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Decoding of full 3D finger trajectories from EEG data

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Abstract. Brain-Machine interfaces and neural prosthesis use the electrical activity generated by cortical neurons in the brain for controlling external devices such as robotic arms. While many research is based on the invasive recording of the brain electrical activity, very few studies have addressed the possibility of generating the control from non-invasive measurements. In this work we study the 3D decoding of the fingertip motion based on non-invasive EEG signals during self-selected and self-initiated reaching movement task. Several strategies of decoding are studied, temporal or time-frequency information of the EEG signals, position or velocity data of the fingertip motion and the partial least squares regression and support vector regression algorithms. The preliminary results reveal positive correlation between the observed and the reconstructed velocities of the fingertip.

Keywords: electroencephalography (EEG), brain-machine interface (BMI), non-invasive neural prosthesis, decoding model.

1. Introduction

Previous studies have demonstrated that electromagnetic brain signals contain sufficient and reliable information that encodes motor information about arms dynamics such as direction, position and velocity. These results have revealed a great potential of use for brain-machine interfaces and neural prosthesis. On the one hand, most of these works are based on invasive techniques to record the brain electrical activity [Andersena et al., 2004]. On the other hand, the decoding of motor information using non-invasive electroencephalographic signals (EEG) is mainly based on the classification of different imagined or executed discrete movement patterns. However, a more natural control of a non-invasive neural prosthesis requires the full continuous decoding of the movement trajectories. Recently, some studies have revealed the feasibility of reconstructing 3D trajectories of the hand from EEG signals [Bradberry et al., 2010] and the relationship between hand speed and EEG activity [Yuan et al., 2010].

This work proposes an EEG-based trajectory decoding paradigm for self-selected and self-initiated reaching movements of the hand. During the experimentation protocol the EEG activity and the arms joints and fingertip motion data were simultaneously recorded while the participants performed movements of the hand form an initial point to several fixed and free target points. The decoding model was trained with temporal or time-frequency information of the EEG activity and with position and velocity information of the fingertip. The preliminary results indicate that the decoding model is able to reconstruct, not only movements of the hand towards predefined fixed targets points, but also movements of the hand towards self-chosen free targets points.

2. Materials and Methods

2.1. Experimental protocol

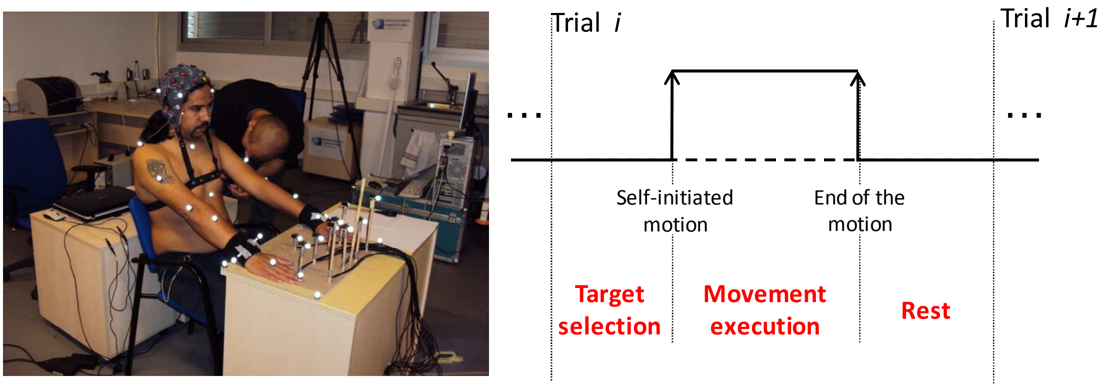
Seven right-handed male healthy subjects participated during a reaching task in which the fingertip is moved from an initial point to several target points within the 3D field vision. The subjects were instructed to perform random natural movements of the hand from the start point to *(i)* eight fixed target points ***(fixed target task)*** and *(ii)* any self-chosen 3D point in the continuous space of the near field vision ***(free target task)***. The targets were self-selected and the movements were self-initiated. Subjects were asked to maintain the gaze at a fixed point, do not blink and do not move the eyes and the body during the mental target selection and movement execution.

Fig. 1 shows a snapshot of the experimental setup and a time diagram of the realization of one trial. ~200 trials per target were acquired in the fixed target task while ~80 trials were recorded in the free target task.

2.2. Data recording and preprocessing

EEG signals from 28 electrodes and vertical and horizontal EOG were recorded at a sampling frequency of 256Hz and band-pass filtered from 0 to 60Hz. A 3D VICON motion recording system was used to simultaneously record the position of visual markers placed in the head, shoulder, arms joints and in the right fingertip at a sampling frequency of 100Hz (see Fig. 1a). Push bottoms in the start point and in the eight fixed target points serve as event markers for both recording systems.

In the preprocessing, the EEG data was re-sampled at 100Hz, noisy trials were discharged by visual inspection and an ICA-based EEG artifact rejection was performed. Position data was referenced to the head center and the velocity was then calculated by numerical integration.



(a) (b)

Figure 1. *(a) Snapshot of the experimental setup. (b) Time sequence of the task execution.*

2.3. Decoding model

In order to reconstruct the motion of the fingertip from the EEG information, a decoding model has to be trained, where the predictor is the EEG information and the prediction is the motion information of the fingertip.

Two different types of characteristics of the EEG were studied as predictor data, first, the temporal information of the EEG signals (following), and second, the time-frequency representations of the EEG signals based on wavelet transform (following Chao et al., 2010]). Two types of prediction data were also studied, first, the position, and second, the velocity of the fingertip. Finally, the partial least squares regression (PLS) [Wold et al., 1984] and support vector regression (SVR) [Smola and Bernhard, 2003] algorithms were used as decoding techniques.

Several schemes of decoding model have been studied, *(i)* prediction data is the position of the fingertip and the predictor data is either the temporal information or the time-frequency information of the EEG signals, *(ii)* prediction data is the velocity of the fingertip and the predictor data is either the temporal information or the time-frequency information of the EEG signals, and *(iii)* when the decoding technique is either the PLS or the SVR algorithm. Note that, an individual decoding model is constructed for each of the three variables of the fingertip position or velocity.

This work focuses in two schemes of decoding model, the prediction data is the velocity of the fingertip, the decoding technique is PLS algorithm and the predictor data is the temporal information or the time-frequency information of the EEG.

3. Results

For the two selected schemes of decoding model, a 10-fold cross validation process was performed with data from the fixed targets task. The performance was evaluated in terms of the correlation coefficient between the predicted and observed velocities. The mean and standard deviation of the correlation coefficient was computed across the validation folds. Fig. 2 shows the decoding accuracy for both schemes. These results reveal two characteristics, the positive correlation between the observed and the reconstructed velocities and the high accuracy in the decoding of some velocities trials (revealed by the large values in the standard deviation).

In order to study the proportion of trials reconstructed with high or low decoding accuracy, the percentage of trials versus different ranges of correlation coefficient was computed in both decoding models and Fig. 3 shows these results. For the case of decoding model based on temporal information of the EEG, the mayor percentage of trials is reconstructed with accuracy below 0.2; on the contrary, for the case of decoding model based on time-frequency information of the EEG, the mayor percentage of trials is reconstructed with accuracy between 0.2 and 0.4. Note that in both cases, some trials are reconstructed with high accuracy.

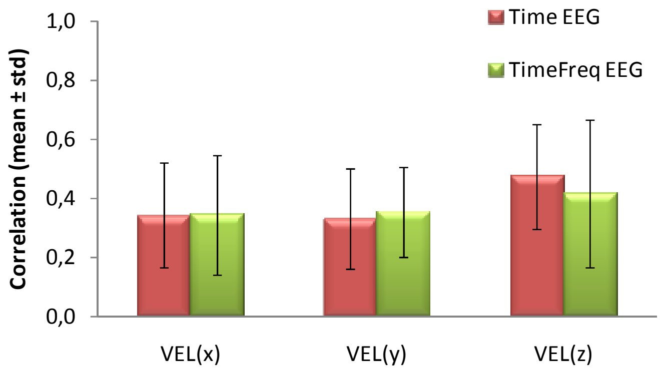


Figure 2. *Decoding accuracy of the fingertip velocity components from temporal characteristics of the EEG (red bars) and time-frequency representations of the EEG (green bars). Mean and standard deviation results of the ten-fold cross validation process with data from the fixed targets task.*

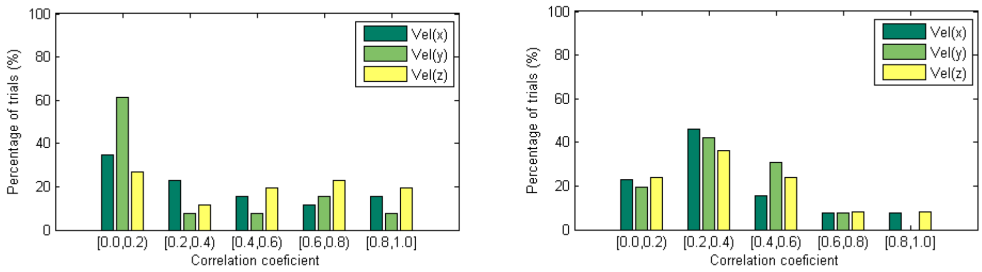


Figure 3. *Percentage of trias versus correlation coeficient for the case of (a) decoding model based on temporal information of the EEG and (b) decoding model based on time-frequency information of the EEG.*

In addition, the importance of the sensors in the decoding process was measured in terms of the magnitude of the regression coefficients. This analysis showed that sensors placed over the left motor cortex (contralateral to the moving hand) have the greatest contribution in the decoding process.

In order to study the generalization capability, the decoding model was trained with the entire information of the temporal EEG and velocity data recorded from fixed targets task, and then it was validated with the data recorded from free targets task. Results indicate that decoding accuracy in a continuous space when the training is performed in a discrete space is lower. Further studies have to be done to better generalize velocity profiles in a continuous space.

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