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Decoding of Executed Movements and Source Imaging

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Abstract

A brain-computer interface (BCI) in combination with a neuroprosthesis can be used to restore movement in paralyzed persons. Usually, the control of such BCIs by the deliberate modulation of brain oscillations is unnatural and unintuitive. Recently, low-frequency brain signals have been found to encode movement information and can be used to decode movement trajectories. These signals are potential candidates for new types of BCIs which can be used to naturally control neuroprosthesis by imagining movement trajectories. We analyzed the contributing brain areas in the source space and found motor areas but also parietal and lateral areas encoding movement information.

1 Introduction

A brain-computer interface (BCI) allows the control of devices trough brain-signals. In combination with a neuroprosthesis, e.g., functional electrical stimulation (FES), a BCI can be used to restore motor functions in paralyzed persons [5]. One type of non-invasive BCIs – so called sensorimotor rhythm (SMR) BCIs – are usually based on the deliberate modulation of brain oscillations [7] by movement imagery (MI). However, the control of SMR-based BCIs is not natural and intuitive, because MIs are assigned artificially to control functions (e.g., a foot MI controls the elbow function). Furthermore, SMR-based BCIs do not decode the imagined movement trajectories, but the general activity at sensorimotor areas during MI. As opposed to non-invasive BCIs, invasive BCIs were already used to decode trajectories of imagined movements and to control robotic arms [2, 3]. On the downside, invasive BCIs have the drawback that they require a major surgical intervention with the risk of infection. Gratifyingly, Bradberry et al. [1] discovered that low-frequency electroencephalography (EEG) signals can be used to decode executed movement trajectories, and also our group decoded 3D hand positions from EEG signals [6]. In this work we decoded frontal and lateral hand movements from brain sources reconstructed from the EEG. Notably, we did not trained a decoder using all sources simultaneously and interpreted the decoder weights. This can lead to wrong interpretations as these weights must be seen as a filter and not as a pattern. Instead, we decoded the movements from each brain source separately and calculated the correlation coefficients with the measured movements, and obtained maps showing the involved brain regions when decoding movements.

2 Methods

2.1 Subjects

We recruited 8 right-handed and 1 left-handed subjects who got compensated for their participation (5 males, 4 females). Most of them had already participated in BCI experiments. Subjects sat comfortably in a chair with their arms supported by arm rests.

2.2 Paradigm

We recorded 3 runs. In the first run (frontal run) subjects moved their right arm in front of them while the gaze was fixated on a cross on a screen. The second run (lateral run) was similar to the first run, except that subjects moved their right arm laterally. In the third run (ball run), subjects moved their right arm in front of them again, but now observed and followed with the eyes a moving ball on the computer screen. Subjects were instructed to execute the arm movements independently from the ball movements. In all runs, we asked subjects to execute round, natural movements (not jaggy) with the extended right arm, and to keep the hand closed with the thumb being on the upper side. Each run comprised of 8 65 s long trials, with subject specific breaks between the trials to avoid muscle fatigue (usually around 1 minute). A trial started with the presentation of a cross (run 1 and 2) or a ball (run 3), respectively, on the computer screen. Two seconds later a beep chimed indicating to the user to start with the movement. In run 3, also a ball on the screen started to move. Additionally to the arm movement trials, we recorded two trials where we instructed the subjects to follow a moving ball on the screen with the eyes, but avoid any arm movement. These two trials were used to remove the influences of eye movements from the EEG with a linear regression method [8], and to calculate the noise covariance matrix used for source imaging (after removal of eye movements).

2.3 Recording

We recorded the EEG with 68 passive Ag/AgCl electrodes covering frontal, central and parietal areas, and the electrooculogram (EOG) with 3 electrodes placed above the nasion and the two outer canthi of the eyes. Reference was placed on the left mastoid, ground on the right mastoid. We assured that all impedances were below 5 kOhm. All biosignals were recorded with g.USBamp amplifiers (g.tec medical engineering GmbH, Schiedlberg, Austria). We applied an 8-th order Butterworth bandpass filter with cut off frequencies at 0.01 Hz and 100 Hz, a notch filter at 50 Hz, and then sampled the signals with 512 Hz. The position of the right hand was tracked with a Kinect sensor device (Microsoft, Redmond, US). Here, the x-axis was orientated leftward, y upward, and z backward with respect to the subject. We also recorded the electrode positions with a CMS 20 EP system (Zebris Medical GmbH, Isny, Germany).

2.4 Preprocessing

We computed the independent component analysis for each run in the frequency range 0.3 Hz – 70 Hz, using the extended infomax algorithm [4], and removed independent components suspected to be muscle or technical artefacts. Subsequently, we applied a zero-phase anti-aliasing filter and downsampled data to 16 Hz for computational convenience. Then we applied a zero-phase 4-th order Butterworth band-pass filter with cutoff frequencies interesting for decoding at 0.2 Hz and 2 Hz. Afterwards, we removed influences of eye movements on the EEG with a linear regression method [8], and removed samples exceeding a threshold of 5.9 times the median absolute deviation (MAD) of a channel to get rid of remaining artefacts. MAD is a robust deviation measure, and the threshold corresponds to 4 times the standard deviation when the data are normally distributed. Furthermore, we filtered the measured positions with the same band-pass filter as used for the EEG (i.e. 0.2 Hz – 2 Hz), and centered and scaled them to a standard deviation of one. Finally, we omitted the first 5 seconds of each trial to exclude possible existing movement onset effects.

2.5 Source Imaging

To transform the data from the sensor space into the source space we used the software Brainstorm [9]. We calculated the head model using the Colin27 model included in Brainstorm, and coregistered the electrode positions. Using the head model and a noise covariance matrix, we calculated 15028 brain sources with the weighted minimum norm estimation (wMNE) method. The noise covariance matrix was calculated from the two trials without arm movements after we removed eye movements from them.

2.6 Decoding

We analyzed all runs separately using a 10-fold cross-validation. For this purpose we divided each run in segments of 10 s length and assigned these segments to train and test sets. The decoder [6] itself comprised of 2 multiple linear regressions between a brain source (voxel) and the 2D position in the movement plane (frontal or lateral, respectively). We used the current time step and time lags at ca. 60, 130, 190 ms of the EEG as the input for the decoder. X and y positions were decoded in the frontal and ball runs, and y and z positions in the lateral run. We decoded the positions from the test sets, and calculated the Pearson correlation coefficients between the decoded and the measured 2D positions. Subsequently, we calculated the average of the correlation coefficients across the 10 test sets. Finally, we averaged the correlation coefficients over the movement plane dimensions, i.e. x/y or y/z, respectively. This procedure was performed for every single voxel, and we got one correlation coefficient for each voxel, run and subject.

To asses the chance level, we randomly permuted the coordinate segments and performed a 10-fold cross-validation as described above and repeated this procedure 50 times. Thus, we got 50 correlation coefficients for each voxel, run and subject, and then, fitted a normal distribution to these 50 chance correlation coefficients (this is reasonable as the correlation values are usually around 0 and not at the limits 1/-1). Subsequently, we calculated the p-values of the correlation coefficients based on the chance level distributions.

2.7 Results

The maximum correlation coefficient reached by a subject averaged over all subjects were (mean value/standard deviation) 0.47 ± 0.09 (frontal), 0.52 ± 0.13 (lateral), and 0.47 ± 0.10 (ball). The corresponding chance level correlations were 0.12 ± 0.03 (frontal), 0.12 ± 0.02 (lateral), and 0.11 ± 0.02 (ball). Figure 1 shows the subject averaged correlations of each voxel in each run and their average over the runs. Before averaging, all non-significant correlations were set to 0. Observable are higher correlations on the central and left motor cortex, parietal areas, and right lateral correlations.

3 Discussion

We have successfully decoded executed movements from frontal and lateral arm movements on a per brain source (voxel) basis. The subject averaged correlations indicate a contribution of the primary motor cortex. This was expected, as subjects executed movements. However, also contributions from parietal and lateral areas are observable. These contributions can be external sources projected onto the margins of the head model. Such an external source could be muscle activity, although muscle activity is thought to be most prominent in higher

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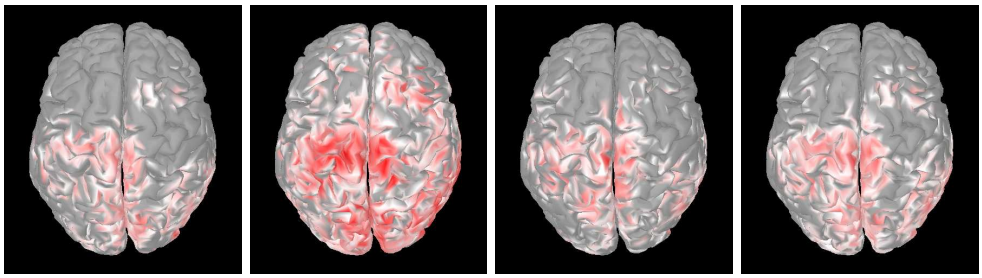

frontal run lateral run ball run average

Figure 1: Subject averaged correlations on a per voxel basis for all 3 runs and the average of them. Red corresponds to the maximum value of 0.33 in the lateral run, white to 50 % of the maximum value, and correlations below 50 % of the maximum are not shown.

frequency ranges. To summarize, the findings indicate that indeed brain sources carry decodable movement information, but the measurements are potentially contaminated by external sources.

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