Filling a Glass of Water: Continuously Decoding the Speed of 3D Hand Movements from EEG Signals

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***Abstract*— We present a new system for the continuous decoding of hand movement speed in three-dimensional (3D) space from EEG signals. We recorded experimental data of five subjects during mimicking the natural task of filling a glass of water. The proposed system uses filter bank common spatial patterns and linear regression to estimate the speed of hand movements from artifact cleaned EEG signals. Average Pearson correlations between the speed trajectories predicted from EEG and the speed trajectories measured using a high-precision motion tracking system are r=0.41 for the x-axis, r=0.36 for the y-axis, r=0.48 for the z-axis, and r=0.17 for absolute speed in 3D space.**

I. INTRODUCTION

In the last years, Brain Computer Interfaces (BCIs) have evolved into practical and useful applications for communication and control. In the near future, robotics devices, such as intelligent assistants and advanced prostheses will support healthy and severely movement-impaired people in their daily lives. Our vision is to combine methods for robot Programming by Demonstration (PbD) [1] and Brain Computer Interfaces, we term this concept *Programming by Imagination* (PbI). For example, this would be highly relevant for future applications in the health care domain as a method of teaching new skills to a (semi-autonomous) assistance robot for amyotrophic lateral sclerosis and locked-in patients. One crucial element for such a system is the decoding of hand movement kinematics from brain activity.

BCIs usually follow a pattern recognition approach to discriminate between a set of well studied discrete types of neural activations that can be classified with high accuracy using machine learning methods. However, such BCIs can only recognize a small set of predefined classes, such as different types of motor rhythms (e.g. discriminating motor imagery of left hand from right hand) or event related potentials (e.g. detecting P300 event related potentials). Historically, the application of EEG for BCIs is considered to be limited to such classification tasks because of its noise sensitivity and low spatial resolution. However, recent advances in the field of neuroengineering enabled EEG based BCIs that can continuously derive information about complex human behavior. Besides invasive approaches (e.g. [2], [3]), only very few research has challenged to decode hand movement kinematics from non-invasive EEG signals:

Fig. 1. A subject wearing EEG cap and sensor gloves during the experiment. The directions of the coordinate axes are illustrated.

Yuan et al. [4], [5] decoded the speed of executed and imagined hand clenching of different speeds. They found correlations between EEG activity in the alpha, beta, and gamma frequency bands and the speed of clenching. To decode speed from EEG signals, they developed a linear model based on time-frequency features. They compared the predicted speed trajectories of executed and imagined clenching with a bell-shaped profile as a reference signal. The average correlation coefficient between the reference profile and their decoding results was r=0.32. For the prediction of the active hand (left versus right) they achieved an average classification accuracy of 74 %. Bradberry et al. [6] continuously decoded hand movement speed from EEG signals collected from five subjects during a 3D center-out reaching task. They applied separate linear decoding models for hand speed in the three Cartesian axes. Using 34 out of 55 electrodes they achieved average Pearson correlations r=0.19, r=0.38, and r=0.32 between the measured and the predicted hand movement speed in the x, y, and z axes, respectively. Lv et al. [7] used a drawing task and reconstructed the speed of hand movements of five subjects from EEG signals. They used features from multiple frequency bands and applied Kalman filtering and smoothing. Pearson correlation between

This work was partly supported by the Deutsche Forschungsgemeinschaft (DFG) with the Collaborative Research Center 588 Humanoid Robots - Learning and Cooperating Multimodal Robots.

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the measured and the predicted speeds were r=0.37 for the horizontal and r=0.24 for the vertical dimension. They found that slow potentials (0.1-4 Hz) and oscillatory rhythms in (24-28 Hz) carried most information of hand movement speed.

The decoding of kinematics from EEG is still not sufficiently researched, especially experiments with natural daily life movements have not been investigated in the context of BCIs before. In this paper, we present a new method to decode the speed of hand movements from EEG signals using the filter bank common spatial patterns (FBCSP) algorithm to automatically select predictive frequency bands and spatial filters, which has not been applied to the decoding of movement kinematics before. We apply a strict artifact removal procedure based on EOG regression and Independent Component Analysis. For the evaluation of our system we recorded data from subjects filling water into a glass (see Figure 1), which is a more natural and complex movement task than those analyzed in previous studies.

II. METHODS

A. Experiments and Recording Setup

Five healthy, right-handed male subjects participated voluntarily in the experiment (ages 26-29 years). Their average score in the Edinburgh handedness scale was 78. None of them was trained to use BCIs.

Each subject performed 50 trials of the natural movement of filling water into a glass, while synchronized EEG, EOG, and hand position tracking were recorded. Figure 1 illustrates the task setup: An empty bottle and a glass were located approximately 30 cm from each other on a table. During the whole experiment the subjects were holding the glass in the left hand and the bottle in the right hand. Each trial was preceded by a 0.8-3.5 seconds resting period. After that, subjects used their right hand to lift, move and turn the bottle in order to mimic filling water into the glass, waited for a short while, and put the bottle back to its original position. Trials and preceding resting periods were labeled manually during the experiment. Each trial took about 5 seconds. After the experiment, all motion trajectories have been visually screened and 15 % of the trials have been excluded from further analyzes because of incorrectly labeled trajectories.

EEG, as well as horizontal and vertical EOG, were recorded using a 32 channels active electrode system (actiChamp, BrainProducts) at 1 kHz sampling rate. Hand positions in 3D space were tracked using a Flock of Birds motion tracking system (Ascension Technology) at 30 Hz sampling rate. The tracking system uses a DC magnetic field to locate the position of the sensor gloves the subject is wearing. It has a very high precision and in comparison to visual tracking systems, there are no problems with occlusion of markers, which makes the method suitable for complex tracking tasks.

B. Artifact Removal

Artifact removal is absolutely crucial for the processing of the data of this experiment. To record high quality signals that contain only small motion artifacts, we used an active electrode system. Most non-brain influences on the EEG signals come from eye movements, muscle activity (mainly arm and neck), as well as humming induced by the magnetic field of the motion tracking system. The influence of the magnetic tracker can be identified as a strong, sharp peak in the spectrum at 34 Hz, and higher frequency harmonics. We removed these disturbances by low-pass filtering the data at 30 Hz using FFT based filtering. For the reduction of eye activity artifacts we applied EOG correction based on linear regression [8] using horizontal and vertical EOG recordings of the left eye. We computed the Independent Component Analysis (ICA) based on the extended Infomax algorithm (runica [9]) to transform the EEG signals into ICA space. All ICA components were carefully checked for characteristic artifact properties of their time domain signals, scalp topographies, and power spectral densities. To identify artifact components, we applied a similar approach as described in Lv et al. [7] and applied criteria from [10], [11], [12], such as spectral power bursts in frequencies above 20 Hz indicating muscle activity, or low frequency frontal activity caused by eye movement artifacts. All ICA components containing artifact activity were removed during the inverse ICA transformation back into the original EEG electrode space by setting their contribution in the inverse transformation matrix to zero (see [9] for details). We decided for a strongly restrictive artifact removal procedure, i.e. 16-22 of 31 ICA components have been removed from the recordings of the different subjects. We also removed some mixed components consisting of brain activity and artifacts to ensure that only clean brain activity signal parts are used. The absolute correlation coefficients between all remaining ICA components and horizontal as well as vertical EOG channels, were checked to be smaller than r=0.05.

C. Hand Speed Decoding from EEG

After artifact removal, independent linear regression models were trained and evaluated for the x, y, and z axes, as well as absolute hand movement speed.

Frequency filtering and spatial filtering are important preprocessing steps for BCI applications to reduce volume conduction effects and emphasize activity in relevant brain areas. Therefore, we applied the multiclass filter bank common spatial patterns (FBCSP) algorithm [13], [14], which we applied to the prediction of continuous outputs instead of multiclass classification as originally proposed. FBCSP is one of the most effective BCI methods and was the winning approach for multiple tasks in BCI Competition IV [15]. For the training of FBCSP, we split the recorded EEG data into three classes: hand movements in positive axis direction, hand movements in negative axis direction, and no hand movements. A speed threshold of $1.5\frac{cm}{sec}$ was used to determine the classes. Then, we applied a filter bank of 4 Hz wide bandpass filters between 1 and 28 Hz (1-4 Hz, 4-8 Hz, 8-12 Hz, 12-16 Hz, 16-20 Hz, 20-24 Hz, and 24-28 Hz). From the frequency filtered data, we calculated common spatial patterns [16] using a 1-vs-rest

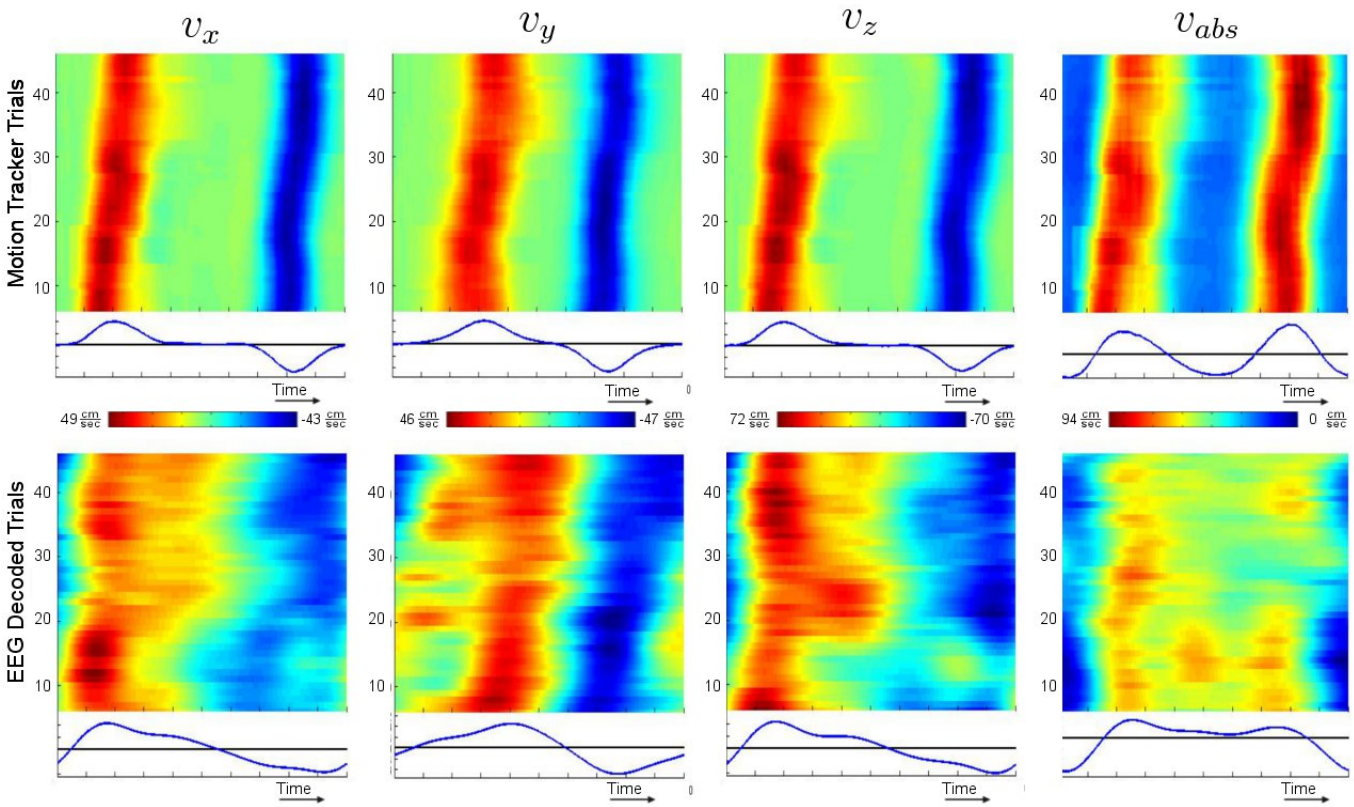

Fig. 2. Trial images showing all speed trajectories of subject 2. Each row in each image corresponds to one trial. The average trajectory is plotted below each image. Top: Trajectories of right hand speed measured by the motion tracking system in the x-axis (v_x), y-axis (v_y), z-axis (v_z), and absolute speed (v_{abs}). Bottom: Hand movement speed trajectories predicted from EEG signals. Trials are scaled to equal length and speed trajectories are z-normalized.

multiclass scheme [14]. The two most discriminative spatial filters for each of the three classes (first and second columns of the CSP transformation matrix) were then applied to transform the training data (see e.g. [14] for details). From the transformed data, logarithmic variance features were calculated. We selected the spatial filters that had the highest mutual information between their calculated features and the hand movement speed measured by the motion tracker using kernel estimation based mutual information feature selection (MIBIF algorithm [13]). Considering the distribution of the calculated mutual information values, we decided to select $d = 10$ of the 42 generated spatial filters (7 frequency bands x 2 filters x 3 classes) for the experiments in this paper.

After frequency and spatial filtering, logarithmic variance features were calculated sample-wise using a sliding window of 1 second length, which appeared to result in a reasonable smoothing without loosing too much temporal resolution.

Continuous speed estimates $\hat{v}_t$ at sample number t were decoded from the EEG features using linear regression. Before training the regression models, EEG features were downsampled to 100 Hz, which enables the regression model to capture a larger time interval with a small model order and reduces computational cost. We modeled the relationship between the calculated EEG features (independent variables $f_{1,t}, ..., f_{d,t}$) and the hand movement speed measured by the motion tracking system (dependent variable v_t) using a 1st order multilinear regression model: $\hat{v}_t = \beta_0 + \sum_{i=1}^{d} \beta_i f_{i,t}$. The model coefficients β_j were estimated using the least squares criterion.

In a final post-processing step the decoded hand speed trajectories were smoothed by low-pass filtering at 1 Hz.

III. RESULTS

To evaluate the system performance, we applied a 10 fold cross-validation. In each of its iterations, all parameters for hand speed decoding (i.e. CSP filters and regression model coefficients) were learned from the training data and applied to the evaluation data.

Pearson correlation coefficients were calculated between the trajectories measured by the motion tracker and those predicted by the EEG decoding system and were averaged over all folds of the 10 fold cross-validation. Figure 3 shows the Pearson correlation results of all three axes (v_x, v_y, v_z), and of absolute hand speed ($v_{abs} = \sqrt{v_x^2 + v_y^2 + v_z^2}$). The axial directions are illustrated in Figure 1. Correlation coefficients averaged across all subjects are r=0.41, r=0.36, r=0.48, and r=0.17, for the x, y, z axes, and absolute speed, respectively. One-tailed t-tests of the correlations against r≠0 across the cross-validation folds are significant ($p < 0.01$). The average variance of the correlations across cross-validation folds is rather high ($\bar{\sigma}^2 = 0.011$), which can be explained by poor performance of few cross-validation folds, where the predicted hand speed trajectories are delayed or nearly no speed change is detected by the decoder (for example Figure 2 v_z trials 10-15). Nearly all correlations of the four conditions are significant in all 10 cross-validation

folds ($p < 0.0001$). Paired t-tests show that v_x, v_y, and v_z have significantly larger correlation coefficients than v_{abs} ($p < 0.01$), which indicates that movement speed in the x, y, and z axes appears to be easier to decode from brain activity than absolute movement speed.

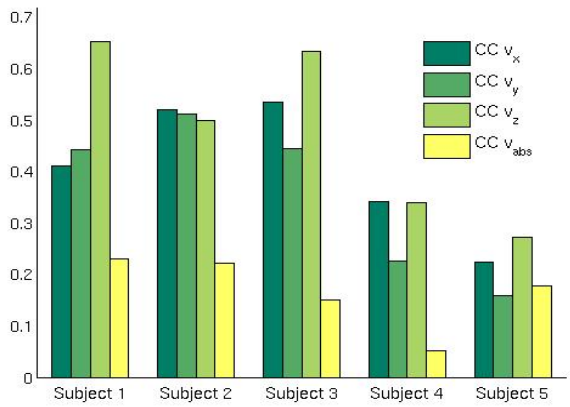

Fig. 3. Pearson correlation coefficients (CC) between speed trajectories measured by the motion tracker and predictions from EEG. Axial directions as in Figure 1.

Figure 2 shows the decoding performance of subject 2 in more detail. In Figure 2 top, the hand speed trajectories measured by the motion tracker are illustrated. Speed trajectories in the three axes and absolute speed are shown in separate plots. Each image shows all trials of the experiment, i.e. each row of an image corresponds to one trial of filling water into the glass. The curve below each image shows the speed trajectory averaged over all trials. Plots are scaled to equal length and speed trajectories are standardized to zero mean and unit standard deviation (z-normalized). Figure 2 bottom shows the corresponding speed trajectory predictions from EEG data of the proposed decoding system as trial images. Below each image, their averaged speed trajectories are shown.

The artifact removal procedure is a very important processing step, since systematic task dependent artifacts have a strong influence on the system at most of the subjects. Obmitting it, results in an absolute (relative) difference of the average correlation coefficients $\Delta r = 0.16$ (36%), $\Delta r = 0.14$ (28%), $\Delta r = -0.05$ (-8%), $\Delta r = -0.04$ (-23%), $\Delta r = 0.12$ (45%), for the five subjects respectively.

The FBCSP algorithm has the advantage that relevant signal parts are identified automatically and no expert knowledge is required to identify predictive electrode locations and frequencies, which is an important property for potential applications. The FBCSP algorithm most frequently selected CSP filters in the frequency range of slow potentials (1-4 Hz) and high beta activity (24-28 Hz), i.e. these frequency bands contain most mutual information between the EEG features and the measured speed trajectories. This supports the findings of Lv et al. [7], who also reported these frequency ranges to carry most information of hand speed in their experiments.

IV. DISCUSSION

In this paper, we showed that complex movement kinematics of natural motor actions, such as 3D hand movement speed during filling a glass of water, can be decoded from non-invasive EEG signals. In most of the trials, the shapes of the predicted speed trajectories strongly resemble those measured by the high-precision motion tracking system. Positive and negative speed trajectory parts can clearly be identified, which correspond, for example in the y-axis, to hand movements towards the direction of the glass and back again. The proposed decoding algorithm can be applied in real-time for online applications.

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