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].

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