Classifying imaginations of rhythmic arm movements in two planes from EEG

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Introduction

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 comprising 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 a classification accuracy of 69 %. Furthermore, we showed indirectly that algorithm principles used in decoding executed movements [1] [2] can also be applied when decoding imagined movements.

Paradigm

We instructed 9 healthy right-handed subjects, seating 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 (see Figure 1). The cue was in form of an arrow pointing right or up, corresponding to MI of the arm in the transverse or sagittal plane. Subjects were asked to fixate the gaze on the cross on the screen to suppress eye movements. A metronome ticked for 20 s with a frequency of 1 Hz, and subjects were instructed to imagine arm movements according to the beat of the metronome (see Figure 1). We recorded 8 MI runs, each with 5 trials per class, in total 80 trials per subject.

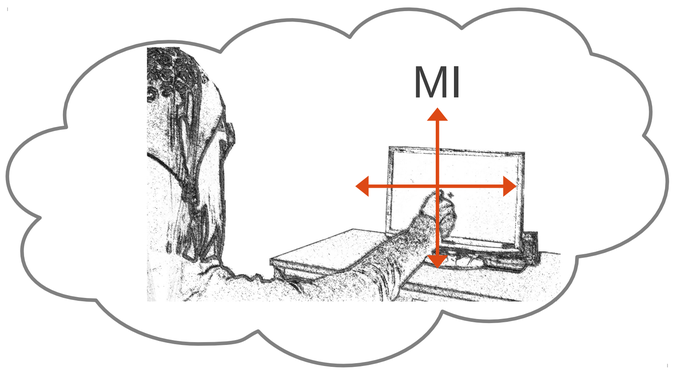

Figure 1: Subjects imagined a movement of the arm in the transverse or sagittal plane.

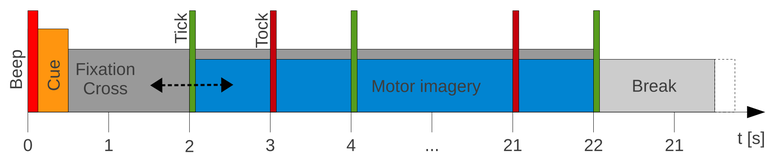

Figure 2: This figure shows the sequence of a trial.

Methods

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. Two linear models – one for each coordinate – decoded arm positions 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. 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 (see Figure 3). Results were obtained using a 10x10 cross-validation.

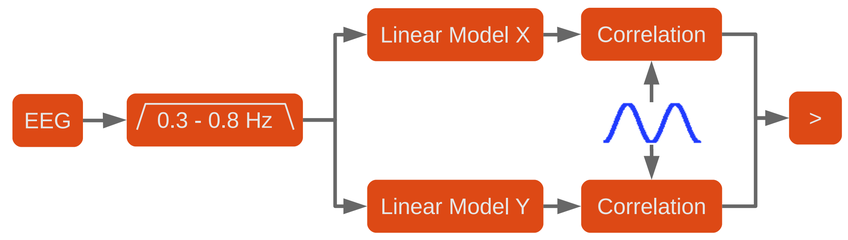

Figure 3: This diagram shows the basic blocks of the classifier.

Results

Mean values and standard deviations of classification accuracies are shown in Table 1. Classification accuracies are significant above 59 % ($\alpha = 0.05$). 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. We also analysed how the classification accuracy changes in dependence on the length of the window (see Figure 4). 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.

subject	s1	s2	s3	s4	s5	s6	s6	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

Table 1: Classification accuracies for all subjects are shown. Significant classification accuracies are written bold. The window length used for correlation was fixed with 17 s.

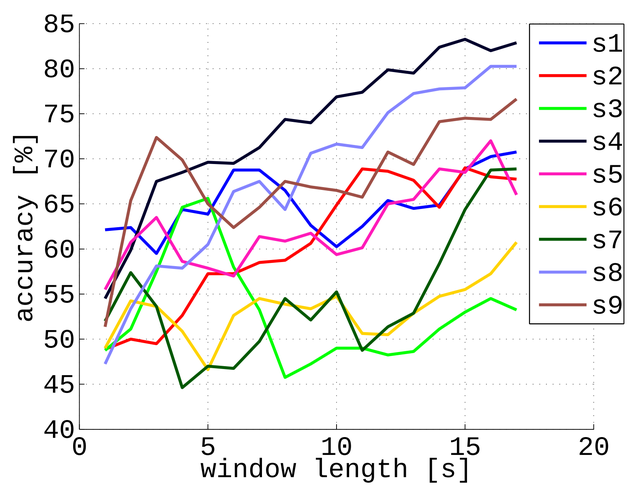

Figure 4: This plot shows the accuracy in dependence of the correlation window length.

Discussion

Eight out of 9 subjects reached significant classification accuracies. Three subjects show also significant classification results when decoding from EOG signals. Although we removed eye activity from the EEG, it 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. 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 2 overlayed processes used for decoding. As we used the same decoder principles as in [2], we showed indirectly that movement decoding is also feasible with MI.

References

1. TJ Bradberry, RJ Gentili, and JL Contreras-Vidal, Reconstructing Three-Dimensional Hand Movements from Noninvasive Electroencephalographic Signals, *The Journal of Neuroscience*, 30(9):3432–3437, 2010
2. P Ofner, and GR Müller-Putz, Decoding of velocities and positions of 3D arm movement from EEG, *Proceedings of the 34th Annual International Conference of the IEEE EMBS*, 6406-6409, 2012

Acknowledgments

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