of the spelling performance, based on the number of failures observed in the last trials. The device update is allowed when an unexpected series of failures is observed. For that, a counter **`fail_counter`** is used for counting the number of failures since the last success. Two global parameters need to be set: **`TRAINING_SET_SIZE`** sets the maximal size of the training set and **`FAIL_MAX`** the maximum number of failures allowed since the last success.

```
training_set ← training_session()
spatial_filter, classifier ← calibrate_device(training_set)
fail_counter ← 0
(feature_vectors_set, letter) ← extract_last_example(training_set)
loop
   (previous_feature_vectors_set, previous_letter) ← (feature_vectors_set, letter)
   feature_vectors_set ← vectorize_and_filter(EEG_input, spatial_filter)
   letter ← classify(feature_vectors_set, classifier)
   if letter is a backspace then
      fail_counter ← fail_counter + 1
   else
      if previous_letter is not a backspace then
         fail_counter ← 0;
         training_set ←add_new_example(previous_feature_vectors_set, previous_letter)
         training_set ←delete_oldest_examples_if_needed(TRAINING_SET_SIZE)
      end if
   end if
   if (fail_counter = FAIL_MAX) then
      spatial_filter, classifier ← calibrate_device(training_set)
      fail_counter ← 0;
   end if
end loop
```

2.2. Dataset and Simulations

For our simulations, we use an EEG dataset from a P300 experiment reported in [Maby et al., 2010]. There was no backspace key in the initial experiment, but a standard 6x6 grid. This dataset contains 20 different subjects, each subject having had to spell out 220 letters where every row and every column was flashed 5 times per letter. The correct response is known for every trial and every subject.

For every subject, we run 1000 different simulations. For each simulation, we shuffle the 220 trials, take an initial training set of 25 examples, calculate an xDAWN spatial filter [Rivet et al., 2009] and a LDA classifier [Krusienski et al., 2008]. Then we test the online recalibration from trial #26 to trial #220. At trial #101, the EEG signal from one electrode taken at random is replaced by a white noise, causing a drop in the rate of successful recognition. The spelling correctness is measured at each trial by comparison with the expected response recorded in the dataset.

3. Results

Just after training, the average spelling accuracy is around 84%, which is a typical performance for a five repetitions P300 setup. Then, as there is no backspace key in the initial experiment, we introduce artificial backspace hits in the series. Considering the 70% lower bound in spelling accuracy after training (which is true for all subjects except for one), we use 30% false positive backspace hits (irrelevant hit when the spelling is correct), and 30% false negative (no hit when the spelling is incorrect).

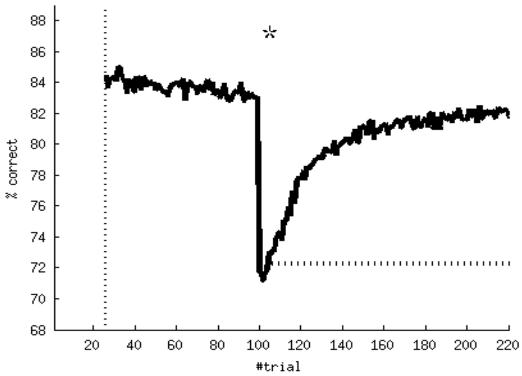

Figure 1 : Online recovery using automatic recalibration, with 30 % erroneous backspace hits, and an electrode breakout taking place at trial # 101 (*). The average spelling accuracy is calculated at each time step over 20 subjects x *1000 simulations. The horizontal dotted line gives by comparison the spelling accuracy attained when no recalibration is made. Trials #1 to #25 are used for the initial training .* ***TRAINING_SET_SIZE*** *= 25,* ***FAIL_MAX*** *= 3.*

After running 1000 x 20 experiments, the average spelling accuracy is calculated at each time step and reported on Fig. 1. The effect of a single electrode break (out of 32) appears quite strong, with a big drop from almost 85% correct to less than 72% correct. There is no improvement (and possibly a slight decrease) up to trial 100, then, after the electrode breakout, the spelling accuracy is found to almost recover to its initial level in about 50 trials.

4. Discussion

The spelling error information contained in a backspace hit has been shown useful for the device adaptivity to unexpected changes. We have proposed an easy take-home adaptive algorithm that should now be validated in real-world experiment and compared and/or combined with other adaptive algorithms proposed in the literature.

Acknowledgements

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Effects of Attention and Passiveness on Event-related Potentials

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Abstract.

Event-related potentials (ERPs) are frequently used to support clinical assessment of patients with disorders of consciousness (DOC). Usually, patients are told to passively "just listen" while ERPs are recorded. However, comparative data from healthy particicpants is needed and this data is usually recorded under different, mostly active, conditions. Here, we investigated whether the passive listening of tone streams and semantic stimuli can result in misleading ERP responses. Healthy participants performed three different attention tasks (divided, passive and focus attention). Preliminary results revealed that the ERP responses are modified in respect to the attentive modulation regardless of the perceived subjective effort.

Keywords: MMN, N400, attention, EEG, event-related potentials

1. Introduction

In clinical assessment of DOC patients ERPs have been proven to be a successful tool to detect residual cognitive functions [e.g. Kotchoubey et al. 2005]. In research, ERP components related to specific brain processes could be extracted (e.g., mismatch negativity (MMN) and N400). Those components could also be found in DOC patients. When applying such paradigms in DOC patients, they are hardly ever provided with an instruction beyond "just listen", viz. the paradigms are passive. In healthy participants this passiveness can lead to drowsiness, inattentiveness and eventually frustration which then results in undistinguishable ERP responses. However, comparative data from healthy participants are indispensable if the ERP data of DOC patients should be interpreted in terms of cognitive processing.

Research in attentive modulation of MMN and N400 responses has a long history. To this research we append the investigation of the effect of passiveness on ERPs. Based on the well-studied MMN [Sussmann, 2007] and N400 component [Kutas & Federmaier, 2011] we investigated whether reduced levels of attentive awareness lead to a continuous attenuation of these components. Most importantly, we wish to clarify how passive listening, commonly used in patients, is mastered by healthy participants compared to active tasks.

2. Material and Methods

The sample included seven participants (one male, mean age = 36.1 yrs, SD = 9.2). EEG was recorded with a 32 active electrodes system (Brain Products, Germany) with a sampling frequency of 512 Hz. The experiment consisted of three different pseudo-randomly presented attention tasks. In the divided attention task (I) participants watched a movie during auditory stimuli presentation and pressed a key when a certain scene appeared. In the passive attention task (II) participants were required to carefully listen to the auditory stimuli. And finally, in the focus attention task (III) participants were required to indicate with a specific key the odd in the oddball paradigm or to use two different keys for semantically congruent and incongruent stimuli. Auditory stimulation was realized in three different paradigms: (1) an oddball with 1000 harmonic tones (900 frequents with a duration of 50 ms, 100 odds of 25 ms), (2) a word-prime paradigm with 200 word pairs (100 semantically related, 100 unrelated) and (3) a sentences paradigm (100 semantically congruent, 100 incongruent). A scale for subjectively experienced effort ranging from 0 to 220 [Eilers et al., 1986] was administered after each paradigm.

EEG data were band-pass filtered between 0.1 and 25 Hz and segments from 0 to 500 or 1000 ms depending on the paradigm were averaged. Finally, grand averages were obtained.

3. Results

We only analysed the mean amplitude values of the relevant ERP components (MMN between 100 and 220 ms, N400 between 200 and 600 ms) by performing a repeated measures ANOVA including three factors (divided, passive and focus attention).

Results reveal that an MMN was elicited in all three tasks. The differences between deviants and standards varied significantly according to the task ($F(2,5) = 20.1$, $p = .000$) with the difference being largest in (II) and smallest in (III). In the word-prime paradigm an N400 was only elicited in (III). The differences between related and unrelated word pairs varied significantly according to the task ($F(2,5) = 14{,}5$, $p = .001$) with the difference being largest for (III) and smallest for (II). In the sentence paradigm an N400 was elicited in (II) and (III). The differences between congruent and incongruent sentence endings did not differ significantly depending on the task ($F(2,5) = 1{,}54$, $p = .254$).

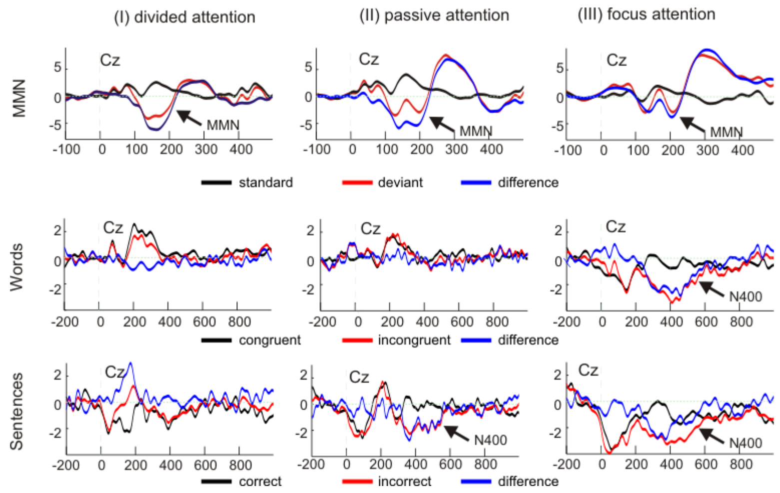

Figure 1: *Brain responses to standards and deviants (congruents/related and incongruents/unrelated) and the respective differences recorded at Cz for each paradigm and task*

Subjective ratings for experienced effort indicate (I) as the least tiring task (M = 36.7, SD = 42.7 over all paradigms). Tasks (II) (M = 84.7, SD = 47.7) and (III) (M = 79.1, SD = 53.3) were by trend perceived as broadly more effortful.

4. Discussion

Both, MMN and N400 are modulated by the attention tasks. The found attenuation of the MMN component, especially in the focus attention task, seems to contradict previous research showing no MMN alternation following divided attention or even an enhanced MMN in focussed attention [Sussmann, 2007]. Keeping in mind we talk about preliminary data, we suspect the attenuation to be caused by the elicitation of the following P300 component in the passive and focus attention task.

As expected, there was no N400 elicited when attention was drawn away from the stimuli [McCarthy & Nobre, 1993]. Interestingly, in the passive attention task an N400 was not elicited when participants only listened, even though the subjectively perceived effort was as high as in the focus attention task. These results are contrary to our expectation because we expected mere listening to be less effortful than pressing a key.

Critically, we need to analyse more ERP components to ensure no overlapping effects influencing the attenuation of our expected components. To obtain clearer results more participants need to be recorded.

Acknowledgement

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Steering Timing Prediction in a Driving Simulator Task

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Abstract. In this paper we present the preliminary results of a pioneering attempt to predict the timing of steering actions in a driving task. The subjects drove a car at constant speed on a simulated highway in a Driving Simulator. The EEG activity during periods of straight driving and during lane change actions has been recorded. Classifiers were build on the signals recorded from the motor cortex area for straight and pre-steering periods. The onset of the steering actions was detected 641 ms before the action with 68.8% true positive rate.

Keywords: Car simulator, motion related potential, classification, steer timing prediction

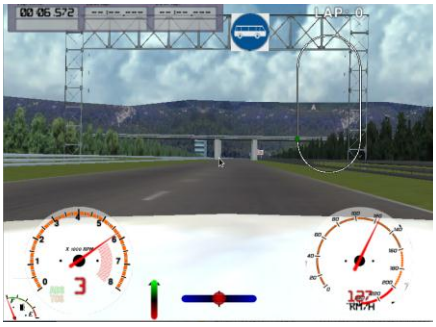
1. Introduction

Brain-computer interfaces (BCI) provide means of interaction by decoding brain signals correlated with certain tasks or cognitive states. We are trying to develop a BCI especially taylored for facilitating the interactions between drivers and intelligent cars. The cognitive state of the driver or the intentions for future actions could be used to create an easier to control interface with the vehicle, leading to less stress and improved safety. Several in the lab studies aimed at detecting movement intention showed encouraging results (Lew et al., 2012). While attention level detection has been studied both in real and simulated driving environments (Ito et. al., 2006) only few attempts have been made to predict drivers' motion while driving (Haufe et. al., 2005). While most of the previous motion timing detection studies have been performed in simplified protocols, this study aims at detecting steering action movements from non-invasive EEG measurements in a natural driving task performed in a realistic driving simulator.

2. Material and Methods

2.1. Experimental protocol

A simple but realistic driving simulator was used for this experiment. It simulates one of the highways in Switzerland. 6 subjects were instructed to drive at constant speed and to do a lane change to the left and another one to the right on certain parts of the course. The timing of the lane changes was self paced. Steering and pedal positions, vehicle dynamics as well as 10/20 extended 64 EEG channels have been recorded together.

a)  b) 

Subject sitting in the driving simulator (a) and the visual field while driving (b)

2.2. Signal processing and preliminary analysis

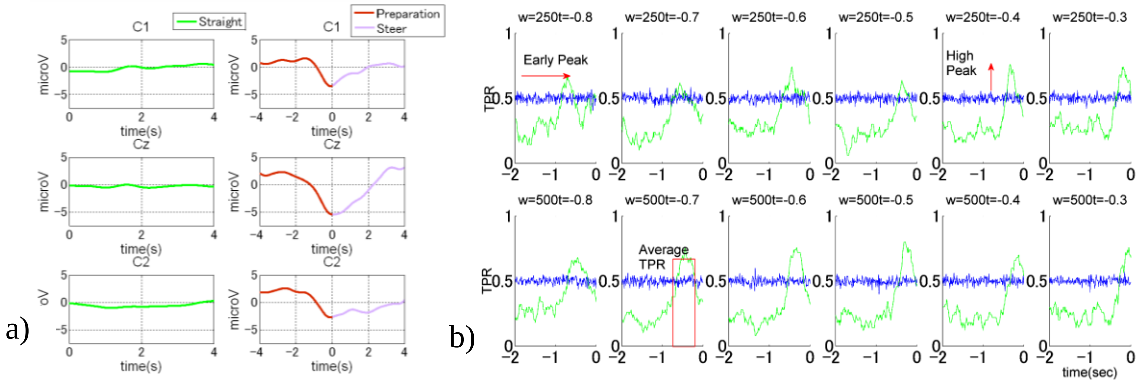
The EEG signals have been preprocessed using CAR, filtered between [0.1Hz 1Hz] and the mean value has been substracted from each channel.

3 types of epochs have been defined and any time the driver changed the lane was defined as a trial. Periods of 4 seconds on straight lines with no large steering actions are called Straight Epochs. Periods of 4 seconds before the start of the steering action are called Preparation Epochs and the 4 seconds after the start of the steering called Steering Epochs. For this study, left and right steering actions were considered together, while the comparison was done between the Preparation Epochs and the Straight Epochs.

LDA classifiers were trained on windows of Preparation and Straight trials data. In order to see the influence of the training data position in time, the training window has been chosen in 6 different positions (ending 800ms before the onset of the movement, until 300ms before movement in steps of 100ms). Also two lengths of the window were chosen, 250 ms and 500 ms. In total 12 different classifiers were trained. Each of them were then applied at each 10ms time points of the 4s trials. True Positive Rates (TPR) for each time point were calculated in a 5-folds cross-validation process. Here TPR is calculated as the percentage of test samples from Preparation data that have been correctly classified as Preparation.

3. Results

Figure 2(a) shows the grand averages for the 3 types of epochs on Cz, C1 and C2 for one subject. In average there were about 60 epochs of each type per subject. For the preparation trials a negative potential builds up more than 1 s. before the onset of the movement, in line with Motion Related Potential reports.



(a)EEG averages of C1 Cz C2. 0s is the onset of the steering action. The grand averages for the Straight trials show no significant time locked activity. In the second half or Preparation a negative potential locked on the onset of movement builds up and recovers in the first half of Steering (b) TPR for different training intervals and window lengths. Blue line is chance level and green line is TPR at that time on all the Preparation Epochs.

Figure 2(b) shows the TPR at each time point for the 12 classifiers. The ones trained on a 250 ms window (w=250) are up and 500ms window ones are down (w=500). Each plot represents a different time of interest for which the classifier was trained (e.g., t=-0.8 means that the training window ends 800 ms before the onset) and 1 means 100% correct classification.

We aggregated the results from each subject based on 3 types of criteria

1) **Fastest TPR Peak**: the classifier with the fastest peak was chosen for each subject. The average for the detection time was **-668±136 ms** with a TPR of **66.3±3.5 %** when a 250 ms window was used
2) **Highest TPR Peak**: the classifier with the highest peak was chosen for each subject. The average for the detection time was **-494±152 ms** with a TPR of **71.8±4.5 %** when a 250 ms window was used
3) **Highest mean TPR**: the classifier with the highest average TPR between -750ms and -250 ms was chosen for each subject. The average for the detection time was **-641±94 ms** with a TPR of **68.8±6.6 %** when a 500 ms window was used

4. Discussion

It is important to stress the fact that the data has been recorded during driving which means the subject has been performing not only movements of limbs as in previous in lab studies, but has been involved in several cognitive processes like attending the continuous visual input and controlling the vehicle. Considering this situation, the fact that our classifiers were able to predict the onset of steering 641 ms earlier with a TPR of approx. 69% is rather promising. We have also seen that there are no large differences when using a shorter window which leaves the door open to lower computational means.

A natural line for future works is to try to classify not only the onset of the movement but also the direction of the movement. Another line is obviously to come up with online detection methods and to develop a real interaction method. Having such a system in place is also essential in answering another open key question: What is the required accuracy for such a system for the driver to feel comfortable in the interaction?

Acknowledgements

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Hybrid-P300 BCI: Usability Testing by Severely Motor-restricted End-Users

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Abstract. In this study the usabilty of a hybrid-P300 BCI communication application was evaluated by four severely motor restricted possible BCI end-users. The P300 BCI was combined with EMG for error correction (see also abstract Riccio et al.). The prototype was evaluated in terms of *effectiveness* (accuracy), *efficieny* (time needed to complete task) and end-user's *satisfaction*. In two copy-spelling tasks accuracy was high (*M*=92.5% and *M*=98.75%), but lower in the free-spelling sentence (*M*=85.02%) and email task (*M*=75.34%). The hybrid letter correction could be used by all end-users and improved efficiency. Overall, end-users were moderately to highly satisfied with the BCI, but least satisfied with the *adjustment* (*M*=3.25 of 5), *effectiveness (M*=3.25 of 5) and *aesthetic design* (*M*=3 of 5) of the BCI, as assessed with the Extended Quest 2.0. One end-user could imagine using the BCI in daily life.

Keywords: Hybrid-BCI, P300, EMG, evaluation, usability, motor-restricted end-users

1. Introduction

The hybrid approach in BCI research aims to increase efficiency and effectiveness, enabling the end-user to use not only EEG activity, but also EMG activity as input channel for the BCI. The present study investigated the feasibility of a hybrid P300 BCI system, which is the second prototype of the P300-Qualilife communication prototype, evaluated by end-users in the study of Zickler and colleagues (2011). The new hybrid prototype includes a new P300-stimulation, with bigger central dots or grid stimulation, a pause mode and the undo-option based on electromyographic (EMG) activity, enabling to delete wrong selected letters in the matrix. Based on the findings of Zickler et al. (2011), showing that low speed, low effectiveness and complex adjustment were the main obstacles for BCI use, the current hybrid prototype includes (1) individual adaptation of flashing sequences, (2) EMG-undo letter correction, (3) easy-to use active EEG-cap. The P300 hybrid BCI including EMG is the first to be evaluated by patients.

2. Material and Methods

2.1. Subjects

Four patients (age: A:47, B:41, C:26, D:52, 3 male) participated in this study. End-user A was diagnosed with brainstem stroke, end-user B with muscular dystrophy (Duchenne), end-user C with spinal muscular dystrophy (SMA), end-user D with ALS (spinal form). Patients were severely motor restricted, with only residual muscular control, therefore they were considered as potential end-users for the hybrid-P300-BCI.

2.2. Hybrid-P300-BCI application

EMG was recorded from two active electrodes, which were placed individually, depending on the end-user's residual movements (A, C, D: hand; B: face). 8-channel-EEG was recorded from scalp positions Fz, Cz, P3, Pz, P4, Po7, Po8, Oz with a 16-channel amplifier (g.tec, Austria).

2.2. BCI Protocol

BCI protocol consisted of three sessions on three separate days: In the first session (S1) a screening was performed, in which the best stimulus modality (least number of sequences needed) and number of sequences (necessary to reach 100% offline) were identified (results of S1 not shown in this paper). In the second session (S2) end-users completed a copy-task, in which the EMG was used for error correction and compared to BCI. End-users had to copy-spell two 8-letter words and delete the last character with either the BCI (*CP-BCI*), or the EMG (*CP-EMG*), and respell the letter again. In session three (S3) end-users had to write a sentence in the free-spelling mode with 10 characters using the EMG-correction for wrong selections and choose the pause mode (*Sentence*; 14 selections). Next, this text had to be sent by email, after terminating the pause mode (*Email*; 11 selections).

2.3. Evaluation

According to ISO 9241-210:2010 the BCI device was evaluated in terms of its *effectiveness*, *efficiency and satisfaction*. *Effectiveness* was defined as the percentage of correct responses achieved with BCI (accuracy). Hybrid-accuracy included error correction. *Efficiency* was defined as the time needed to complete tasks. End-users' satisfaction regarding different aspects of the BCI (Dimensions, Weight, Adjustment, Safety, Comfort, Ease of use, Effectiveness, Professional services, and reliability, speed, learnability and aesthetic design) was assessed with the Extended Quest 2.0 [Demers et al., 2000, Zickler et al., 2011]. End-users rated their satisfaction with the EMG vs. BCI correction with a visual analogue scale (from 0 to 10; VAS Satisfaction).

3. Results

3.1. Effectiveness and Efficiency

See table 1 for accuracy (% correct) and time needed to complete the tasks, number of sequences and stimulus type for each end-user:

Table 1. *Accuracy and time (in seconds) for end-users A-D, for S1:CS-EMG and CS-BCI and S2: Sentence and Email. *End-user D could not finish the task due to lack of control and exhaustion, only last selection is missing.*

End-User	Stimulus	Sequences	CS –EMG	CS-BCI	Sentence	Email
A	**grid red**	**5**	**100** (223.63)	**100** (244.90)	**100** (302.95)	**100** (142.25)
B	**dot red**	**6,7**	**90** (257.39)	**100** (282.38)	**81.82** (533.92)	**85.71** (230.86)
C	**grid red**	**9**	**100** (358.64)	**100** (394.92)	**78.26** (687.91)	**67.74** (739.19)
D	**dot green**	**10**	**80** (392.40)	**95** (432.38)	**80** (831.58)	**47.89*** (1781.55)
Mean			**92.5**	**98.75**	**85.02**	**75.34**

3.3. Satisfaction (Extended Quest 2.0 and VAS Satisfaction)

Overall, end-users A and D were highly satisfied with the BCI (M=4.13 to 4.5), B and C were moderately satisfied (M=3 to 3.75). End-users were least satisfied with the *adjustment* (M=3.25 of 5), *effectiveness* (M=3.25 of 5), and *aesthetic design* (M=3 of 5). They were moderately satisfied with s*peed* (M=3.5 of 5). End-users were quite satisfied with *ease of use* (M=4 of 5). End-users were highly satisfied with both letter correction methods (BCI: M=8.25, EMG: M=8.50, VAS Satisfaction).

4. Discussion

The results show that end-users achieved high effectiveness, comparable to the results of Zickler and colleagues (2011), even with lower sequences, and thus in less time (in 3 of 4 end-users). End-users reported that they had problems selecting items in the sentence and email task, because the symbols (dot/grid) were too close to each other. This resulted in lower performance in this task. The copy-spelling tasks revealed that the hybrid approach is more efficient meaning that less time is needed to correct erroneous selections, especially for end-users with high number of sequences. However, from the end-users perspective, main reasons for dissatisfaction remain, i.e. complicated *adjustment,* low *speed* and low *effectiveness.* Only *ease of use* has been rated better than that of the first prototype [Zickler et al., 2011]. Despite these obstacles, one end-user could imagine using the BCI communication device in her daily life (end-user D).

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Comparison of Asynchronous SSVEP-based BCI Detection Approaches for Assistive Technologies

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Abstract. In recent years, there has been increased interest in using steady-state visual evoked potentials (SSVEP) in brain–computer interface (BCI) systems. The SSVEP approach currently provides fast and reliable communication. Processing and detection methods suitable to be implemented in a SSVEP based asynchronous BCI application are proposed. A well-known Spatial Filter processing methodology has been implemented, and two novel SSVEP detection methods, which are compared in this paper, have been successfully developed. The most successful one has been integrated within the assistive technologies free open source platform AsTeRICS[1], where it can be used for the deployment of new applications based on this BCI modality.

Keywords: EEG, SSVEP, Enobio, BCI, AsTeRICS

Introduction

Brain-computer interfaces (BCIs) constitute the ideal paradigm to develop technologies oriented at assisting or repairing human cognitive or sensory-motor functions. Steady state visual evoked potential (SSVEP) is a resonance phenomenon arising mainly in the visual cortex when a person is focusing the visual attention on a flickering light source. When SSVEP is elicited, it is manifested as oscillatory components in the user's EEG, particularly in the signals from the primary visual cortex, matching the frequency of the stimulation and its harmonics. Due to their fast and reliable communication, SSVEP based BCI paradigms have been widely used in the recent years. Our approach relies on an asynchronous BCI application where the subject decides voluntarily when to interact with the application. This document presents the methods to be used in a SSVEP based application. We have conducted the performance comparison described in the following sections, and successfully implemented the outperforming one in the AsTeRICS assistive technology platform. We first describe the main stages of the system, namely for processing through spatial filters the occipital EEG channels, and for detecting the VEP on the resulting signal spectra.

Material and Methods

2.1. Processing: Spatial Filtering

Processing parameters are calculated from a set of training signals acquired during *N* non-stimulation periods duration *Tn* followed by *N* stimulation periods duration *Ts* where the visual stimulus is presented at a frequency *fs*. Spatial filters are calculated at each stimulation period according to [Friman et al. 2007]. Each calculated spatial filter is applied to the entire training signal and the SSVEP energy in the stimulation and non stimulation periods extracted. The area under the ROC curve (AUC) is calculated where the stimulation periods are marked as the positive class and the non-stimulation periods as the negative class. The spatial filter with the largest AUC is chosen to be used in the detection process of the stimulation frequency *fs*.

2.2. Detection

It has been acknowledged that the frequency spectrum of measured brain signals shows a decrease in power with increasing frequency. This spectral behavior may lead to difficulty in distinguishing event-related peaks from ongoing brain activity in the electroencephalographic (EEG) signal spectra. SSVEP spectral response is characterized by a peak at the stimulation frequency and/or its harmonics, entailing that the energy at the frequencies where the response appears is larger than in the surroundings. A window based spectral analysis has been performed to detect the stimulation frequency (*fflicker*) responsible of eliciting the evoked potential. We compute the following *N* frequency features *f(w)* within each stimulation period:

$$f(w) = \frac{2 \cdot PSD_w(fflicker)}{PSD_w(fflicker-1) + PSD_w(fflicker+1)} + \frac{2 \cdot PSD_w(2 \cdot fflicker)}{PSD_w(2 \cdot fflicker-1) + PSD_w(2 \cdot fflicker+1)} \quad (1)$$

Detection Method 1

An average of *f(w)* at each stimulation frequency under evaluation is calculated. The stimulation frequency selected as the one responsible of eliciting the evoked potential is the one with the largest average.

1 http://www.asterics.eu/index.php?id=26

Detection Mehod 2

The weight factor W computes the number of windows where the feature f(w) is larger than 1. The average of the frequency features f(w) is multiplied by the calculated weight factor W. The stimulation frequency chosen as the one responsible of eliciting the evoked potential is the one that maximizes this weighted sum value.

2.3. Experimental Procedure

Five male caucasian subjects S1 to S5 aged 32, 29, 31, 31, 30, respectively participated in six recording sessions. Oscillatory visual stimuli were presented at 12, 14, 16, 18, 20 and 22Hz. Visual stimulus was rendered using an array of flickering light emitting diodes (LEDs) through a diffusing panel of 100 squared cm. EEG was acquired using 3 Enobio® channels. Channels used were placed in O1, Oz and O2. Each recording session consisted of two independent recordings (test and training) per stimulation frequency. In each recording *Ts=4s* and *Tn=8s* . 5 sequences of stimulation/non-stimulation periods were used for training, and 10, for testing.

Results

The goal of this study is to evaluate if the proposed processing and detection methods are suitable to be implemented in a SSVEP based asynchronous BCI application. For each subject and stimulation frequency spatial filters are calculated in the training measurements. The detection process is carried out in the test measurements, after its corresponding spatial filtering, at each stimulation period. The following table shows the percentage of positive detection for both method 1 (M1) and 2 (M2). Detection method 2 detects with perfect accuracy 18 out of the 30 evaluated test recordings versus 9 of method 1. The average detection of method 2 is larger for every subject at every stimulation frequency. Detection accuracy for the best 2 and 4 stimulation frequencies (suitable to be used in a BCI application with respectively 2 and 4 degrees of freedom) is better in method 2 for every subject at every stimulation frequency (last two columns).

Positive detection percentage rate for detection method 1 (M1) and 2 (M2)

	12Hz		**14Hz**		**16Hz**		**18Hz**		**20Hz**		**22Hz**		**Best 2 Avg**		**Best 4 Avg**	
	M1	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**	**M1**	**M2**
S1	50	70	**100**	**100**	40	**100**	40	**100**	90	90	**100**	**100**	**100**	**100**	85	**100**
S2	50	80	90	80	70	40	70	90	**100**	90	90	**100**	95	**100**	87.5	90
S3	**100**	**100**	80	**100**	70	90	70	80	20	80	50	60	90	**100**	80	92.5
S4	60	**100**	90	**100**	90	**100**	90	**100**	**100**	**100**	90	**100**	95	**100**	92.5	**100**
S5	90	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	90	90	**100**	**100**	**100**	**100**
Avg	70	**90**	92	**96**	74	**86**	74	**94**	82	**92**	84	**90**	96	**100**	89	**96.5**

Discussion and future work

Two real-time and very reliable detection methods have been presented. They deliver an excellent detection accuracy as shown in the described tests. The proposed method 2 has been integrated in an asynchronous binary (2 stimulation light sources) BCI application in the AsTeRICS platform. This study is based in one stimulation light source, so the effect of background stimulation light sources shall be evaluated in further studies.

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Towards Realtime Detection of Anticipatory Brain Potentials

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Abstract. Methods for detection of a movement before it happpens may lead to new BCI applications. Previous studies have shown the possibility of detection with high performances using slow cortical potentials (SCPs) with non-causal filtering methods in the range of [0.1 1]Hz. In this study, we evaluate the feasibility of the realtime detection of SCPs by using causal filtering methods, which is the prerequisite for online realtime implementation. We recorded EEG from 6 subjects while driving a car simulator.The protocol is a variant of the contingent negative variation (CNV) with *Go* and *No-go* conditions. The results presented here support the possibility of realtime detection of the anticipatory SCPs with an average of 0.80±0.11 in area under the curve (AUC), yielding better average performance than using non-causal filtering methods.

Keywords: EEG, Car simulator, CNV, SCP, Online

1. Introduction

Monitoring driver's cognitive state by analyzing his brain signals could enhance driving experience with intelligent cars. Predicting driver's forthcoming actions would help the controller of such a car to make decisions in-line with the driver's intention. Recently, some studies reported the realtime detection of movement intention, in particular from EEG. [Niazi et al., 2011] as well as [Lew et al., 2012] have exploited slow movement-related cortical potentials, or readiness potentials, to predict a forthcoming self-paced movement 66.6±121ms and around 500 ms before the action onset respectively. In our case, we analyze SCPs to decode anticipatory brain activity in preparation to an imperative stimulus that people can predict (e.g., a traffic light turning red or green). Previously we achieved high offline single trial detection of anticipatory SCPs, average of AUC 0.76±0.12 using non-causal filtering in the range of [0.1 1] Hz [Khaliliardali et al., 2012]. In this study, we focus on the possibility of the realtime detection of anticipatory SCPs filtered in the same spectral range with causal filtering to predict brake and accelerate actions.

2. Material and Methods

EEG signals (64 channels) were recorded from 6 subjects (24-32 years, 1 female) while driving a car simulator in front of a projector screen. The task is to drive a virtual car along a highway and either to brake (*Brake* trial) or to drive (*Drive* trial) depending on the visual stimulus --a countdown (4-3-2-1 and 'Go'/'Stop' at a rate of 1s) that appeared at the center of screen. This protocol is similar to classical CNV protocol [Walter et al., 1964] but with sequential warning stimuli. Hence all epochs are *No-go* except the last one that is a *Go* epoch in which subjects are supposed to do specific action after cue ([Khaliliardali et al., 2012] for more details). EEG was preprocessed using CAR and then filtered in [0.1 1] Hz (Buttterworth, order 4), as this is the most informative frequency range of CNV potentials [Garipelli et al., 2011]. The goal is to discriminate between *Go* and *No-go* epochs on a single-trial basis using QDA classifier. Separate classifiers were built for *Drive* and *Brake* trials. For each epoch, the Cz potentials at six equally spaced time points (i.e., at -0.84s, -0.670s, -0.52s, -0.37s, -0.22s, -0.07s) are used as a feature vector. This number of features reported to sufficiently represent the evolution of CNV potentials in 1s [Garipelli et al., 2011].

3. Results

The grand average of Cz for one subject is shown in Fig. 1. The onset of the appearance of 'Go/Stop' cue on the screen is defined as 0s. As it can be seen, the CNV potentials are prominent during the *Go* epoch no matter whether the signal is unfiltered or filtered with a causal/non-causal filter. This CNV potential is a negative deflection in the signal with a maximum peak around the imperative stimulus. In the case of using a non-causal filter (black line), we can observe a clear difference between *Go* and *No-go* epochs (increasing negativity for *Go* and almost flat or slightly positive response for all the other *No-go* epochs).

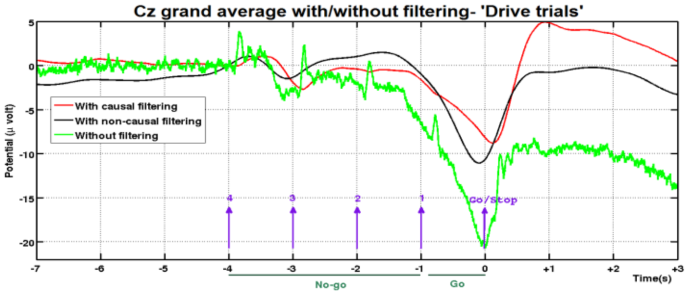

Figure 1. *The grand averages of Cz potentials for* Drive *trials—green: signals without filtering, red: using causal filtering, black: using non-causal filtering. In Go epoch; subjects did an action correspondingly after 'Go/Stop' sign. In No-go epoch; subjects did nothing after the cue (4, 3, 2, 1). This plot is for the best subject, the same phenomena observed for the others.*

In the case of using a causal filter (red line), we observe the same characteristics of the signal, although the highest peak is slightly delayed (as expected for this kind of filter). Table 1 summarizes the results of single-trial classification, expressed as the AUC, for the three kind of EEG --either unfiltered, or filtered in a causal and non-causal way. The AUC values in the table using non-causal filtering correspond to the offline analysis. The values with causal filtering evaluate the feasibility of realtime detection of these potentials. According to Table 1, the classification performance using causal filtering yields better average performance than with using non-causal filtering and also than without using any spectral filtering. This could be because of the positive phase response of this filter design which consequently lead to negative delay and prediction of the signal especially when there is no change (i.e. for the DC and ramp) [Castor-Perry, 2012]. This characteristic of this prediction filters would compensate for the expected delay when they are applied causally.

Table 1. *The performance of classification (AUC) withoutspectral filtering, with causal ,and non-causal filtering.*

	Without filtering		**Non-causal filtering**		**Causal filtering**	
	Drive	***Brake***	***Drive***	***Brake***	***Drive***	***Brake***
Sub 1	0.82	0.93	0.87	0.96	0.90	0.99
Sub 2	0.80	0.82	0.90	0.92	0.90	0.95
Sub 3	0.65	0.63	0.69	0.83	0.77	0.87
Sub 4	0.64	0.57	0.66	0.68	0.70	0.66
Sub 5	0.48	0.57	0.53	0.74	0.64	0.80
Sub 6	0.76	0.65	0.73	0.78	0.75	0.73
Mean±SD	0.69±0.12	0.69±0.14	0.73±0.13	0.81±0.10	0.77±0.10	0.83 ±0.12

4. Discussion

Detection of SCPs before the action onset has been demonstrated for offline analysis (using non-causal filtering methods in the range of [0.1 1] Hz), however the realtime implementation of these methods is the main requisite for online applications. In this study, we investigated the possibility of the realtime detection of these potentials during simulated car driving. The results confirm that it is feasible to detect these anticipatory SCPs with an average of 0.80±0.11 in AUC in realtime (using causal filtering). We will test these methods in online experiments with more subjects in the simulated car driving setup. This is a preliminary step before moving to testing in a real car.

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Clustered Common Spatial Patterns

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Abstract. We propose to cluster class-wise covariance matrices in order to identify different groups of covariances contributing to the same condition. Each cluster represents a different brain pattern associated with one class. Further, we present Clustered Common Spatial Patterns, a new algorithm that applies this technique prior to CSP. We show that CCSP can outperform CSP in a binary imagery movement task. Although in this work we consider only the case of CSP, this clustering technique could also be used to improve other feature extraction methods.

Keywords: Brain Computer Interface, Feature Extraction, Spatial Filters, Common Spatial Patterns, Clustering.

1. Introduction

The traditional training of CSP filters [Ramoser et al., 1998] uses the class spatial covariance matrices, $\tilde{C}_1$ and $\tilde{C}_2$, to construct m spatial filters (SF). We will denote this operation as $csp(\tilde{C}_1, \tilde{C}_2, m)$. In situations where more than one covariance structure contributes to a class, such as in presence of spatial shifts of the informative channels, $\tilde{C}_1$ or $\tilde{C}_2$ might over-represent the covariance structures from which more samples (trials) were observed. This can affect the generalization performance of the SF if covariances associated with infrequent trials become typical in the testing phase. Here we describe a new methodology to address this problem, Clustered Common Spatial Patterns (CCSP), and show that this technique has the potential to outperform standard CSP.

2. Clustered Common Spatial Patterns (CCSP)

CCSP performs per-class clustering of covariance matrices and combines the learned clusterings to learn SF. We illustrate the algorithm using K-means clustering [Bishop, 2007] and propose a simple way of combining the cluster centroids to construct the SF.

Consider a set of trials $\{X_{j,i} \in M_{n\times t} : j \in \{1,2\}, i \in \{1,\ldots,s_j\}\}$, where j indexes the class label, s_j is the amount of trials of class j, n the number of electrodes and t the number of time samples per trial. Define two sets of $n \times n$ spatial covariance matrices $Z_j = \{C_{j,i} : i = \{1,\ldots,s_j\}\}$, where $C_{j,i}$ is the covariance matrix of $X_{j,i}$. Given $(K_1, K_2) \in \mathbb{N}^2$, CCSP applies K_j-means clustering to Z_j resulting on K_j cluster centroids $\{C_j^1,\ldots,C_j^{K_j}\}$. CCSP performs CSP by replacing the per-class covariance matrix by the per class mean cluster centroids. In other words, CCSP is equivalent to $csp(\frac{1}{K_1}\sum_{k=1}^{K_1} C_1^k, \frac{1}{K_2}\sum_{k=1}^{K_2} C_2^k, m)$.

3. Results

We use EEG data consisting of 70 train and 70 test trials from 8 subjects performing imagery movement collected using a 64 electrodes Biosemi system. The data were downsampled at 250 Hz, linearly detrended and bandpass-filtered in the frequency band 8-30 Hz. An automatic variance based routine was applied to remove noisy trials and channels from the train set.

In Fig. 1 we illustrate the idea of clustering the covariances. The training set covariance matrices from class 2 of one subject are projected onto their first two PCA components [Bishop, 2007] as small squares.

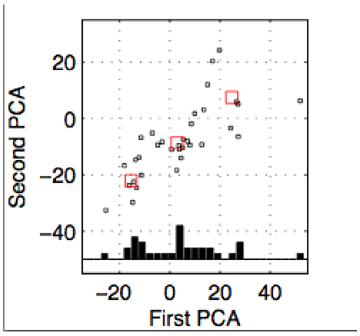

Figure1.Training set covariance matrices of class 2 projected onto their first two PCA dimensions (small squares) for one subject.The big squares represent 3 cluster centroids learned from the train covariances. The x-axis shows a histogram of the data projected onto the first PCA dimension.

Using $K_2 = 3$ we identify a clustering structure and we represent the learned cluster centroids as big squares. On the x-axis we present a histogram of the first PCA dimension of the plotted data. Note that the top cluster represents trials with a higher variance wrt to both dimensions which most probably can be identified as outliers. The lower clusters represent two groups of covariances with different number of elements that can be associated to two types of covariances corresponding to class 2.

Next we compare CCSP with CSP. For both methods we used the log-variance of the data projected onto 6 filters as features for classification. As classifier we used a SVM [Bishop, 2007]. Table 1 shows the classification results for CSP and CCSP with $m = 6$ and $K_1 = K_2 = 4$.

Subject	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
CSP	97.1	94.2	78.5	71.4	64.2	60	52.8	50
CCSP	100	92.8	90	77.1	54.2	67.1	77.1	58.5

Table1.Columns indicate subject number. Rows show the percentage of correctly classified test trials for CSP and CCSP with $K_1 = K_2 = 4$ respectively.

We can see that for this choice of parameters CCSP improves wrt CSP for 6 out of 8 subjects. In some cases (subjects 3 and 7) the increase in performance is notable. On the other hand, for subjects 2 and 5, CCSP performance decreases wrt CSP. We can conclude that clustering the train covariances can help us to learn better filters, and as a result CCSP can provide an efficient improvement wrt CSP.

4. Discussion

Clustering covariance matrices is not an easy task due to the high dimensionality of the space. To alleviate this problem, in this work we used the projection of the vectorized upper triangular parts of the covariance matrices onto their two first PCA dimensions as input to the clustering algorithm. Further, to avoid local minima, each clustering solution was chosen as the most likely out of 20 solutions obtained with different initializations.

There are several lines of ongoing research. First, we are studying how the quality of the clustering affects the learned filters (choice of (K_1, K_2), local minima, dimensionality reduction previous to clustering). Further, alternative ways of learning the filters after clustering are being investigated. For instance, one could learn one CSP filter for each cluster centroid and select the ones maximizing the variance between classes. Alternatively, one could learn filters using only the most dense clusters. Preliminary results suggest that these choices could improve the presented CCSP.

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Classifying Imaginations of Rhythmic Arm Movements in Two Planes from EEG

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Abstract. A brain-computer interface (BCI) can be used to control a limb neuroprosthesis with motor imaginations (MI) to restore limb functionality in paralyzed persons. However, existing BCIs lack a natural control and need a considerable amount of training time or may use invasively recorded brain signals. A new approach is the direct decoding of movements which has already been shown non-invasively for executed movements. In this work we show indirectly that algorithm principles used in decoding executed movements can also be applied when decoding imagined movements. Healthy subjects performed rhythmic arm movement imaginations in the transverse and sagittal plane. We were able to classify the correct movement plane with an average classification accuracy of 69 % considering only significant results. This shows that the classification of movement imaginations with the same hand in two different planes is possible.

Keywords: EEG, movement decoding, motor imagery

1. Introduction

A brain-computer interface (BCI) measures biosignals originating in the brain and uses them to control devices. One important application of a BCI is the restoration of upper limb functionality of paralyzed persons. The ideal solution is to detect the actual movement imagination (MI) in a non-invasive way and then naturally and continuously control an arm neuroprosthesis. Naturally means here that the arm neuroprosthesis movement corresponds exactly to the movement imagination . This would enable the user to control the paralyzed arm with the same motor commands as someone with a non-paralyzed arm would use. Sensorimotor rhythms (SMR) based BCIs detect power modulations in certain frequency bands in the EEG resulting from MI which can be used as control signals for neuroprostheses. However, SMR based BCIs have the disadvantage that they can only detect the process of MI, but not the MI itself. That leads to an artificially assignment of imaginations to neuroprosthesis movements (e.g. foot MI correspond to an arm extension). However, there exist evidences that low frequency EEG components in the time-domain carry valuable information. For example, [Bradberry et al., 2010] showed a direct and continuous 3D velocity decoding of executed arm movements using low-frequency electroencephalographic (EEG) signals. Our group showed in [Ofner et al., 2012] the velocity and position decoding of executed arm movements using a similar decoder. In this work we tried to prove that the decoder used in [Ofner et al., 2012] can also be used to decode MI. This would be a further step towards a natural, non-invasive arm neuroprosthesis control using MI. However, as we noticed in preliminary experiments, the correlation coefficient when decoding MI is quite low (< 0.4). Furthermore, the decoder is easily influenced by eye movements. Thus, we setup a paradigm which prevents eye movements and subjects imagined rhythmic movements based on a metronome.

2. Material and Methods

Nine healthy, right-handed subjects were comfortably seated in an armchair and were instructed to imagine waving the extended right arm in front of the upper body either in the transverse or in the sagittal plane. We asked subjects to do natural, round (not jaggy) rhythmic imagined movements and to perform kinesthetic MI. A trial started with a short beep tone and a cue visible for 0.5 s. This cue was in form of an arrow pointing right or up, corresponding to MI of the arm in the transverse or sagittal plane. Subsequently a cross was shown for the rest of the trial in the middle of the screen. Subjects were instructed to fixate the gaze on the cross to suppress eye movements. 1.5 – 2.5 s after the trial start a metronome started to tick for 20 s with a frequency of 1 Hz and subjects were instructed to imagine arm movements according to the beat of the metronome. Here, a beat corresponded to an end position of the rhythmic MI (left and right or up and down, respectively). Thus, the MI itself was performed with 0.5 Hz. We recorded 8 MI runs, each with 5 trials per class in random order. In total 80 MI trials were recorded for each subject. A session started with one run consisting of 5 trials per class performing motor execution, so that subjects got used to the movement. We recorded the EEG using 68 electrodes covering frontal, sensorimotor and parietal areas. Reference was placed on the left ear, ground on the right ear. In addition, the electrooculogram (EOG) was recorded with 3 electrodes. Signals were acquired with g.USBamp amplifiers (g.tec, Graz, Austria) with 256 Hz sampling frequency after band-pass filtering between 0.01 Hz and 100 Hz with an eighth-order Chebyshev filter and applying a notch filter at 50 Hz. After recording, we removed linear trends from trials. To reduce the computational effort, we filtered all signals with a 5 Hz zero-phase, fourth-order, low-pass Butterworth filter and down sampled data to 16 Hz. Afterwards we removed the influence of eye activity on the EEG using the EOG channels and a linear regression method. We decoded the x/y position of the imagined arm movement with a decoder similar to [Bradberry et al., 2010; Ofner et al., 2012]. First, we applied a fourth-order, zero-phase band-pass Butterworth filter with cutoff frequencies at 0.3 Hz and 0.8 Hz. To decode positions, we used two linear models – one for each coordinate – consisting of data from all EEG channels and three time lags in 60 ms intervals. We found the parameters of the linear models with multiple linear regressions. Here, we assumed that subjects imagined movements according to a sine oscillation with a frequency of 0.5 Hz within the transverse (x) or sagittal plane (y). To classify at trial, we decoded movement positions between second 2 and 17 relative to the start of the metronome, correlated the decoded movements separately for each coordinate with a sine oscillation of 0.5 Hz and assigned the trial to the coordinate (i.e. plane) with the higher correlation. We applied a 10x10-fold cross-validation and reported the mean value and standard deviation of the accuracies across validation folds for each subject.

3. Results

Mean values and standard deviations of classification accuracies are shown in Table 1. Classification accuracies are significant above 0.59 with $\alpha = 0.05$ [Billinger et al., 2012]. A classification based solely on EOG channels yield significant classification accuracies for subjects s7 (62 %), s8 (71 %) and s9 (77 %), and between 41 % and 57 % for all others. The mean classification accuracy over the remaining subjects with significant decoding accuracy (s1, s2, s4, s5, s6) is 69 %. The grand average is 70 % with a standard deviation of 10 %.

Table 1. *Mean values and standard deviations of classification accuracies for all 9 subjects, significant classification accuracies are written bold*

subject	*s1*	*s2*	*s3*	*s4*	*s5*	*s6*	*s7*	*s8*	*s9*	*grand average*
mean value[%]	**71**	**67**	55	**82**	**65**	**59**	**70**	**82**	**78**	70
std. dev.[%]	17	15	16	13	15	17	15	13	14	10

4. Discussion

Eight out of 9 subjects show significant classification results. Three subjects show also significant classification results when using solely EOG signals. Although we removed eye activity from the EEG, it still cannot be guaranteed that there is no residual eye activity left in the EEG which was mistakenly classified. Thus, at least 5 subjects showed significant classification results due to EEG activity when classifying arm MI in two planes. Filter properties of the skull, etc., may lead to a dependency of the classification accuracy on the imagined movement frequency. A possible triggering of evoked potentials through the metronome would not have impaired the classification results, because the external influence of the metronome was the same in both classes. As we used the same decoder principles as in [Ofner et al., 2012], we showed indirectly that movement decoding is also feasible with MI. Also [Bradberry et al., 2011] demonstrated an MI decoder, however eye movements were not prevented and results could also be reaching with a random decoder [Poli et al., 2011].

Acknowledgements

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Control Accuracy of a Motor Imagery based BCI in Comparison to the P300 and SSVEP Approaches

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Abstract.

EEG based brain-computer interfaces (BCIs) are mostly using evoked potentials (P300), steady state visual evoked potentials (SSVEP) or motor imagery (MI) as control strategy. Recently it was shown that P300 and SSVEP based system reach high accuracies for almost all users after short training intervals. In this study it was investigated if comparable accuracies can be reached with a motor imagery based BCI using Common Spatial Patterns (CSP). Measurements on twenty healthy people were performed, and an overall accuracy was calculated (80.7% grand average). The reached accuracy levels as well as the time needed for one session and the number of used electrodes are compared.

Keywords Motor-Imagery, ERDS, P300, SSVEP, EEG.

1. Introduction

There are three popular noninvasive BCI approaches: The Motor Imagery based BCI, the P300 approach and the approach via steady state visually evoked potentials (SSVEP). Both, the P300 and SSVEP require an external stimulus and are therefore called synchronous BCIs. In contrast, motor imagery (MI)-based BCIs do not need an external stimulation source and can be controlled asynchronous, but mostly a trigger signal is used to indicate a time point when the BCI system makes the decision., for example the MI approach normally requires more training and has a lower accuracy but is well suited e.g. for rehabilitation purposes [Ang et al, 2010].

2. Material and Methods

20 healthy users participated in the study. For spatial filtering the method of Common Spatial Patterns (CSP) [Müller-Gerking et al., 1999] was used, followed by an LDA that classified the normalized variance of the spatial filtered EEG. 7 runs were performed for each session. The first run was performed for creating a first set of CSPs and classifier. With this first set, another four runs were performed while giving online feedback to the user. The merged data of these four runs were used again to set up a second set of CSPs and a classifier that used a higher number of trials and was thus more accurate. Finally, to test the online accuracy during the feedback sessions, two more runs were done. One trial lasted eight seconds, the cue appeared after three seconds, feedback was given from 4.25 seconds until the end of the trial.

Table 1. *Accuracies of the current MI measurements and two studies evaluating the P300 and the SSVEP approach*

	MI-BCI (N=20)	*P300 (N=81)*	*SSVEP (N=53)*
Percentage of users with accuracy level above 90 %	30	72.8	86.7
Percentage of users with accuracy level below 80 %	45	11.1	3.8
Chance level in percent	50	1/36	1/4
Number of electrodes	64	10	10
Assembling time in minutes and type of EEG electrode	10 (active)	2 (active)	2 (active)
Recording time for classifier setup in minutes	4x6	5	5

3. Results

Table 1 summarizes the reached accuracy levels and also provides results from two other studies, evaluating the control accuracy of a P300 paradigm [Guger et al., 2009] and an SSVEP based BCI [Guger et al., 2012]. The levels of 90% and 80% were chosen for a better comparability to the results of the two other studies. The higher percentage of users with accuracy levels above 90% was reached with the SSVEP and P300 approaches, compared to the MI-based BCI. The accuracy results of the MI-BCI study reflect the performance of the last two runs of each subject. The grand average result of the MI-BCI was at 80.7%.

4. Discussion

The overall accuracy of BCI users is better with P300 or SSVEP, compared to MI. Hence, when creating BCIs for communication or control, the MI-task may not be the best choice. Comparability of the performance of different BCI approaches is always difficult, when looking at the bit-rate a MI-approach will always be worse compared to P300 or SSVEP. But there are several special application that can be only done with a MI-based BCI, e.g. when using the BCI for motor rehabilitation [Ang et al, 2010]. At the end the choice which approach is used to run the BCI depends on the device that should be controlled. Also the combination of several approaches into one BCI could be of interest, creating a hybrid BCI [Allison et al. 2012]. The time for performing one session with the CSP based approach is also considerable long; at first it takes more time to mount 64 electrodes on the user's head, and then we took five runs before setting up the final classifier. If time is critical one could choose a minimal setup, resigning the advantages of spatial filtering and also reduce the amount of training runs. In this case though one has to expect a lower classification accuracy [Guger et al, 2003] compared to the methods used here. Additionally, the assembling time could be reduced even more when taking advantage of new, dry electrodes.

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Designing Wearable BCIs: A Software Framework

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Abstract. Endowing Brain Computer Interfaces with specific functionalities may require developing custom software. The Tobi Architecture was introduced with the aim of maximizing reuse of code, by supporting interoperation of diverse processing modules. Here we describe the design of a portable motor-imagery based BCI-switch, to be included in an assistive system aimed to restore grasping in SCI patients. A lightweight Single Board Computer was used as processing hardware, on which software modules compliant with the Tobi Architecture were installed. Absence of a keyboard/monitor user interface, and reduced computational power, motivated us to introduce two innovations in the original software framework. As a result, a hardware prototype with minimalistic user interface, and with reduced computational power is available for user testing. We demonstrated that existing modules, general purpose modules and dedicated modules can be interconnected in an efficient software tool, running on a wearable hardware platform.

Keywords: Embedded PC, software architecture, motor imagery, BCI switch

1. Introduction

Applications of BCIs outside a research laboratory demand specific non-functional properties of the system, including robustness, usability, and portability. In this respect, the use of a personal computer to run BCI software applications may impose limitations, e.g. when the BCI is designed to control a prosthesis. On the other hand, developing software customized for an embedded hardware platform limits the possibility of rapid prototyping. In the context of the TOBI project, we proposed a versatile software development framework, based on a set of definitions, that provides a standardized data flow for real-time biosignal processing [Müller-Putz, 2011; BCIStandards, 2012]. This approach facilitates portability of the application across operating systems, and across hardware platforms. Effectiveness has already been demonstrated with the implementation of a distributed application, whose modules, coded in different programming languages, ran on a network of 7 personal computers. Exploiting the properties of the standard framework, with limited coding efforts, a BCI prototype running on a PC can potentially be ported to an embedded hardware.

Here we describe a solution to realize a BCI switch controlled by motor imagery, running on a Single Board Computer (SBC), designed to support FES-based (Functional Electrical Stimulation) motor restoration in Spinal Cord Injured (SCI) patients.

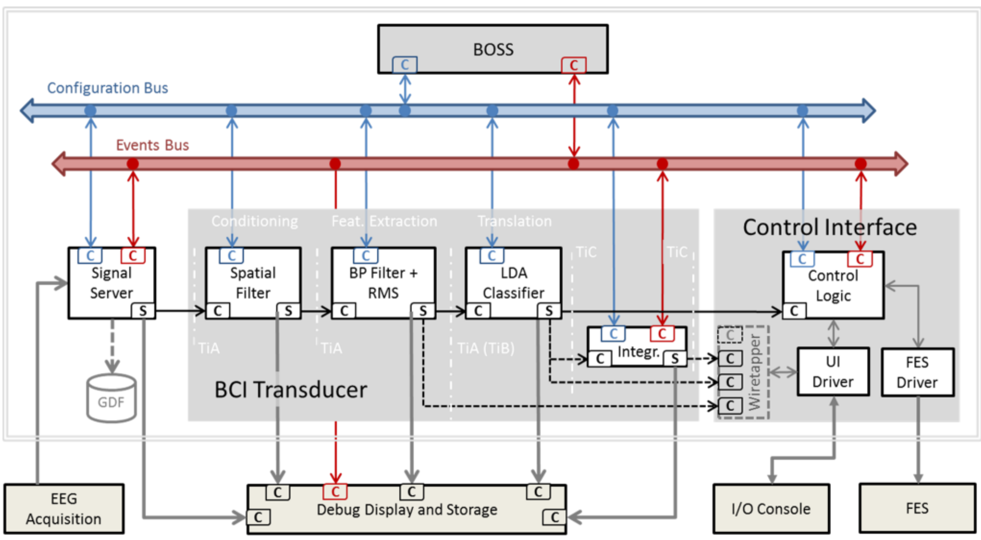

Figure 1. *Logical architecture of the wearable BCI switch for FES control. White blocks correspond to separate processes. The acquisition hardware is virtualized by the Signal Server. An optional display (external to the embedded hardware) of the internal data flow is available for debugging purposes. The hardware user interface and the FES device are virtualized by the respective drivers. Events and configuration settings are distributed through dedicated buses. Inter-process communication is supported by TCP connections, or System V message queues.*

2. Material and Methods

The BCI is designed as a brain-controlled switch for SCI patients [Rohm 2012], to select between two types of grasps (lateral, palmar) or a pause mode. Hand muscles contraction is induced by Functional Electrical Stimulation (FES), whose intensity is controlled through a shoulder joystick.

2.1. Hardware

The system runs on a Single Board Computer (ACME Systems FOX Board G20, ARM9@400Mhz Atmel CPU, Debian 6.0 Linux, 107×82×37 mm) with serial ports and network connectivity. Serial ports provide the communication with the EEG acquisition (gMobilab, GTec, Austria) and FES (MotionStim, Medel, Germany) hardware. A separate, hardware display console (see example in Figure 2) is connected through a custom data link; it features a LCD display for user feedback and operational instructions, LEDs to monitor the system's state, buttons and potentiometers to provide user inputs to the BCI.

2.2. Software

The BCI Transducer is implemented as a set of modules (processes) developed in C++, which communicate through the TOBI Interfaces [BCIStandards, 2012]. These interfaces provide a standardized format for data blocks, and a transport layer for Inter-Process Communication based on TCP. Figure 1 shows an overview of the processing pipe. A Control Interface is responsible of defining state transitions between grasp modes, to deal with the hardware user interface, and to send commands to the FES device.

In addition to previously described features of the TOBI Architecture, this system features: (i) a configuration facility (BOSS), eliminating the need for user interaction to start and configure the processing pipe; (ii) a second IPC channel, based on System V message queues, reducing the CPU resources required for transport of messages.

Performance was evaluated by measuring the average CPU share of processes connected to a client and a server when the system is operational (all processes are using the IPC channel to convey data and events).

3. Results

The BOSS allows the BCI system to start automatically shortly (~40s) after power is supplied. An operator can choose between calibration or operation modes by pressing a switch on the console; the classifier bias is changed by turning a knob. The new IPC transport layer reduced the average CPU load per process in the pipe from 11±2% to 4±2%.

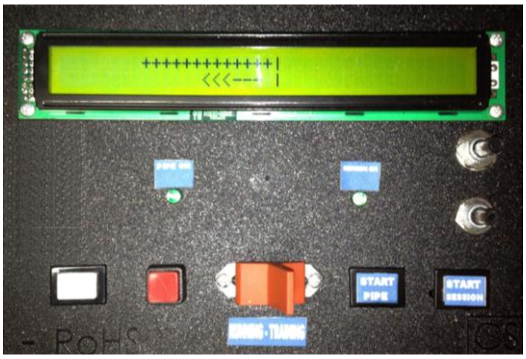

Figure 2. *Hardware user console. Near the top, an LCD display shows feedback during a training trial. Buttons near the bottom are used to interact with the BOSS. The knob on the right sets the LDA classifier's bias.*

4. Discussion

The Tobi Architecture supports the development of a wide range of implementations. Previous results showed that they support interconnection of pre-existing BCIs, regardless of programming language, and distributed solutions over LAN, independent of operating system.

In this work we introduced new features to the Tobi Architecture to simplify configuration and to improve performance of communication between processing modules. With this improvement of the framework, existing modules (such as the Signal Server), general purpose modules (e.g. bank of frequency filters) and dedicated modules can be interconnected in an efficient software tool, implementing BCI functionalities on a wearable hardware platform.

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Effects of Adaptation Intensity in Motor Imagery BCI

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Abstract. The effects of continuous classifier adaptation in Motor Imagery (MI)-based Brain-Computer Interaction (BCI) on a subject's ability to improve and stabilize his BCI performance through feedback learning have been largely neglected in favor of gains in online classification accuracy. In this work, we investigate the influence that adaptation intensity may have on the subject's ability to learn and consolidate a MI strategy. Preliminary results with one disabled and two healthy subjects show that there exists a natural trade-off between online accuracy maximization and subject learning which needs to be carefully accommodated by supervised BCI adaptation methods.

Keywords: BCI adaptation, adaptation intensity, Motor Imagery, Mutual Learning

1. Introduction

The benefits of online classifier adaptation in Motor Imagery (MI) Brain-Computer Interfaces (BCIs) have been established by an abundance of recent adaptation methods whose common ground is the attempt to cope with lack of robustness by continuous classifier parameter re-estimation.

Viewed from a control perspective, adaptation algorithms act as controllers performing simultaneously: a) set-point tracking, by updating the classifier parameters to better account for the recent history of the non-stationary brain patterns, and b) disturbance rejection, by avoiding abrupt parameter changes in fear of adapting to noise. These conflicting goals are traded-off through some algorithm-dependent parameter reflecting the rate of convergence to the most recent brain patterns, which is called hereby adaptation intensity and is explicitly or implicitly present in all adaptation algorithms (e.g. parameter η in [Vidaurre et al., 2011]).

The selection of the value of adaptation intensity is rather underestimated, either being fixed through experimenter's intuition or calculated on calibration data to maximize classification performance. In this work we investigate its importance regarding not only the effects on online accuracy improvement, but also on the ability of the adaptive scheme to generalize over future data and reinforce gradual performance improvements, which we consider a sign of graceful, well co-ordinated mutual learning between the machine and the subject.

Our preliminary results with three subjects where the adaptation intensity has been varied in a supervised protocol suggest that moderate adaptation intensity should be preferred in order to avoid possibly misleading online accuracy improvements that do not generalize well and thus may not reflect actual underlying learning.

2. Materials and Methods

We perform online experiments with a 2-class MI BCI, by means of a gUSBamp amplifier (gTec, Austria) and 16 active electrodes over the sensorimotor areas. Power spectral density (PSD, Welch method) features are extracted from the last 1 sec-long window, every 62.5 msec (16 Hz output rate), based on pre-calculated feature selection on calibration data [Galán et al., 2007]. A hard classification decision is performed with a Quadratic Discriminant Analysis (QDA) classifier on each extracted brain pattern, driving accordingly a feedback bar left/right by a predefined step, until a visually marked trial-decision threshold is reached.

We propose a generative adaptation framework for continuous estimation of the MI class distributions' first two moments (means μ, covariance matrices Σ) in a buffer of the last N acquired samples, $\mathbf{x_k}$, as:

$$\mu_t^i = \frac{N-b_t^i}{N}\mu_{t-1}^i + \frac{1}{N}\sum_{k=t-N+1}^{t}\alpha_k^i x_k \ , \quad \Sigma_t^i = \frac{N-b_t^i}{N}\Sigma_{t-1}^i + \frac{1}{N}\sum_{k=t-N+1}^{t}\alpha_k^i (x_k-\mu_t^i)^T (x_k-\mu_t^i) \ ,$$

$\alpha_k^i = p(x_k|c_i)$ (in {0,1} for the supervised case), $b_t^i = \sum_{k=t-N+1}^{t} a_k^i$, i =1,2, and t discrete time index.

The sample at time t is classified by QDA based on the updated mean and covariance matrix estimates at *t-1*. This framework essentially implements online Maximum Likelihood (ML) parameter estimation on N latest observed samples of each class, replicating the current estimates N-b_i times to cover for currently missing samples of class i in the buffer, so that that parameter N is the single, constant factor affecting the adaptation intensity. Among the advantages of this approach are its natural extension to the unsupervised case through Expectation-Maximization-based ML estimation, the inherent ability to gradually estimate any kind of feature distribution variation (shift, rotation, scaling), the low computational complexity and ease of implementation, as well as its applicability to different kinds of classifiers with slight modifications and any number of classes.

Three subjects (S1-S3) performed 8 MI runs with varying adaptation intensity (where small buffer sizes indicate high intensity), as well as a final run without adaptation. Each run consisted of 15 trials of each class (10 for S3) with 10 second trial timeout in a cued protocol. All runs started from the same initial classifier, which for S1 (experienced BCI subject) and S3 (severely paralyzed end-user) was based on calibration data collected several months/weeks ago, respectively; for S2 (novel BCI subject) it was trained on the same day.

3. Results

We extract single-sample classification performances employing the Matthews Correlation Coefficient (MCC, where 1=perfect, 0=random classification), which accounts for both accuracy and bias simultaneously. Online performance gains through adaptation for each run are evaluated as the difference $MCC_{online} - MCC_{initial}$, where MCC_{online} is the performance observed by the user during online operation of the adaptive method and $MCC_{initial}$ is the offline simulated performance using the initial classifier without adaptation.

Assuming that the feature distributions of the final, non-adaptive run reflect the subject's currently learned and consolidated MI strategy, we evaluate the ability of our algorithm to capture this state for the different adaptation intensities used. To do so, we compute offline the differences $MCC_N - MCC_{initial}$, where MCC_N is the performance achieved when the resulting classifier of the adaptive run with buffer size N is applied on the last, non-adaptive run, and $MCC_{initial}$ is the equivalent metric for the initial classifier applied on the last run's data.

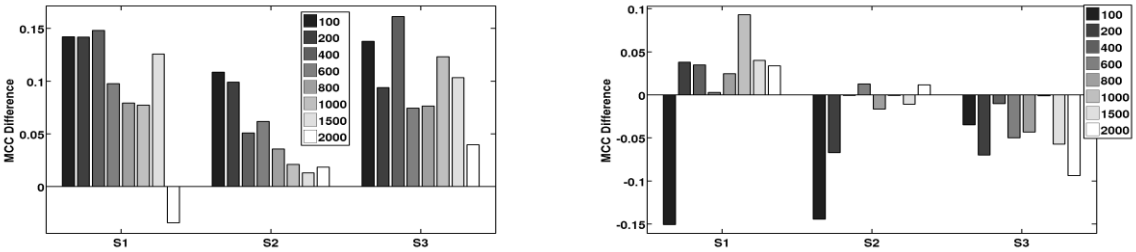

Figure 1. *a) $MCC_{online} - MCC_{initial}$ on each adaptive run (b) $MCC_N - MCC_{initial}$ on final run*
Legends refer to buffer size N = inverse of adaptation intensity

In accordance with the literature, Fig. 1(a) illustrates that online adaptation outperforms the initial classifier, the trend of improvement being proportional to the adaptation intensity. However, Fig.1(b) reveals that the adaptive runs' results in general yield little (S2) or no improvements (S3) over the initial classifier, while mild improvements are demonstrated for S1. Intense adaptation (small buffers N=100--400) results seem to be the most inadequate in terms of generalization capability, while the effects of adaptation intensity on generalization seem to be less significant for milder intensities. Moderate intensity (N=1000, buffer size of latest 1000/16=62.5 seconds of data) seems to optimally accommodate the trade-off between online performance improvement and generalization across all subjects. It should be noted, nevertheless, that the poor effectiveness of adaptation for S2 and S3 could also be the result of confusing the subject through the continuously alternating feedback behavior (by modifying the adaptation intensity at each run), or of random performance variations.

4. Discussion

Long-term experiments with more subjects should be carried out to derive more reliable conclusions. Despite that, our results, although preliminary, point towards two main conclusions. Firstly, online performance can largely overestimate the actual learning benefits of continuous adaptation, as it overfits the latest generated MI patterns to yield high online accuracy but poor subsequent generalization. This undesirable effect naturally correlates with adaptation intensity advocating against intense adaptation. Secondly, the class of feature-tracking adaptation frameworks (like the one we apply here) can recover performance loss associated with feature distribution alterations occurring among BCI sessions (case of S1). However, there is little evidence that it can actually assist and guide the subject's learning process towards improved and stable performances (at least in the short-term), thus hardly qualifying as *co-adaptive*, mutual learning methods. The establishment of a novel BCI adaptation framework targeting these goals will be the subject of our future work.

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Attention and P300-based BCI Performance in People with Amyotrophic Lateral Sclerosis

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Abstract. The purpose of this study was to investigate whether attentional features correlate with P300-based brain–computer interface (BCI) performance in people with amyotrophic lateral sclerosis (ALS). Six participant with ALS used a P300-spelling application in copy mode and performed a rapid serial presentation task (RSVP), aimed at investigating selective attention. Preliminary findings showed a significant correlation between performance reached in the attention task and the amplitude of the P300 elicited in the BCI task. A tendency to a significant negative correlation was found between the performance reached in the attention task and the number of stimulus sequences needed for correct character classification. We speculated that attentive processes would influence P300-based BCI performances.

Keywords: Brain computer interface, Amyotrophic Lateral Sclerosis, attention, P300,

1. Introduction

Reasons for performance variability across subjects reported in BCI studies are unclear. Performance predictors of P300-based BCI were not fully investigated. Mak and coll. (2012) identified some electroencephalographic (EEG) features as predictors of P300-based BCI performance. However, the knowledge about the cognitive capabilities reflecting a successful use of P300-based BCI is limited. People suffering from Amyotrophic Lateral Sclerosis (ALS) are included in the range of potential users of BCIs. Cognitive dysfunctions, mostly regarded as attention, concentration and verbal fluency were reported in association with motoneuron failure in ALS (Ringholz et al., 2005). In this study we investigated the influence of the attentive features of ALS patients on P300-based BCI performances. We hypothesized that the attention capacity in the ALS group would influence the P300 elicited during a P300-based speller BCI (*P300-Speller*, Farwell and Donchin, 1988) task and consequently the performances in controlling such kind of BCI.

2. Material and Methods

2.1. Participants

Six participant (2 women; mean age=57.5) with ALS diagnosis were included in the study. One participant was discarded from the analysis for a technical problem in the data acquisition.

2.2. Experimental Protocol

The experimental protocol consisted of two sessions:

i) participants had to copy spell seven predefined words (5 characters each), by controlling a *P300-Speller*. The EEG was recorded using 8 active electrodes (g.LADYbird, g.tec, Austria - Fz, Cz, Pz, Oz, P3, P4, Po7, Po8). All channels were referenced to the right earlobe and grounded to the left mastoid. EEG was amplified using 8 channels EEG amplifier (gMobilab, g.tec Austria) and recorded by the BCI2000 software.

ii) temporal attention capacity of participants were screened by using a *rapid serial visual presentation (RSVP)* task (Fig. 2): two targets were embedded in a stream of distracter stimuli, all presented at central fixation on a monitor with a white background, at a presentation rate of 100ms each. Distracters were black capital consonants. The first target (*RSVP-T1*) was a green letter, which could either be a vowel or a consonant. The second target (*RSVP-T2*) was a black capital “X”. In 20% of trials *RSVP-T2* was not present, whereas it followed *RSVP-T1* with no (lag 1), one (lag 2), three (lag 4) or five (lag 6) intervening distractors in 20% of trials for each condition. After stimulus presentation two successive screens appeared asking to the subject to decide whether the green letter was a vowel and whether the black X was contained in the stimulus stream (Kranczioch et al. 2007). Due to the motor disabilities, the subjects were asked to give a binary response (yes or no) to the operator with the residual communication channel. A total of 20 practice trials were conducted before the start of the experiment and followed by 160 trials presented in randomized order (32 trials for each of the five conditions).

Fig 1 (a)

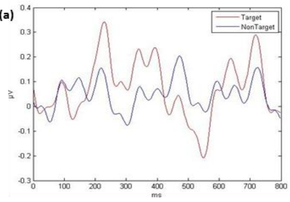

Fig 1(b)

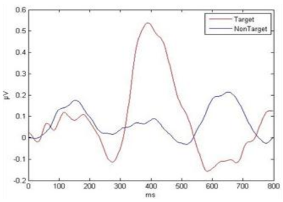

Fig 2

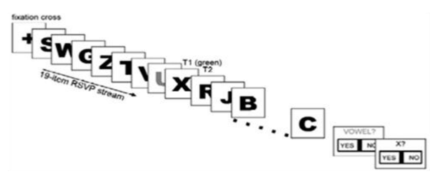

Figure 1. *Response toTarget(red) and Non Target(blue) of the participants with the worst (a) and best (b) accuracy in RSVP-T1identification over an exemplary channel (Cz).*

Figure 2. *RSVP task trial with two target and T2 presented at lag 1. T1 is the green "U" and T2 the following black "X".*

2.3. Data Analysis

ERP data was reorganized in 800ms long overlapping epochs and, starting at the stimulus onset, segmented epochs were then averaged for Target (*T*) and Non Target (*NT*). Target P300 peak amplitude was determined as the maximum (positive potential) voltage in a defined time window (300-600ms) at Cz electrode for *T* stimuli (*T-amp*). For *NT* stimuli the amplitude was determined as the voltage at the *T* peak latency (*NT-amp*). The *NT-amp* was subtracted to the *T-amp* (*T-NTamp*). A Stepwise Linear Discriminant Analysis (SWLDA) was applied to select the most relevant features in discriminating between Target and non-Target stimuli. We performed a 7-fold cross-validation, in order to calculate the number of sequences needed to reach a classification accuracy of at least 70% (*S-70%*). For the RSVP task analysis, mean accuracy for *RSVP-T1* (defined as the percentage of trials in which the participant correctly identified *RSVP-T1*) and *RSVP-T2|T1* (defined as the percentage of trials in which the presence of *RSVP-T2* was correctly reported when *RSVP-T1* was correctly identified). A correlation analysis (Pearson's correlation) between *T-NTamp*, the RSVP task data and *S-70%* was performed.

3. Results

The mean amplitude was 0,25µV for *T-NT*. Mean accuracy was 78% *RSVP-T1* and 71% for *RSVP-T2*. A significant positive correlation was found between *RSVP-T1* accuracy and *T-NTamp* (r=.98, p<0.01) showing that subjects with higher *RSVP-T1* accuracy had a larger *T-NTamp.* A strong yet, no-significant negative correlation was observed between *RSVP-T1* accuracy and *S-70%* (r=-.85, p=0.07) indicating that participants with higher *RSVP-T1* accuracy possibly needed a reduced number of stimulus sequences for correct classification, which improves P300-Speller performance. Figure 1 shows that the *Tamp* at Cz for the participant with the lowest *RSVP-T1* accuracy **(a)** was lower in comparison with *Tamp* at Cz of the participant with the highest **(b)** *RSVP-T1* accuracy.

4. Discussion

These preliminary findings support our initial assumption. Considering *RSVP-T1* accuracy as a parameter reflecting the selective attention, the positive correlation observed between *RSVP-T1 and* the *T-NTamp* and the tendency to a significant negative correlation between *RSVP-T1* and *S-70%* lead us speculate that attentive processes, likely to be impaired as a consequence of ALS, would influence P300 elicited during a P300-speller task and consequently the P300-based BCI performances. This study may contribute to the effort of developing BCI paradigm adaptable to ALS user capabilities. We are currently increasing the number of observations in order to consolidate these preliminary results.

Acknowledgements

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Decoding Locomotor Information from Cortical Modulations in Bipedally Walking Rats

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Abstract. To design appropriate rehabilitation strategies and neuroprostheses for severely paralyzed patients, it is imperative to firstly achieve a deeper understanding of the information that can be extracted from the cortex of healthy subjects during locomotion. Chronic recordings from ensembles of cortical neurons in the sensorimotor cortex of healthy female Lewis rats were used to predict offline limb kinematics (low-level information) and gait phases (high-level information) during a range of bipedal locomotor tasks. The obtained results suggest that high-level locomotor states rather than limb kinematics can be robustly and effectively extracted from motor cortex during bipedal walking.

Keywords: Sensorimotor cortex, rat, decoding, locomotion, spikes

1. Introduction

So far, only a few studies have investigated to what extent it is possible to decode locomotor-related information from neural activity in the brain of both animals and humans, and they exclusively focused on treadmill walking [Fitzsimmons et al., 2009; Song et al., 2009; Presacco et al., 2011]. Here, we investigated the amount of high- and low-level information that could be extracted during a range of bipedal locomotor tasks in healthy rats.

2. Material and Methods

Female Lewis rats (*n* = 6, R1-R6) were trained to walk in a bipedal posture while supported vertically and medio-laterally by a robotic postural neuroprosthesis [Dominici et al., 2012]. After training, the animals could: (1) step continuously on a treadmill, (2) walk overground along a straight runway, (3) along a curved path, and (4) climb a staircase. After completion of training, the rats were chronically implanted with a 32-microwire array that spanned the entire extent of left hindlimb sensorimotor cortex. To isolate single- and multi-units from raw neural data, we developed an automatic method based on a wavelet detection algorithm [Nenadic et al. 2005; Citi et al., 2008] and the superparamagnetic clustering technique [Quiroga et al., 2004] with wavelet coefficients as inputs. To confirm the quality of sorted units, we analyzed spike waveform and interspike interval histograms (ISIHs) to distinguish stable units. We only considered units with a reproducible waveform and exhibiting stable ISIHs across all trials (within a task) for decoding analysis [Dickey et al., 2009]. By using support vector machine (SVM)-based nonlinear decoders [Chang and Lin, 2011], we first sought to extract phase-dependent tuning. Next, we aimed at decoding changes in skeletal landmark positions and hindlimb joint angles.

3. Results

We found that high-level information was readily extracted from ensemble cortical modulations in all rats for all tasks. The reconstruction of low-level information in our study (see Fig. 1, central panel) outperformed prior studies in rats, which obtained R-sq ~ 0.4, on average, for the best decoded variable [Song et al., 2009]. However, decoding performance in the medio-lateral axis was generally poor. For all tasks, the decoding performances increase as a function of neuronal sample size, and model-training time. However, in comparison with direct kinematics decoding, high-level state variables, such as gait phases, were more reliably decoded (R-sq > 0.9, see Fig. 1 bottom panel).

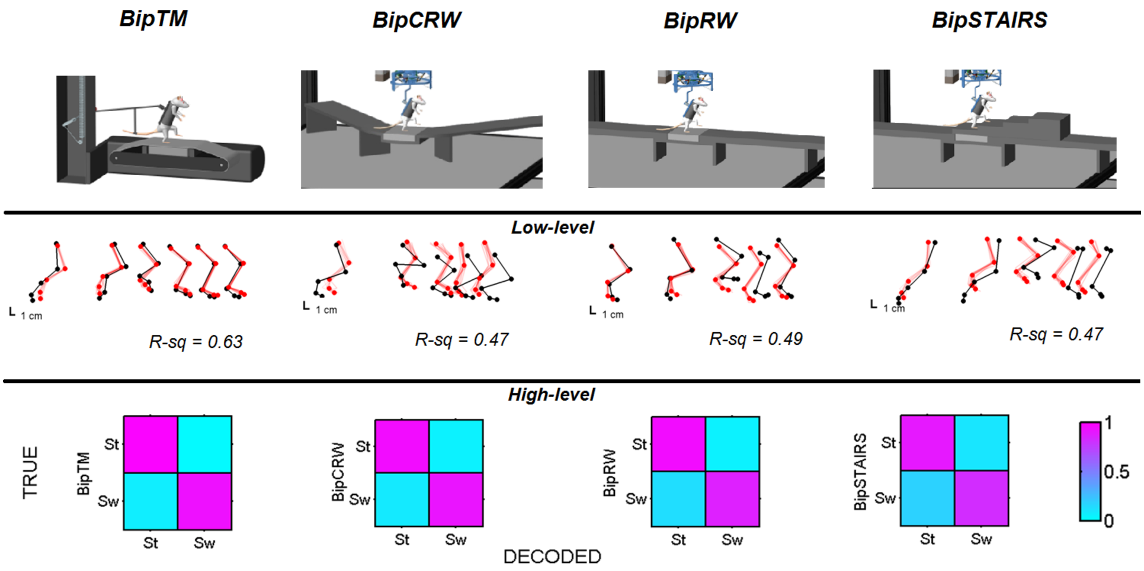

Figure 1. *Decoding Low-level and High-level information. (**Top panels**) The four bipedal tasks analysed: treadmill (BipTM), curved runway (BipCRW), runway (BipRW), and staircase (BipSTAIRS).(**Middle panels**) Results for decoding low-level information in the four tasks (expressed as squared Pearson's correlation coefficient, R; values averaged across all kinematic variables). Predicted (red) and actual (black) hindlimb configurations are shown for a typical gait cycle. (**Bottom panels**) Results for decoding high-level information in the four tasks: confusion matrices showing obtained performances for decoding the stance and swing phase of the gait cycle (expressed as % correct).*

4. Discussion

Overall, the obtained results suggest that high-level locomotor states rather than limb kinematics can be robustly and effectively extracted from motor cortex during bipedal walking. High-level motor states are discrete descriptors of motor actions and are well suited for prosthetic applications where the user selects quickly from individual categories, e.g. during standing-to-walking switching [van den Brand et al., 2012], or where discrete motor goals can be translated into kinematic control signals by an external controller [Kim et al., 2006]. Our study contributes to this concept, suggesting that high-level states instead of kinematics would yield a more robust and effective control system of lower limb neuroprostheses for the rehabilitation of paralyzed patients.

Aknowledgements

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Evaluation of MI-BCI Performance in Ten Spinal Cord Injured End Users

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Abstract. Highly paralyzed people have only a few residual motor functions that can be used for control of conventional assistive devices (ADs). These devices can be extended to accept input from a Motor-Imagery-Brain-Computer Interface (MI-BCI) to make them accessible for such individuals. However, it is still unclear to what extend disabled individuals are able to control an MI-BCI. In this study, the outcomes of MI-BCI training sessions with ten high spinal cord injured (SCI) subjects are presented. Only one subject achieved a performance greater than 70%, three subjects were around 70%. The average performance of all subjects was 70.5%, which is significantly lower than in healthy subjects.

Keywords: EEG, BCI, Motor Imagery, tetraplegia, performance

Introduction

Individuals with a spinal cord injury (SCI) suffer from restricted limb functions depending on the level of lesion. [Zickler et al., 2011] have shown that the main needs of highly paralyzed individuals are manipulation and communication. However, in highly lesioned tetraplegic subjects only a few residual motor functions are preserved that can be used for control of conventional assistive devices (ADs). For this purpose non invasive Brain-Computer Interfaces (BCI) exploiting the subject's electroencephalogram (EEG) are combined with standard interfaces of ADs offering a new opportunity for access. In even higher lesioned subjects in whom residual movements are mostly absent, the BCI remains the last option for control.

However, it is still unclear to what extend highly disabled individuals are able to control a Motor-Imagery-Brain-Computer Interface (MI-BCI). In this study, the outcomes of MI-BCI training sessions with ten SCI subjects are presented.

End user and BCI-training description

The participants are ten high spinal cord injured individuals with a level of lesion at C4/5 (characteristics and neurological status listed in table 1). They have been trained with the Graz-BCI and EPFL-BCI in offline and online training sessions. Offline training consisted of a three-class paradigm (right hand vs. left hand vs. feet), the online sessions of a two-class-paradigm without a resting state.

For the Graz-BCI training 13 EEG electrodes (Laplacian montage over C3, C4 and Cz) were used. All channels were referenced to the left mastoid and grounded to the right mastoid. Impedances were below 10 kΩ. The EEG was amplified with a g.tec USB amplifier (g.tec, Graz, Austria), bandpass (8^{th} order butterworth) filtered between 0.5 and 100 Hz and sampled at 512 Hz. A proprietary offline analysis software developed in Matlab was used to perform Distinction Sensitive Learning Vector Quantization (DSLVQ [Pregenzer et al., 1995]). Subject specific spatio-frequency features that maximize the separability between the different mental tasks have been obtained for online training. For the EPFL-BCI, 16 electrodes at similar positions were used and a Gaussian Classifier was calculated after analysis of the offline data.

Results

In table 1 the number of recorded runs and the achieved online performance is listed. Only evaluable online runs were taken into account (free of artefacts, no speech during runs).

HE11IM was trained with the Graz-BCI, but no online runs were recorded. These offline runs suggest a high performance (~90%), which was not seen in the EPFL-BCI online runs. The reason for this remains unclear. A similar behaviour could be seen in GU26HE, who was extensively trained with the Graz-BCI and achieved an average performance of 70% (training since August 2011; performance varying over time). However, the EPFL-BCI suggested a performance below 60% after 27 offline runs.

In GE26EN EEG signals were generally contaminated with EMG artefacts. The main difficulty is that this subject became tired very quickly during BCI training sessions.

The inhomogenity in the number of runs arises from the fact that some subjects were visited more often due to the distance of their home, their availability and their involvement in further studies.

Both online and offline runs consisted of 30 trials/run except for GU26HE (24 trials/online run).

*Subject description and results (SD=rounded standard deviation). *Due to low information content in the offline data, the online classifier was difficult to train.*

Subject ID	*Sex*	*Level of Injury*	*Date of injury*	*ASIA impairment scale*	*Age*	*Handedness*	*Number offline runs*	*Number online runs*	*Average of online performance*	*SD*
GU26HE	m	C4	2009	AIS B	41	right	57	415	70%	12
HE08RF	m	C3	2010	AIS B	42	right	37	51	81%	17
UL23EN	m	C3	2007	AIS B	21	right	36	25	69%	14
HE11IM	m	C4	2002	AIS A	32	right	15	5	68%	12
GI21EN	f	C5	2008	AIS B	49	right	5	1	30%(*)	0
MA26ER	m	C4	2004	AIS A	53	right	10	13	65%	12
GE26EN	m	C5/6	1991	AIS B	38	right	16	10	60%	6
PA19MI	m	C5	2006	AIS A	34	left	11	15	66%	8
SI07CH	m	C5	2008	AIS B	23	right	3	4	61%	8
IR26IM	m	C4	2011	AIS A	52	n/a	9	6	51%	9

Discussion

Only one out of 10 SCI subjects achieved an average performance greater than 70% which is in line with results from [Pfurtscheller et al., 2009]. In [Onose et al., 2012] the course and performance of an MI-BCI training with the goal of controlling a robotic arm in chronic SCI subjects has been investigated. The authors have included two C4, three C6 and four C7 end users, who – like our end users – achieved an average performance of 70.5%, which is also in line with our results. This is in contrast to the mean classification accuracies of healthy, BCI-naive subjects who achieve between 80.0% and 83.3% for left versus right hand MI and hand versus feet MI [Alkadhi et al., 2005]. A low correlation of 0.18 between time since injury and BCI performance in our end users indicates that the low performance is not associated to negative long term plasticity. If the moderate performance is sufficient for AD control was not in scope of our study nor to compare different BCI systems.

The reason for the low average performance of tetraplegic user is unclear. It can be speculated that the missing sensory loop restricts the vividness of the imagined movements and therefore the performance [Pfurtscheller et al., 2008]. More investigations in a larger population of individuals with high SCI are necessary to gain more insights in SCI induced changes on brain oscillations.

Acknowledgments

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Prediction of Fast and Slow Delivery of Mental Commands in BCI

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Abstract. Providing adaptive shared control for Brain-Computer Interfaces (BCIs) can result in better performance while reducing the user's mental workload. In this respect, online estimation of speed of command delivery is an important factor. This study aims at real-time differentiation between fast and slow trials in a motor imagery BCI. In our experiments, we refer to trials shorter than the median of trial lengths as "fast" trials and to those longer than the median as "slow" trials. We propose a classifier for real-time distinction between fast and slow trials based on estimates of the entropy rates for the first 2-3.5 s of the electroencephalogram (EEG). Results suggest that it can be predicted whether a trial is slow or fast well before a cutoff time. This is important for adaptive shared control especially because 61% to 71% of trials (for the five subjects in this study) are longer than that cutoff time.

Keywords: BCI, Shared control, EEG, Entropy

1. Introduction

In order to have an effective control for brain-computer interfaces (BCIs), the level of assistance provided by these systems should be adaptive so as to complement the user's capabilities which change over time. During online operations, non-stationary nature of EEG can lead to changes in the accuracy and the speed in delivery of mental commands. Our goal is to study the possibility of detecting slow trials well before reaching a cutoff time. This will allow us to define the level of assistance provided for the user accordingly. To tackle this issue, we have used an information theoretical approach to characterize the signal.

2. Material and Methods

In our BCI system, the users voluntarily modulate EEG oscillatory rhythms by executing two motor imagery tasks. Each EEG channel was then spatially filtered with a Laplacian derivation before estimating its power spectral density (PSD) in the band 4-48 Hz with 2 Hz resolution over the last second. A statistical Gaussian classifier was implemented to estimate the probability distribution over the mental commands given an EEG sample [Millán et al., 2004].

Five subjects were recorded in a two-class motor imagery. In our experiments, we refer to trials shorter than the median of command delivery time as "fast" trials and to those longer than the median as "slow" trials. In order to predict whether a trial is slow or fast, Shannon entropy as a measure of information content of a signal was calculated for fast and slow trials. To take into account the temporal structure, we estimated the entropy rate of the signal by considering the conditional entropy of sample i, given the previous m samples. For reasonable m, a reliable estimate of this conditional entropy is computationally expensive. To alleviate this problem, we employ a linear model and instead estimate an approximate version of the desired conditional entropy [Saeedi et al., 2012]. An autoregressive model of the original signal was built. Then, Shannon Entropy of the residuals was calculated for each trial using Maximum Likelihood estimation [Hausser et al., 2008].

The autoregressive model was estimated using Yule-Walker method. In this study, we tried to consider the optimal order for this model, looking at "reflection coefficients" which indicate the time dependence between y[n] and y[n-k] after subtracting the prediction based on the intervening k-1 time steps. According to that an AR model of order 5 seems to be appropriate for the five subjects in this study. Also, we studied the AR model of order 10 for comparison. For each order, two different cases were considered: first, building an AR model per trial and second, considering a single AR model for all the trials. For the latter, the AR coefficients were the average of AR coefficients in the first run.

For measuring the entropy rate, we considered the first T s of data in each trial, where $T = 2 + 0.5 \times i$; $0 \leq i \leq 4$. If the length of trial was less than T s, entropy was estimated for the whole trial. The entropy values for the 16 channels constructed the features for classification of fast vs. slow trials. A Linear Discriminant Analysis (LDA) classifier was used for discrimination between the two classes (slow and fast trials) and ten-fold cross-validation was used to assess the performance. The performance is assessed only for trials longer than T.

3. Results

Table I shows the area under the ROC curve (AUC) for classification of fast vs. slow trials considering two different orders (5 and 10) for the AR model. Assuming AUC around 0.7 to be reasonable for our application (highlighted numbers in table I), the model of order 5 seems to perform better for all the subjects, except S3. The important point here is that considering a single AR model of order 5 for all the trials, the classification performance gets better for S3 and S2, while it remains almost the same for the others. On the other hand, considering a single AR model of order 10 for all the trials does not improve the performances.

Among the different cases in this study, considering a single AR model with order of 5 for all the trials yields the best performance for the subjects. In this case, 2s of data in the beginning of a trial for S2 is sufficient to make a reliable prediction about being fast or slow. The same prediction can happen having 2.5s of data for S1, S3, S4 and 3.5s of data for S5. This is really important as the required time for having reliable prediction is less than median delivery time. In a more quantitative way, a reliable prediction of being fast or slow can be achieved for more than 60% of trial (69%, 63%, 61%, 71%, and 66% for S1-5 respectively).

Table 1. *The performance of classification (AUC) between fast and slow trials considering the first T s of data in two cases for each AR model order (5,10):an AR model per trial and a single AR model for all trials*.

		An AR model per trial , Order = 5					An AR model per trial , Order = 10				
Subject	Median Time	2s	2.5s	3s	3.5s	4s	2s	2.5s	3s	3.5s	4s
S1	3.31	0.55	0.68	0.81	-	-	0.55	0.68	0.84	-	-
S2	2.78	0.64	0.82	-	-	-	0.61	0.77	-	-	-
S3	3.34	0.58	0.71	0.78	-	-	0.66	0.77	0.88	-	-
S4	4.25	0.53	0.72	0.81	0.81	0.70	0.48	0.56	0.59	0.80	-
S5	5.9	0.64	0.62	0.65	0.72	0.70	0.62	0.57	0.56	0.64	0.59
		An AR model per trial , Order = 5					An AR model per trial , Order = 10				
Subject	Median Time	2s	2.5s	3s	3.5s	4s	2s	2.5s	3s	3.5s	4s
S1	3.31	0.55	0.69	0.74	-	-	0.55	0.66	0.48	-	-
S2	2.78	0.69	0.77	-	-	-	0.50	0.50	-	-	-
S3	3.34	0.63	0.78	0.91	-	-	0.69	0.80	0.93	-	-
S4	4.25	0.55	0.75	0.80	0.85	0.75	0.53	0.65	0.68	0.78	0.56
S5	5.9	0.54	0.54	0.60	0.69	0.66	0.54	0.50	0.53	0.63	0.68

4. Discussion

This study aims at real-time differentiation between fast and slow delivery of commands in a motor imagery BCI. The mentioned results reveal that it is possible to predict whether a trial is slow or fast well before a cutoff time (2- 3.5 s), based on measuring the entropy rate of the filtered EEG signal. Estimation of the entropy rate was done by assuming an AR model of two different orders for the EEG signal. According to the classification results, an AR model of order 5 is appropriate for our application while a model of order 10 seems to overfit the data. For the former case, we got better results even by considering a single AR model for all the trials, which reduces the computational cost. As 61% to 71% of trials take longer than the cutoff time, this method seems to be a good predictor of the time efficiency for delivering BCI commands. In fact, all slow trials can reliably be captured within the first 2-3.5 s of the trial. This prediction is very important, as it makes it possible to regulate the shared control parameters accordingly.

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The Concept of ECG-based Hybrid BCI

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Abstract. Traditional BCIs rely primarily on EEG signals. Due to the non-stationary and non-linear characteristics of these signals, BCIs often suffer from limited accuracy in psycho-cognitive tasks. Also, some users are unable to produce distinct EEG features for different mental tasks and as such are unable to achieve reasonable control of such a BCI system. In order to address these limitations, this paper introduces a hybrid-BCI (hBCI) based on a combination of ECG and EEG signals. The hBCI uses a power spectrum based technique for feature extraction, and Fisher's linear discriminant analysis for classification. Compared with a traditional BCI, the hBCI provides higher performance during offline analysis. The hBCI is also successfully being used in an online task. We report on both the offline and online performance of the hBCI system.

Keywords: Motor Imagery, ERD/ERS phenomena, ECG Recording, RR Interval, Power spectral density, Fisher's LDA.

1. Introduction

The most widespread approach to BCI utilizes only EEG as its input. As EEG signals typically exhibit non-stationary and non-linear characteristics, in addition to a low signal-to-noise ratio, such BCIs often perform poorly in terms of accuracy and interaction speed. Recently, [Pfurtscheller et al., 2010] introduced the concept of the hybrid-BCI (hBCI) and suggested several potential implementations of such a system.

The impact of locomotor imagery on autonomic responses was demonstrated in [Decety et al., 1991]. The mean heart rate and blood oxygen content increase with mental effort during movement tasks. [Scherer et al., 2007] used the property of increased heart rate during motor imagery in self-initiation of BCI. In the design of an ECG-based hBCI [Shahid et al., 2011], concurrent EEG and ECG were considered and an enhanced offline classification accuracy was reported. In this paper, we investigate the impact of the combination of ECG and EEG on online classification performance.

2. Method

Since ECG is known to be correlated with motor imagery-related EEG [Pfurtscheller et al., 2008], we implemented the idea of simultaneous processing [Pfurtscheller et al., 2010] in our ECG-based hBCI. 12 EEG channels and 3 channels of augmented unipolar ECG were taken as input. The EEG electrodes were placed at Fz, FC3, FCz, FC4, C3, C1, Cz, C2, C4, CP3, CPz, and CP4 (with reference to Fpz and ground to earlobe). The unipolar ECG electrodes were placed at left arm (LA), right arm (RA) and left leg (LL) (with ground to earlobe as above). Signals from all locations were sampled at 512Hz and recorded through a gUSBamp.

As is common with BCIs, the recorded signals were processed in two stages: feature extraction and feature classification. For each channel, 16 Hz features were extracted from 2-second windowed (buffer) signal. The feature was computed from the ratio of "total log-power of band-passed buffer signal" and "total log-power of buffer signal". For ECG we used a fixed 2-15 Hz band-pass filter. But, with EEG we searched for the band-pass filter that provided highest Classification Accuracy (CA) in the training stage. To estimate CA, we used a 5-fold cross-validation technique where 80% of data were used to establish Fisher's linear discriminant analysis (FLDA) method [Duda and Hart 2001] that estimates a hyper-plane in the feature space to separate the features into the two different classes. The remaining 20% of the data were used for performance analysis (estimation of CA).

To find the "best" band-pass filter, our training system first computed CA with each of 19 band-pass filters (8-12Hz, 8-13Hz,⋯⋯, 8-30Hz); and found the filter band (called the *usable band*) for which the highest CA was obtained. The training system afterward split the *usable band* into 2 groups and recomputed CA with 2 band-pass filters. This leads to a higher dimensional feature space, i.e., 2 channels of features were extracted from each channel of the EEG. Lastly, the system found an effective filter band (single or double) which resulted in the highest CA in training. The training system returned the parameters of the "best" band-pass filter and the corresponding FLDA classifier (offline-mode analysis). These parameters were then used in the online mode.

3. Experiment Setup

In order to test the concept of proposed hBCI, we recruited 5 healthy subjects who had some experience of using a motor imagery (MI) BCI. Each subject first performed one offline session (= 60 trials) of a typical 2-class binary paradigm (2 s rest and 8 s MI), while 12 channels of EEG, 3 channels of ECG and one channel of breath monitoring signal were recorded. After a short break (while we performed offline analysis), each subject then proceeded to operate the hBCI in online mode (employing continuous feedback) with a newly trained classifier.

4. Results and Analysis

In designing our hBCI, we first examine the frequency domain features of ECG in offline recordings. Fig 1(a) displays a typical characteristic of ECG band-power in training time course. The sum of log band-power decreases or increases from rest state when subject performs motor imagery. To obtain similar characteristics some subjects may need different band-pass filters. As described in Sec 2, we then look for the set of optimal parameters. The instantaneous CA is plotted over the entire trial period (Fig. 1(b)), and the highest CA marked as "expected CA". The CA starts rising from 2nd second of motor imagery and peaks at around 9 seconds. The distribution of 2 seconds feature dataset around the highest CA time point should be consistent. Table 1 compares the offline performance of the hBCI to a traditional BCI with differing numbers of channels. The offline and online accuracies were computed from 60 and 30 trials respectively. With the exception of p008, the offline CA of the subjects increased when they used the hBCI. They also attained more than 90% accuracy in online mode. In particular, S02 showed huge improvements in offline mode performance with hBCI. The offline CA of p008 was high with traditional BCI yet this subject did not perform well in online operation, possibly due to a non-optimal EEG electrode placement for left hand vs. right hand imagery.

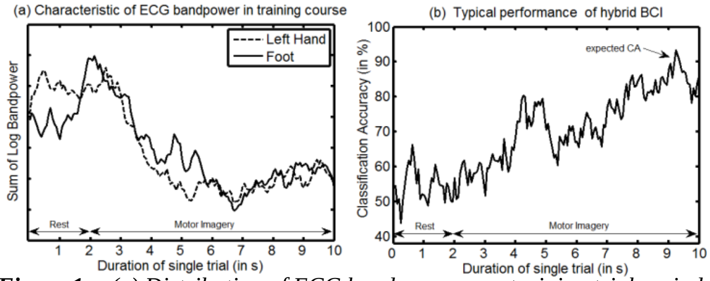

Figure 1. *(a) Distribution of ECG bandpower over training trial period. (b) Distribution of Classification Accuracy over trial period.*

Table 1. *Traditional BCI vs hBCI: performances of different types of BCI.*

Subjects (motor imagery)[φ]	*Offline Accuracy*			*Online Accuracy with hBCI*[ψ]
	16 Chnls EEG	*12 Chnls EEG*	*hBCI(12 EEG+3 ECG)*	*Hit - Miss - Ignore - Performance*
p008 (L/R)	83 %	69 %	75 %	16 - 12 - 2 - 53%
p017 (L/F)	92%	76%	100%	30 - 0 - 0 - 100%
p025 (L/F)	88%	90%	92%	27 - 3 - 0 - 90%
S02 (R/F)	65%	67%	84%	26 - 0 - 4 - 86%
S01 (L/F)	90%	84%	96%	29 - 0 - 1 - 96 %

[φ] L≡Left Hand, R≡Right Hand, F≡Foot. [ψ]Accuracy was computed from 30 online trials

5. Discussion

Brain cells become active (fire) in motor imagery state and so need more oxygen. The need to supply more oxygen leads to an increased heart rate [Decety et al., 1991]. Likewise, we found a notable difference in frequency domain characteristics of ECG (Fig 1(a)) in rest vs. motor imagery. We used this concept in designing an ECG-based hBCI. The extra channels of ECG increase offline performance compared to a traditional BCI. In general we also see improved online performance in accordance with the increase in offline CA.

Acknowledgements

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Error Processing of Self-paced Movements

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Abstract. Decoding of limb kinematics from the scalp electroencephalogram (**EEG**) is receiving empirical support, but feasibility of on-line application in a brain-machine interface (**BMI**) is yet to be resolved. Presumably, however, any real-time operation would be imperfect, i.e., prone to incorrect recognition of user's intent and erroneous movement of any limb avatar. It is therefore necessary to understand EEG correlates of the user's perception of such errors in order to: (i) account for their confounding influence on the signal, and more interestingly (ii) tap into any additional information they may provide about the user's intent. Here we investigate the feasibility of single-trial recognition of error-related potentials induced in subjects operating today's most ubiquitous upper limb avatar: the computer mouse, while we distort the mapping between the cursor and the hand (mouse), simulating imperfect operation of a kinematics-decoding BMI.

Keywords: Brain–Machine Interface (BMI), Electroencephalography (EEG), Error-related Potentials, Self-paced Movement

1. Introduction

Real-time reconstruction of limb kinematics directly from cerebral neuronal activity is receiving increasing interest - particularly for the benefit it could bring to prosthetic devices. Some success in non-human primates [Velliste et al., 2008] and in human subjects [Hochberg et al., 2012] has been achieved in control of robotic limbs with invasive electrophysiology. EEG so far has not been shown to be capable of such applications. However, the possibility of decoding upper limb movements from EEG is now receiving empirical support [Bradberry et al., 2010; Lew et al., 2012], primarily in the most fundamental paradigm: center-out reaching. We assume that if neural decoding were ever to achieve the reliability required for a real-time arm avatar application, the decoding would never reflect the precision afforded by the biological limb. Consequently, some movements of the avatar would be incongruent to a degree with the subject's motor program. It is therefore necessary to understand the EEG correlates of such incongruences in order to: (i) account for their confounding influence on the signal when perceived by the user (error- potentials, compensatory efforts), and (ii) take advantage of any information they may provide on user's intent.

2. Methods

We recorded 64-channel EEG while subjects (n=7) performed a motor task. Four circular targets were displayed on the screen in a square arrangement. As one of the targets changed color, the subjects were instructed to wait at least 2 s and then move the mouse cursor towards it in their own time and manner. After 1 s of reaching the target, another target was indicated and the procedure was repeated. 500 such trials were recorded. In 25% of the trials the hand-to-cursor mapping was randomly off-set by 20°, 40° or 60°, simulating imperfect operation of a kinematics-decoding BMI. This perturbation was removed after 0.5 s of the subjects commencing their movement. The purpose of this was (i) to allow the subjects to reach the target without motor adaptation (out of the scope of this study) while (ii) simulating a correction on the part of the BMI.

3. Results

Averaged EEG epochs, time-locked to movement onset, showed typical negative deflection over central electrodes preceding self-paced movement (readiness potential [Shibasaki and Hallett, 2006]). In perturbed trials the readiness potentials are followed by a tri-phasic waveform (**Fig. 1A**). The morphology of this waveform is consistent with our previous research on error-related potentials (**ErrP**) [Chavarriaga and Millán, 2010]. (Interestingly, the average amplitude of the waveform clearly follows the degree of the perturbation.) We performed single-trial classification of non-perturbed vs. perturbed trials. Since in this study ErrPs are not time-locked to a discrete sensory event, but depend of the subjects' perception of error varying with their spontaneous speed of movement in a given trial, etc., we used spectral features, assuming they are more robust to temporal jitter than the time-domain course of the waveform (tests with time-domain features yielded worse accuracy). Additionally, apart from the ErrP waveform whose spectral signature lies in the theta band, non-phase locked theta has been also reported to reflect error-processing [Trujillo and Allen, 2007]. In our study, discriminant features across subjects were clearly located in 4~8 Hz (theta) band, starting from around 200 ms post-movement onset over vertex electrodes (**Fig. 1B, C**), which we thus found physiologically plausible.

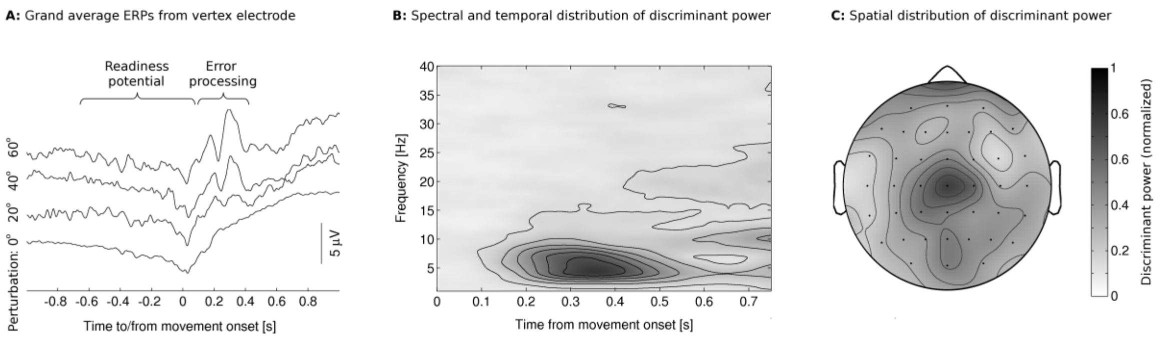

Figure 1. (A) Grand averages across the subject group of 2 s EEG epochs from the vertex electrode, time-locked to movement onset. Trials with different degrees of motion perturbation, or no perturbation, were averaged separately. (B,C) Spatial, spectral and temporal distribution of discriminant power (Fisher score) between perturbed and non-perturbed trials in the frequency domain. Plots show grand averages across the subject group; we ensured that data from each subject contributed equally by rescaling it to unit scale prior to averaging.

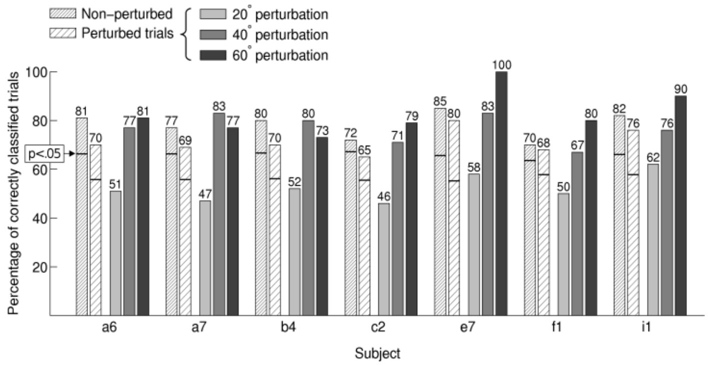

Figure 2. Accuracy of classification of perturbed vs. non-perturbed trials (two class LDA) estimated with cross-validation. Within the perturbed trials class, accuracy for trials with specific degree of perturbation is also shown. Horizontal black lines across the bars denote empirically calculated chance level of $p<0.05$.

Ultimately, for classification we used average spectra from 230 to 460 ms window; this window was identical for every subject. We estimated the performance of a two-class (non-perturbed vs. perturbed trials) LDA classifier by leave-one-out cross validation. In every fold the classifier parameters were calculated on ten most discriminant spectro-spatial features, based on Fisher score from the training data. We report the accuracy of classification in **Fig. 2**. For perturbed trials, we also report accuracy for specific degrees of perturbation. Typically, small (20°) perturbations were misclassified, with larger deviations allowing better accuracy

4. Conclusions

Our results seem promising with regard to on-line detection of incongruences between user's intent and behavior of limb avatar, and as such could perhaps be used to enhance the operation of an arm trajectory-decoding BMI. A number of directions for further study seem worth pursuing: (i) using regression instead of binary classification to model the degree of error – the information which the data apparently holds (**Fig. 1A**); (ii) adding perturbations in different motor paradigms, specifically smooth, complex trajectories; (iii) error-processing of temporal perturbations, i.e. early or delayed movement of the limb avatar.

Acknowledgements

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Liquid Cursor for Multimodal Funnel Display of SMR Modulation

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Abstract. In the classical sensorimotor rhythm (SMR) based brain computer interface (BCI) participants control the direction of a computer cursor movement by either imagining hand or foot movement, provided with visual feedback, but without information about the quality of their control. This study presents results from a multimodal (auditory and visual) SMR based liquid cursor model that not only feeds back amplitude of SMR but also the quality of classification and the degree of uncertainty. Two groups comprising ten subjects each, trained their ability to control a SMR based BCI via motor imagery (MI) during five sessions, by moving a probabilistic cursor through a funnel with unimodal (visual) and multimodal (auditory and visual) feedback. There was no significant difference between the performance of the groups with multimodal and unimodal feedback and no significant training effect could be established across the five sessions. The visual feedback seems to dominate and giving a more complex feedback with additional auditory information had only a small effect on the improvement of performance.

Keywords: EEG, Motor Imagery, Liquid Cursor, Funnel Display, SMR modulation, training application

1. Introduction

Brain Computer Interfaces (BCIs) based on the modulation of sensorimotor rhythms (SMR) classify differences in the electroencephalogram (EEG) patterns caused by different types of motor imagery (MI) [Pfurtscheller et al., 1997]. This gives patients the opportunity to control a cursor on a 2D computer screen by imagining a movement such as with hand and foot [Kübler et al., 2005]. The classical unimodal SMR-BCI feedback is represented as a single cursor bar and provides no information about the quality of the control signal as it only gives feedback about which MI is classified at any point in time. A multimodal liquid cursor model for uncertain display (Figure 1, funnel display) can provide the user with additional information: It shows the actual quality of the control signal by encompassing an area with the liquid cursor, proportional to the uncertainty of the signal and by modulating the moving speed of the liquid cursor through the funnel, equivalent to the stability of the users' control, which is represented by the overall pattern of movement of the fluid along the vertical axis of the funnel display. In combination with auditory feedback, the user is provided with additional information about the current MI. As the user can decide to which feedback he or she pays more attention to, performance may be improved.

The goal of this study was to investigate whether a multimodal funnel feedback can elicit better user performance of SMR-BCI across five training sessions compared to the unimodal version.

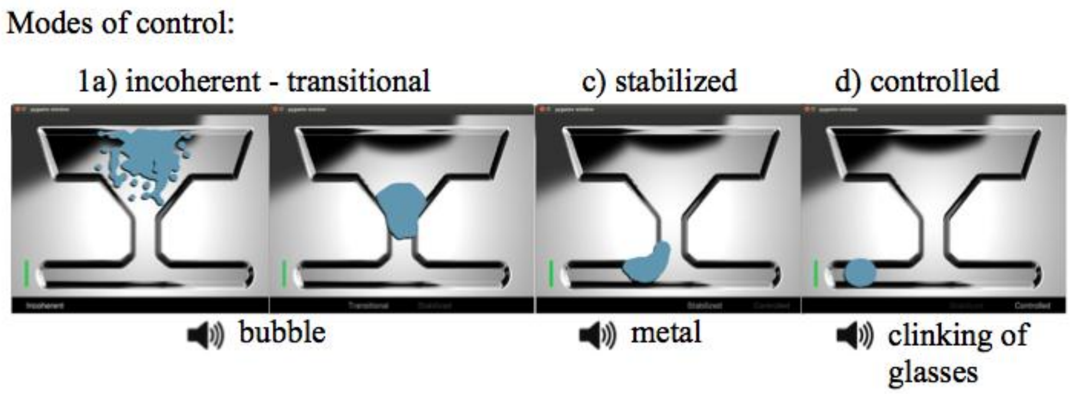

Figure 1: *Feedback sequence of the multimodal funnel display. Multimodality: Each of the three different modes of control is connected to specific sounds. Auditory feedback is displayed simultaneously to changes in the visual display. A user with 'poor' stability would either have the fluid always at/near the top (if their uncertainty was always high) or bouncing up and down from top to bottom and back again without managing to get into the "controlled" state (if their uncertainty was changing from high to low but they couldn't maintain it in the "low" state). A user with 'good' control stability would be able to move the fluid from the top to the bottom in (almost) every trial and then go on to make a left/right selection once in the "controlled" state.*

2. Material and Methods

For each feedback ten healthy, BCI untrained subjects (multimodal: 6 female, aged between 23-51, mean age 30,2 ± 7,8 SD; unimodal: 6 female, aged between 19-46, mean age 27,1 ± 7.5 SD) took part in this study. EEG was recorded from 16 channels located over the sensorimotor cortex (Cz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4) with mastoid ground and reference. Signals were amplified using a g.USBamp device. The task was a two class motor imagery (left/right hand) by moving the cursor to a given direction (6 runs, 20 trials). Following a between-subject design, participants were devided into two groups: one provided with unimodal, the other with multimodal feedback. Both groups performed the same screening task and data was analyzed offline, using linear discriminant analysis (LDA) for signal classification. Five training sessions were performed with one to five days in between the sessions. The classifier was recalibrated at the beginning of the third session.

Multimodality was provided by connecting sounds to different visual modes of control: At the start the liquid is incoherent. Depending on the stability of the user's control it condenses and alters into a transitional mode while it moves to the lower region, acoustically discernible by bubble sounds (Fig. 1a). Once reached the "test tube", the liquid cursor is in a stabilized mode, distinguishable by metal sounds (Fig. 1b). As the input signals become more accurate the user can control the liquid cursor to the left and to the right supported by the sound of clinking glasses (Fig. 1c). No sounds are displayed when moving in the wrong direction.

3. Results

None of the participants were excluded from analysis. Six participants of the multimodal and four of the unimodal group could improve their performance level across all sessions above the critical value of 70% [Kübler et al., 2001]. There was no significant difference in the performance of the multimodal and unimodal group (ANOVA two factor with replication, sample: p=.35, interaction: p=.98, Figure 2), but in average, the multimodal feedback group had the better performance, with the most distinct difference in the last session (not significant, ANOVA single factor p=.36). No significant training effect can be established across the five sessions moreover performance was very variable across each trial.

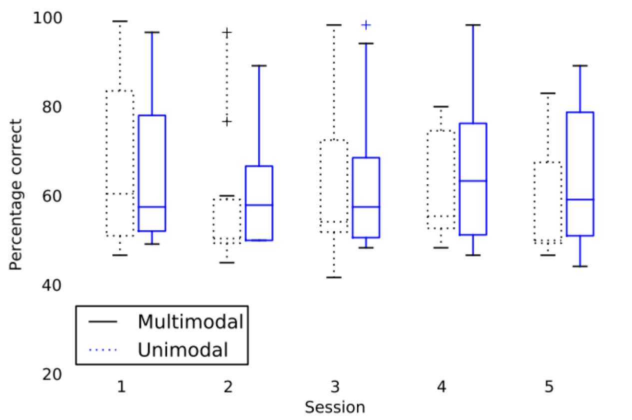

Figure 2: *Changes in the performance (percentage correct) of two groups of subjects testing the multimodal (drawn line) and unimodal (dashed line) feedback across five training sessions. No statistically significant difference in performance between the two feedback groups was found.*

4. Discussion

Motor imagery for cursor control requires focused attention to process the feedback information. The herein presented work revealed that users were able to control the multimodal as good as but not better than the unimodal BCI. The performance of the users does not only depend on the feedback but also on the ability to concentrate. The daily condition of the subject seems to have a strong impact on the performance across each session and can therefore be explanation fo the missing training effects.

Acknowledgements

The work is supported by the EU grant FP7-224631 "TOBI" (Tools for Brain-Computer Interfaces) project. This paper only reflects the author`s views and funding agencies are not liable for any use that may be made of the information contained herein.

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Fixed-Sequence Stimulus Presentation in ERP-BCI

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Abstract. *For an auditory ERP paradigm, randomized stimulus presentation sequences were compared to fixed predictable stimulation sequences. In a study with N=10 healthy subjects, a standard offline analysis of the collected data epochs resulted in comparable classification performance and ERP responses. Making explicit use of the repetitive structure, the classification result could be improved only for the fixed sequence condition..*

Keywords: EEG, AEP, ERP, stimulus design, workload, BCI

1. Introduction

In the field of Brain-Computer Interfaces (BCI), the original two-class oddball paradigm with random presentation sequences (see [1] as an entry point) has been extended to multiple stimuli with balanced probabilities [2]. Exploiting the differences between standard and deviant ERP (event-related potential) responses with Machine Learning methods, these multi-class paradigms are suitable for communication and control. Recently proposed paradigms may provide a communication channel by exploiting the auditory modality [3], [4], [5], [6], [7]. In the auditory domain, however, a multi-stimulus paradigm can have a high demand for spatially directed attention. Supporting the transition from the lab to patient users means, that this high workload needs to be addressed. Therefore the present study investigates the effect of giving up the randomness of stimulation sequences in favor of a simple, repeated, and thus predictable pattern.

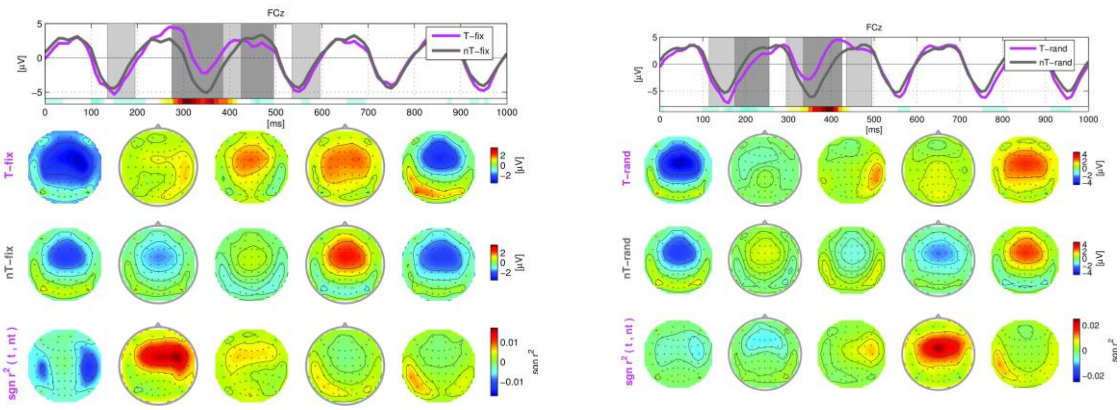

__Figure 1.__ Overview ERP plots for condition rand (__left__) and fix (__right__) for subject no. 2. The top row depicts the average time course of target (T) and non-target (nT) responses for channel FCz. The horizontal colored bar visualizes signed r2 values for each time bin as an indicator for class discriminability. Rows two and three depict scalp plots of average activity in five selected time intervals (see gray shades in the top row). The bottom row shows the distribution of class discriminative information for these five intervals over the scalp.

2. Material and Methods

The experiments conducted followed the AMUSE paradigm described in [7], but used a stimulus onset asynchrony (SOA) of 200 ms. Data of healthy subjects (n=10) who performed a single session with a 6-class spatial auditory ERP paradigm were analyzed offline. The auditory evoked potentials (AEP) resulting from the potentially simpler task (using fixed sequences) are compared with the AEP evoked by pseudo-randomized stimulation sequences. Overall, the experimental setup corresponds to a typical calibration phase of a BCI session, except for the two conditions applied and a relatively large number of 61 EEG channels used.

2.1. Two Conditions: Randomized and Fixed Sequence

Depending on the condition, the sequence of six tones was either pseudo-randomized from iteration to iteration (condition rand), or randomized for the first iteration only, and then kept fix for all 11 to 13 iterations of a trial. In the fix condition, target tones were separated by exactly five non-target tones, while in the rand condition only the expected number of non-target tones was five. In condition fix, subjects had a chance to recognize the regular pattern of stimuli after the second iteration had finished. During the recording, participants were asked to pay attention to and silently count the number of appearances of a cued target tone, while ignoring all other non-target tones. The spatial coding and pitch differences between the six tones were useful cues for this attention task.

2.2. Analysis Methods

The collected data were analyzed offline. The continuous EEG data was filtered (high-pass with a cut-off frequency of 0.2 Hz, low-pass of 30 Hz). Starting with a standard epoch interval of [0–1000] ms relative to a stimulus, the analyzed epochs were enlarged in 12 steps by additional pre-stimulus intervals of 200 ms duration for each step. The largest analyzed epochs thus were located at [-2400–1000] ms around a stimulus. For classification, 12-36 features per channel were used. After removing 50 to 300 outlier epochs based on a simple variance and amplitude criterion, approx. 4200 epochs remained for each condition. Thus, approx. 700 target epochs and 3500 non-target epochs were available for further analysis. Classification was always performed with a shrinkage-regularized Fisher Linear Discriminant Analysis (FDA). Reported error values have been estimated by averaging the outcome of a 5-fold cross-validation that on top was shuffled randomly for another 5 times. Errors represent class-wise balanced errors with a chance level of 50 %.

3. Results

Class-discriminative EEG responses between target and non-target stimuli were observed for both conditions. An examples of the ERP responses of both conditions are depicted in Fig. 1. The binary classification error estimated for standard epochs of was comparable for both conditions (random: 24%, fixed: 25%). Expanding the standard epochs to include pre-stimulus intervals, we found that the regular structure of the fixed sequence can be exploited. Compared to the standard epoch, the MSE improves by 7%, while in the random condition an improvement could not be observed. (Fig 2).

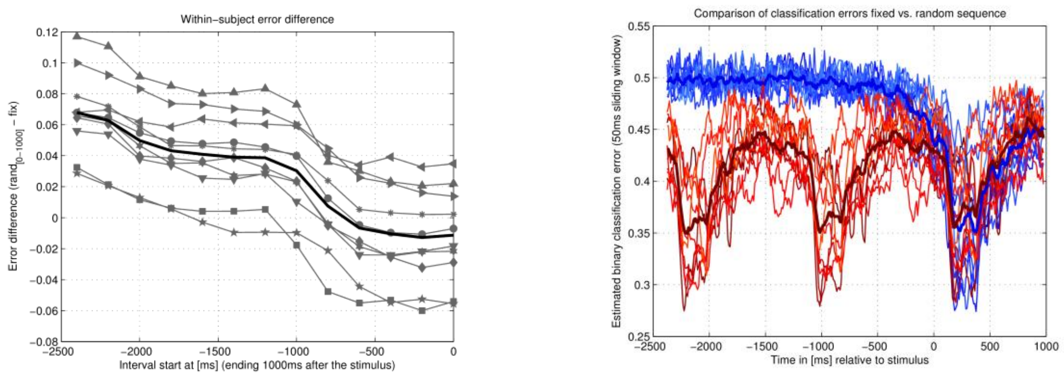

Figure 2. ***(left)*** *The MSE error in condition rand for the smallest epoch [0–1000] ms is compared with the MSE of condition fix for different interval sizes. The x axis indicates the start point of the analyzed intervals of condition fix, while the end was kept constant at 1000 ms post stimulus. Thin lines represent the error differences of single subjects and the thick line represents the grand average.* ***(right)*** *MSE estimated in a sliding window of 50 ms width in steps of 10 ms for ten subjects and two conditions. Errors for condition rand are plotted in blue colors, while errors for condition fix are plotted in red colors. Thin lines represent the errors of single subjects and thick lines represent the grand averages.*

4. Discussion

Our finding, that fixed stimulation sequences elicit class-discriminative ERP responses comparable to randomized sequences will enlarge the toolbox of ERP setups for future BCI designs. It has to be tested, though, if the advantage observed for extended time intervals with fix sequences transfers into the online BCI use. In typical online setups, a decision is based on the agglomeration of evidence over several iterations. This technique is applicable even for randomized sequences, and may exploit sequential information in a similar way than with epoch enlargement for fixed sequences.

Acknowledgments

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Predict Driver's Turning Direction through Detection of Error Related Brain Activity

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Abstract. In this work, we present a BCI system to predict driver's preferred turning direction in front of intersection from scalp EEG signals. In experiments with a car simulator, we show a directional cue before the intersection, and analyze error related potential in EEG to infer if the presented direction coincides with the drivier's intentions. The average classification accuracy for seven subjects is 0.69, which confirms the feasibility of using error related potential to estimate people's turning direction in driving.

Keywords: Car simulator, error related potential, classification, estimate turning direction

1. Introduction

Brain-computer interface (BCI) decodes brain signals to monitor people's cognitive states or predict actions. This technology could be applied in automobile driving system to avoid accidents or reduce driving complexity by estimating driver's action intention or cognitive states. For example, BCI might be used to verify whether the driver is paying attention on driving, or predict his/her intended action (e.g. in front of an intersection, facing traffic lights and lane change). Our study aims to detect brain error processing to estimate driver's preferred choice from error-related brain activity, particularly the turning direction.

Error processing is a basic function of the human brain, which engages an error detection mechanism by comparing mental preference and actual response. It plays a key role in integrating various cognitive processes and adjusting performance [Holroyd and Coles, 2002]. Single trial detection of error potentials has been applied in BCI systems to improve performance [Ferrez and Millán, 2008; Chavarriaga and Millán, 2010]. This work applies the single trial error detection in driving to estimate the turning direction in front of intersection.

2. Material and Methods

Seven subjects participated in the experiment. Subjects sat in the car simulator with eyes fixed in the center of the screen, and drove the car simulator following direction signs located in front of each intersection (Figure 1). Once the car was less than 80m from an intersection, three gray arrows (left, straight and right) appeared in the center of the screen to indicate a new trial. One second later, a bright green visual stimulation is presented, showing a possible driving direction (i.e. replacing one of the grey arrows). The green arrow remained on the screen for 0.5s and all arrows disappear afterwards, as shown in Figure 1. Then, the subject had to drive toward the direction in the sign board. The probability of green arrow to be the same as the sign was 70%. Each session consisted of 30 trials and lasted about 10 min, and each subject performed 5 sessions. EEG signal was recorded from 64 channels according to the extended 10/20 system using a BIOSEMI Active Two system.

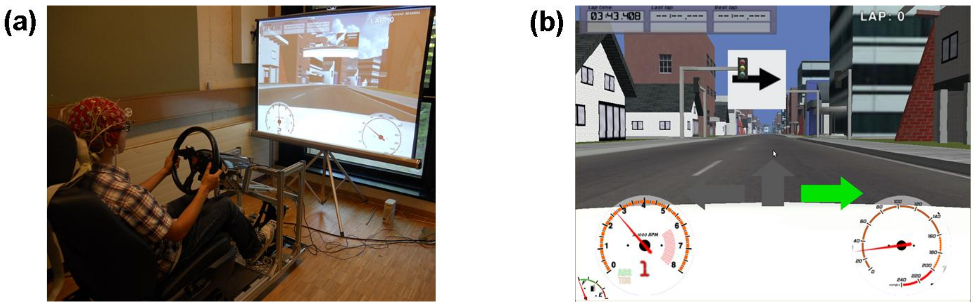

Figure 1. *(a) Experimental protocol in car simulator with EEG recording. (b) Visual cue and stimulation in front of the intersection to evoke error related potential. White board indicates the real driving direction and the green arrow represents the guess of driver's turning direction. Error potential should be elicited in case of mismatch.*

EEG data was filtered with a 4th order Butterworth filter between 1 and 10Hz [Chavarriaga and Millán, 2010]. We used common average reference (CAR) to remove background brain activity, and baseline of each channel was removed by subtracting its average. We used LDA to classify correct and error trials. We chose classification features from EEG channels by canonical variate analysis [Ferran et al., 2007] between 0.2s to 0.7s for 41 EEG channels, since they are related to the error-related brain activity. 10-fold cross validation was used to evaluate the performance of classification.

3. Results

Grand average across all seven subjects are shown in Figure 2.a, segmented from 1.2s before to 1s after visual stimuli, where stimuli are defined as origin of time axis (0s). Both correct and error trials had strong visual related potential around 250ms after visual cue for all subjects. As expected, no significant difference was found after presenting the first cue ($p > 0.05$, t-test). After stimuli, there is a peak around 250ms for both correct and error conditions. Significant differences ($p < 0.05$, t-test) were found in medial frontal electrodes, e.g. FCz and Cz denoted by the green line in the figure, which are around from 200ms to 600ms. Significant differences were found at the subject level (six out of seven subjects) as well. Results of classification (ROC curves) between correct and error are shown in Figure2.b for all subjects. The average classification accuracy across all subjects is 0.69.

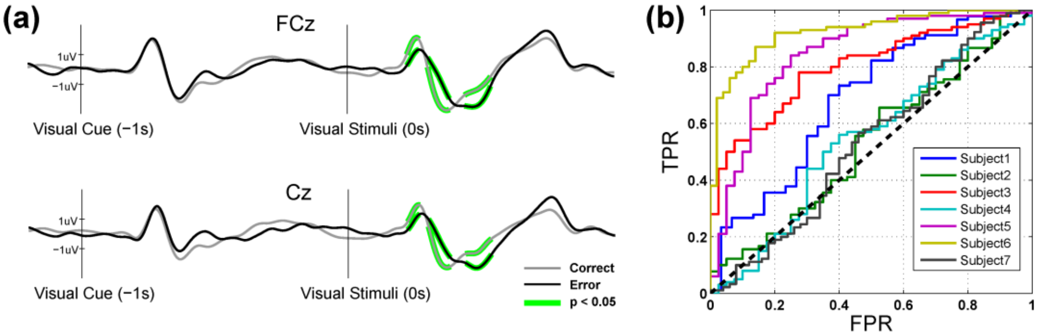

Figure 2. *(a) Grand average of error (Dark) and correct (Gray) related potentials in FCz and Cz. Green thick lines illustrate significant difference between correct and error ($p < 0.05$, t-test). (b) Classification results (ROC curves) between error and correct trials for seven subjects. Each line represents one subject. Random level corresponds to the diagonal.*

4. Discussion

Present study investigates the feasibility of estimating driver's turning direction by detecting error-related brain activity. In the study, we chose the signal from 0.2~0.7s as the input of classification because they are related to the differences between error and correct condition, which can be demonstrated by the statistical test in Figure2.a. Although the obtained accuracy is above random for most subjects, it may still be low for practical applications. As a next step, we will explore brain connectivity as features for the classification, which seems to provide extra information for the classification task [Zhang et al., 2012]. Additionally, since so far we use visual cue and stimuli to evoke error related potential, which may increase the visual burden during driving, we will study other feedback modalities, such as. auditory or tactile. Future work will also address online recognition.

Acknowledgements

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