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MOVEMENT DECODING FROM EEG: TARGET OR DIRECTION?

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ABSTRACT: Arm movements have already been decoded non-invasively from electroencephalography (EEG) signals. In this study we analyzed whether the target or the movement direction of the arm can be decoded from the EEG. Ten healthy subjects executed right arm movements to one out of two targets and simultaneously received feedback on a computer screen. We then inverted the feedback movements to analyze if the EEG carries information about the target or about the movement direction. We found two groups, one encoding the target and one encoding first the movement direction followed by the target. These findings are relevant for the development of future motor neuroprostheses and non-invasive robotic arm control.

INTRODUCTION

Brain-computer interfaces (BCIs) can be used to control neuroprostheses or robotic arms. Together, these technologies allow to restore or replace basic movement function of spinal cord injured (SCI) persons. For example, in [1] a robotic arm was successfully controlled using an invasive BCI. Also non-invasive BCIs based on electroencephalography (EEG) signals can be used to restore movement function in persons with SCI. Our group demonstrated the restoration of grasp function [3], [4] and elbow function [5], [6] with a sensorimotor rhythm (SMR)-based BCI. SMR-based BCIs detect movement imagination (MI) and use it as a control signal. However, the MI itself is often not intuitive (e.g., a foot MI may be used to control the right arm). Furthermore, only the process of imagination can be detected but not the movement itself. For example, imagining squeezing a ball and playing tennis may not be distinguishable with a SMR-based BCI. However, to control a neuroprosthesis in a more natural way or even a robotic arm with its many degrees-of-freedom, more information about the movement needs to be extracted from the EEG. Interestingly, low-frequency EEG signals carry more specific information about the movement and can be used to decode even movement trajectories [7]–[9] or movement directions/targets [10]–[13]. However, the accuracy of a non-invasive movement trajectory decoder is not yet sufficient for real-time control, not to mention the decoding of imagined movement trajectories. The decoding of movement direction or movement target combined with a system which then generates the trajectory may be a more promising approach.

A general issue of studies decoding movement targets is that hand or cursor movements towards a certain target always requires a certain movement direction, i.e. movement targets correspond to movement directions. That blurs the results of such studies because it cannot be determined whether targets or movement directions are being decoded. However, that information is important when training a decoder (e.g., if targets should be shown in the training paradigm). Furthermore, in a real life application there is always a variable number of potential targets. A decoder based on the imagined or attempted movement direction would be independent on the number of targets but not a decoder based on movement targets. To investigate whether a decoder is based on targets or the movement direction, we conducted a study (here with executed movements) where subjects moved their arm to one out of two targets and received feedback on a computer screen. Then, we inverted the feedback and conducted the same number of trials to analyse whether our decoder is based on the movement direction or the movement target. We hypothesize that in case of target decoding, the classification accuracies would be above chance level. Classification accuracies below chance level would indicate the decoding of the movement direction.

MATERIALS AND METHODS

Subjects: For the experiment 10 healthy subjects (one female), all of them right-handed and with normal or corrected-to-normal vision, were recruited. None of them had participated in any prior BCI experiments. They were aged between 25 and 32 (mean 27.7 and SD of 2) years. All of them signed an informed consent.

EEG Measurement: We used 68 passive electrodes covering frontal, central, parietal and temporal areas for recording EEG signals from the scalp. An electrode cap with equidistant electrode positions was used. Also, three electrooculography (EOG) electrodes, positioned above the nasion and below the outer canthi of the eyes were used. Reference was placed on the left mastoid, ground on the right mastoid. All electrode impedances were tried to keep below 5kΩ. An 8-th order Chebyshev band-pass filter from 0.01Hz to 200Hz and a Notch filter at 50Hz was applied. Signals were sampled with

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512Hz using biosignal amplifiers (g.tec medical engineering GmbH, Austria). Moreover, we measured electrode positions with ELPOS (Zebris Medical GmbH, Germany). EEG, EOG and movement data (3D positions and joint angles of the right arm) were recorded with a customized TOBI Signal Server [14] and Matlab (MathWorks, Massachusetts, USA). For recording the movement data a custom made plugin for the ARMEO Spring software was used.

Experimental Paradigm: Subjects were seated in a chair and their right arm was fixed in an ARMEO Spring rehabilitation device (Hocoma, Switzerland). The ARMEO Spring is basically an exoskeleton and supports the subjects' arm from gravity to prevent muscle fatigue. With the sensors of the ARMEO Spring it is possible to keep track of the hand- and elbow position and joint angles.

For the experiment a self paced center-out reaching task was employed. Subjects moved their right arm from a starting position (about 150 degrees elbow flexion, 60 degrees shoulder flexion and 0 degree abduction in the shoulder joint (see Figure 1)) to one of two targets (red and blue) presented on a computer screen. The red and blue target were positioned in the right upper corner and in the left lower corner, respectively (see Figure 2). The final position for reaching the red target required a 100 degree flexion and 20 degree abduction in the shoulder joint and a 150 degree elbow flexion. For reaching the blue target it was a 60 degree flexion, 20 degree adduction and 30 degree internal rotation in the shoulder joint and a 150 degree elbow flexion. The computer screen also showed an arm model as a visual feedback (see Figure 2). The arm model was previously built with the software MSMS (MDDF, University of Southern California, Los Angeles, California). The model received its joint angles and coordinates from the ARMEO Spring and showed the participants their actual hand-/arm position in real time.

The experiment consisted of two conditions: (i) *normal condition* where the virtual arm on the computer screen moved exactly like the subjects' arm and (ii) *inverted condition* where the virtual arm movements were inverted to real arm movements (i.e. subjects had to move their arm to the opposite target to reach the actual target with the virtual arm).

Figure 1: Experimental setup. A subject connected with the ARMEO Spring, EEG mounted in the position in front of a screen which presents feedback to the subject.

The paradigm is shown in Figure 3. At second 0 an audio cue started a trial by either saying „Red“ or „Blue“. The subjects got instructed to immediately look at the specific target to avoid eye movements during the reaching phase which could have affected the classification. Three to 5 s after the trial start a beep sounded representing the go cue. The participants got instructed to start their reaching movements to the specific target 1 to 3 s after the go cue. When the virtual arm on the computer screen touched the specific target, a second beep tone sounded serving as a success cue.

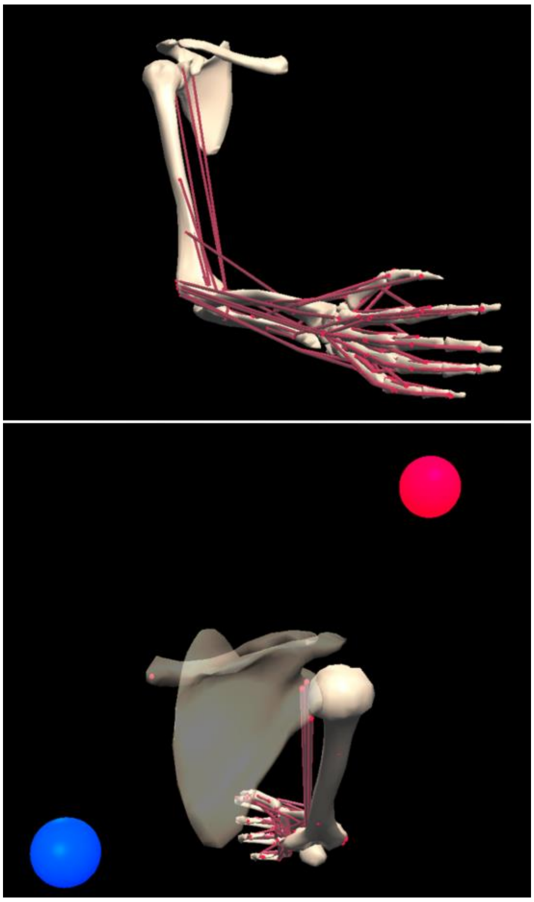

Figure 2: Upper: MSMS arm model, for giving real time feedback to the subjects. Lower: Arm model in experimental setup, i.e. first person view, transparent scapula, all joints in starting position and including both targets

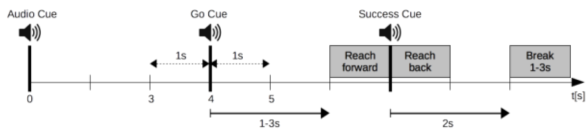

Figure 3: Paradigm and timing of a single trial.

After successfully touching a target subjects moved

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their arm back to the starting position. The trial ended 2 s after the success cue. After a trial, a break between 1 and 3 s followed. Each run consisted of 30 trials (15 trials for each target, randomly distributed). 12 runs were recorded - 6 for normal condition and 6 for inverted condition, always changing the condition after 2 runs. Thus, in total we recorded 180 trials - 90 trials for each condition. Additionally, we recorded 2 resting state runs and 2 runs with deliberate eye movements (not used in this work).

Signal Processing: We removed trials which were suspected to contain muscle, technical or movement artifacts. Therefore the data got filtered from 0.3Hz to 70Hz (4-th order zero-phase Butterworth filter) and trials that exceeded a threshold of 3 times the standard deviation of the absolute value, Kurtosis or joint probability were excluded from any further processing steps.

For determining the movement onset a principal component analysis (PCA) was done on the x/y/z hand position data recorded by the ARMEO Spring. We differentiated the first principal component and detected a movement onset whenever a certain threshold was crossed after the go cue. The threshold was found empirically.

For calculating the movement-related cortical potentials (MRCPs) a 0.3 Hz - 35 Hz 4-th order zero-phase Butterworth band-pass filter was applied and data segments averaged. MRCPs were calculated for both conditions and electrode positions FCz, C3, Cz and C4.

In order to discriminate between the two red and blue targets, we applied a shrinkage linear discriminant analysis (sLDA) [15] to calculate classification accuracies. A 0.3Hz - 3Hz 4-th order zero-phase Butterworth band-pass filter was applied on the raw EEG data to extract low frequency signals. Subsequently, we downsampled data to 16Hz for computational convenience. We computed the classification accuracy within the time window -2s to 2s relative to movement onset. In one analysis, we classified a moving time window of 750ms using data from all band-pass filtered EEG channels, i.e., we used all EEG data within a window of the past 750ms (12 sample points) and then moved the window one sample further. Classification accuracies were calculated using a 10x10 fold cross-validation. This analysis was separately performed for the normal and inverted condition.

In another analysis, we used the data of the normal condition as training data and the data of the inverted condition for testing in order to find out whether it was target or movement direction decoding.

RESULTS

Classification of directions: Figure 4 and 5 show the classification accuracies for the normal condition and inverted condition, respectively. Classification accuracies are scaled from 0 to 1 and time is relative to the movement onset (=0s). The significance level was 61.35% (α = 0.05, adjusted Wald interval, Bonferroni corrected for the number of shown sample points) [16]. The maximum average classification accuracies were 0.78 (normal) and 0.79 (inverted). Table 1 shows the average movement times to the targets for each condition.

Table 1: average time and standard deviation in seconds to reach red and blue target during normal and inverted condition

Target	Normal cond. [s]	Inverted cond. [s]
Red	1,20 ± 0,65	1,36 ± 0,76
Blue	1,41 ± 0,74	1,10 ± 0,65

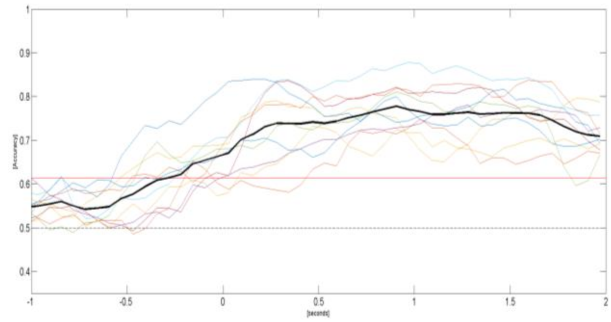

Figure 4: Cross-validated classification accuracies in the normal condition (all subjects and the grand average).

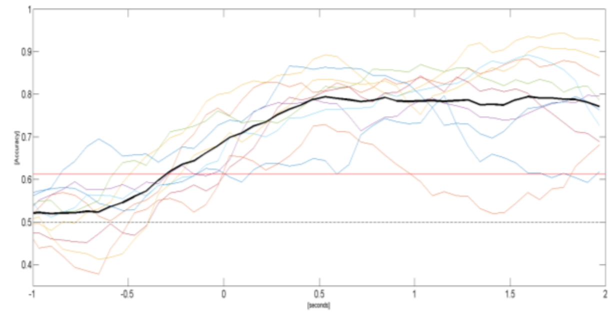

Figure 5: Cross-validated classification accuracies in the normal condition (all subjects and the grand average).

Classification (testing with inverted conditions): We trained the classifier on the normal condition and tested it on the inverted condition. Accuracies below chance level indicate movement direction decoding as hand movements were executed in the opposite direction to the target. Accuracies above chance level indicate target decoding. Two groups arose: group I shows an increasing classification accuracy after the movement onset (Figure 6); group II shows first a decrease of classification accuracy followed by an increase (Figure 7). Time is relative to the movement onset (=0s) and the significance level was 61.35%. The maximum average classification accuracies were 0.71 (group I) and 0.70 (group II).

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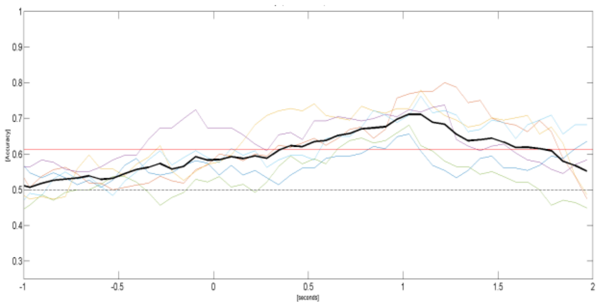

Figure 6: Classification accuracies when training on the normal condition and testing on the inverted condition (group I).

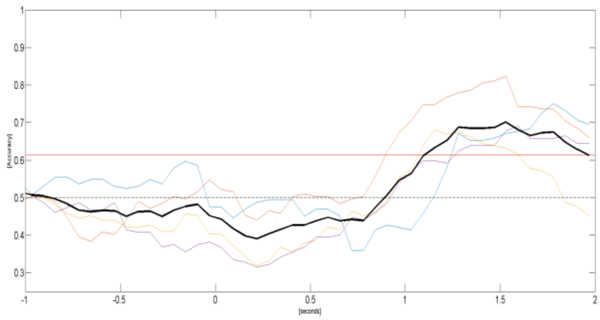

Figure 7: Classification accuracies when training on the normal condition and testing on the inverted condition (group II).

Motor related cortical potentials: Figure 8 and 9 show the MRCPs for the normal and inverted condition, respectively. The figures show the confidence intervals as determined with a bootstrap test ($\alpha = 0.05$) at the electrode positions FCz, C3, Cz and C4. In the normal condition, differences between the two targets are observable at movement onset and around the approach to the target. The inverted condition shows more distinct differences between the targets. These amplitude differences are from ca. 0.5s before movement onset up to 2s after movement onset.

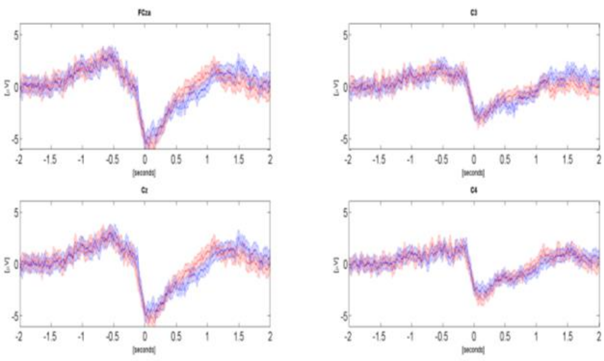

Figure 8: MRCPs evolving in the normal condition. Shown are the MRCPS for both targets (red, blue)

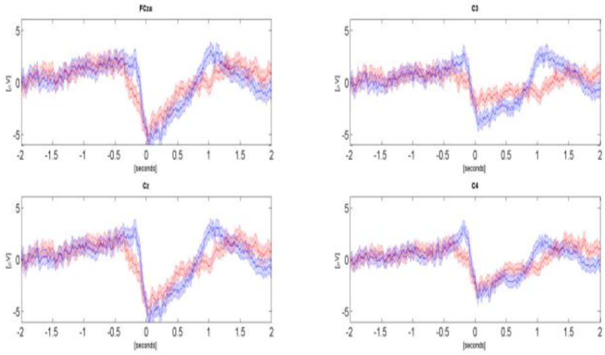

Figure 9: MRCPs evolving in the inverted condition.

DISCUSSION

We demonstrated the decoding of movements to one out of two targets from low-frequency time-domain EEG. Movements were decoded with normal and with inverted feedback. It was possible to decode the movement before movement onset, i.e. in the motor planning phase. Keeping in mind the lag introduced due to the 750ms classification time window, the classification accuracies peaked in the movement execution phase before the targets were reached. Our results are in line with other EEG studies which analyzed time-domain features during movement direction/target decoding [10], [12], [17]. However, also power modulations mostly in low-frequency bands and the high-gamma band have been shown to carry movement direction/target related information [12], [13], [18].
The motivation of our study was to analyze if low-frequency time-domain EEG signals carry information about the movement direction or the target. We did this by inverting the feedback when testing the classifier. In case of target decoding, the classifier would not be affected by the required inversion of movements and classification accuracies would still be above chance level. In case of movement direction decoding, however, the classifier would be affected and classification accuracies would be below chance level, i.e. mirrored around the chance level. Our results can be divided into two groups: in one group the decoder was mainly based on the movement targets, in the other group the decoder first decoded movement directions and then movement targets. This finding has to be considered when novel control systems for future neuroprostheses or robotic arms are developed.
Generally, classification accuracies around the time when the target was reached have to be interpreted with caution. The paradigm was designed to avoid eye movements at movement onset, but subjects may not have suppressed eye movements when approaching a target with the virtual hand as this was a visuomotor task requiring hand-eye coordination. Thus, eye movements may have happened at the end of the reaching movement and the classifier may have picked up the change of the electrical field of the eye dipole.

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Further analysis has to quantify this effect. Furthermore, systematic differences between the movement times of the two targets may be responsible for the successful classification. Different MRCPs may have been evolved not because of different targets but because of different movement times or movements amplitudes (MRCPs are influenced by movement parameters, e.g. movement speed [19]).

The MRCPs show a typical negative peak around movement onset [19]. The inverted feedback condition was more difficult to the subjects than the normal condition and therefore challenged more the motor planning and the movement execution. This higher difficulty probably enhanced the differences between the MRCPs in the inverted condition. The differences before movement onset correspond to the motor planning and are intrinsic. However, the amplitude differences after movement onset are either due to the execution of a motor plan which accounts for the inverted feedback (intrinsic) or due to different movement profiles (extrinsic), e.g. more correction movements. If the differences are extrinsic in nature, the same differences may evolve in the normal condition with the same altered movement profile.

We report here a study with healthy subjects. Further studies have to confirm if the same effects can be found in persons with SCI.

CONCLUSION

We show the decoding of movements to one out of two targets from low-frequency time-domain EEG. Furthermore, we found evidence that the decoding is based on movement targets but also on the movement direction.

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