Towards a Novel Control Paradigm Based on Decoding Imagined Movements From EEG

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Abstract. One way to control a limb neuroprosthesis is a brain-computer interface (BCI). A BCI records brain-signals and converts them into control signals. Here, we propose the basis for a novel control paradigm using the imagined movement of one arm in two orthogonal movement planes. We used low frequency EEG signals (around 0.5 Hz) for classification and obtained an average classification accuracy of 69%.

Keywords: EEG, motor imagery, movement planes, movement decoding

1. Introduction

Beside other things, paralyzed persons suffer from lost motor functions, and neuroprostheses are one possibility to restore motor functions. Such neuroprostheses need a control signal, which can be provided by a brain-computer interface (BCI). A BCI records brain activity and transforms it into control signals. Sensory motor rhythm based BCIs (SMR-BCIs) detect the motor imagination (MI) of different body parts, but are incapable of decoding different movement trajectories of the same body part. Recently, it was shown that it is possible to decode trajectories of executed movements from EEG using low frequencies (< 1 Hz) [Bradberry et al., 2010; Ofner and Müller-Putz, 2012]. However, that was not shown conclusively for MI [Poli and Salvaris, 2011]. We found in preliminary experiments that the decoder performance when decoding MI is unacceptable low (the correlation coefficient is around 0.3) and is easily affected by eye movements. However, such a decoding of MI would have two advantages over SMR-BCIs. First, a direct link between MI and neuroprosthesis movement would allow a natural and intuitive control of the neuroprosthesis. Secondly, it would not be necessary to learn the expression of new brain patterns as in the case of SMR-BCIs. This can lead to a reduced training time. Compared to motor execution, movements cannot be measured directly and subjects have to perform known movement patterns, which are synchronized to the system. However, a synchronization as e.g. imagining to follow with the arm a ball moving on a screen is improper, because this causes eye movements. Thus, we implemented a paradigm where subjects imagined rhythmic movements in 2 planes according to the beat of a metronome.

2. Methods

We instructed 9 healthy right-handed subjects, seated in an armchair, to imagine waving the extended right arm in front of the upper body either in the transverse or in the sagittal plane. A beep tone indicated the start of a trial. Simultaneously, a cue in form of an arrow pointing right or up was shown for 0.5 s and indicated the direction/plane of the movement. After 1.5-2.5 s, a metronome started to tick for 20 s with a frequency of 1 Hz, and was used to synchronize movement imaginations to the system. Subjects were asked to fixate the gaze on the cross on the screen to suppress eye movements. We recorded 8 MI runs, each with 5 trials per class, i.e. 80 trials per subject. We recorded the EEG using 68 electrodes covering frontal, sensorimotor and parietal areas and the EOG with 3 electrodes. We removed the influence of eye activity using a linear regression method. First, we applied a band-pass filter with cutoff frequencies at 0.3 Hz and 0.8 Hz. To decode positions, we used two linear models – one for each coordinate – with 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 corresponding to a sine oscillation with a frequency of 0.5 Hz. To classify at trial, we decoded movement positions between second 2 and 19 relative to the start of the metronome (additionally, we also varied the window length), 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. Results were obtained using a 10x10 cross-validation.

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3. Results

Mean values and standard deviations of classification accuracies are shown in Table 1. The grand average is 70% with a standard deviation of 10%. Classification accuracies are significant above 59% with $\alpha = 0.05$. The mean classification accuracy over subjects with significant EEG based classification accuracies and with non-significant EOG based classification accuracies is 69% (s1, s2, s4, s5, s6). An EOG based classification yield significant accuracies for subjects s7 (62%), s8 (71%) and s9 (77 %), and between 41% and 57% for all others. In addition to the fixed window length of 17 s used for correlation, we also analyzed how the classification accuracy changes in dependence on the length of the window (see Fig. 1). The start offset of this window was fixed to 2 s relative to the start of the MI. The classification accuracy of subjects s1, s3, s5, s7, and s9 peaked at short window lengths. After an eventual peak, all classification accuracies increased with increasing window length except for subject s3.

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

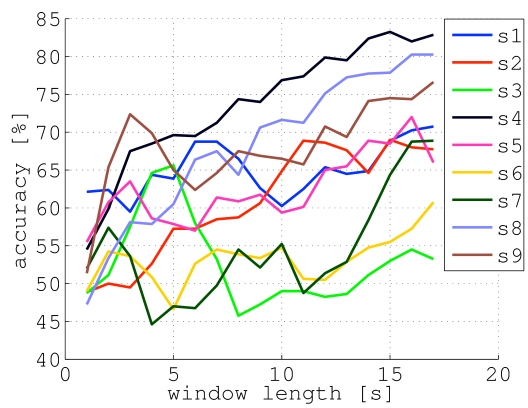

Figure 1. *This plot shows the accuracy in dependence of the correlation window length.*

4. Discussion

We classified in 8 out of 9 subjects the movement planes with significant accuracies. 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. The classification accuracy increased with the window length. This is probably due to the decreasing signal-to-noise ratio of the correlation coefficient. The peak at short window lengths observed in 5 subjects could be an indicator for the presence of two overlayed processes. We proposed a method to *classify* MI of one arm in two planes. This can be the basis for a new mental control strategy for a BCI if the window length can be shortened. Furthermore, as we used the same decoding principles as in [Ofner and Müller-Putz, 2012], we have shown indirectly that *decoding* of MI is possible. However, the performance of such a decoder would be limited.

References

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