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Hand movement decoding by phase-locking low frequency EEG signals

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***Abstract*—Being noninvasive, low-risk and inexpensive, EEG is a promising methodology in the application of human Brain Computer Interface (BCI) to help those with motor dysfunctions. Here we employed a center-out task paradigm to study the decoding of hand velocity in the EEG recording. We tested the hypothesis using a linear regression model and found a significant correlation between velocity and the low-pass filtered EEG signal (<2 Hz). The low-pass filtered EEG was not only tuned to the direction but also phase-locked to the amplitude of velocity. This suggests an EEG form of the neuronal population vector theory, which is considered to encode limb kinematic information, and provides a new method of BCI implementation.**

I. Introduction

IT has long been proven that the neuronal activity achieved by invasive recording methodologies contains limb kinematic information [1][2]. This has prompted the implementation of refined Brain Computer Interface (BCI) systems in animal studies [3]. Although impeded by its low spatial resolution and signal-noise ratio, EEG is promising in human applications for its noninvasive advantages such as reliability, low risk and cost. Thus, work in EEG-based BCI has gained intense attention in the past decades. It has been found that modulation of sensory-motor rhythms (SMR) such as event-related synchronization or desynchronization (ERS/ERD) can be implemented by subjects performing certain types of motor imagery tasks [4]-[7]. Advanced EEG based BCI systems have been demonstrated in 3D movement control [8][9]. However, as a representation of the underlying neuronal activity, which encodes the direction and speed of movement [1], EEG should carry richer information beyond the scope of event-related patterns.

Here, we employed a center-out reaching task to investigate the relationship between the EEG signal and hand velocity using a linear multiple regression model and explored the temporal processes of EEG, which may co-vary with that of velocity.

II. Materials and Methods

A. Experiments

Four healthy subjects (three female and one male) between the ages of 20 and 24 years old were recruited in this study. The study protocol was approved by the Institutional Review Board of the University of Minnesota. Informed consent was obtained from all subjects prior to the study.

Subjects sat comfortably in front of a cuboid structure and were instructed to perform the center-out task to reach the targets distributed at the eight corners of the cuboid (Fig. 1A). Each run was composed of 16 trials, which were equally and randomly arranged among the eight targets. During each trial, subjects began with a rest period with their right forearm in the center of the cuboid and focusing on a fixation in the middle of the screen. After 3 s, the target was presented in one of the corners while the subjects were indicated by a countdown sequence to prepare for movement initiation. Following another 4.5 s, the countdown sequence disappeared and a beeping sound directed the subject to move their hand toward the target. In order to synchronize the movements across trials, a second beep was used after another 1.5 s to mark the time when the subject should reach the target. Once the subjects had reached the target, they moved their hand back toward the center to finish the trial while a third beep sounded 1.5 s after the second beep. The experimental paradigm is shown in Fig. 1. At least 50 trials per target were conducted for each subject.

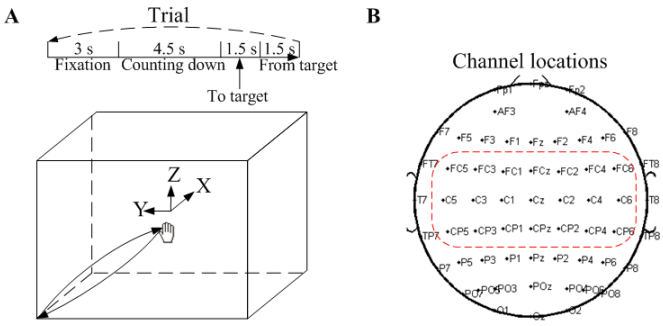

Figure 1. (A) Top: the continuous timing of events in a trial; bottom: an illustration of the hand trajectory during one trial. X, Y and Z show the positive direction of the movement within the space. (B) The distribution of electrodes on the EEG cap. The red box shows the motor area and the electrodes within this area.

The EEG data was collected using a 68-channel cap and SynAmps2 amplifier (Neuroscan Compumedics) at a sampling rate of 1000 Hz. Among the 68 available electrodes, 62 were used as signal channels and two channels recorded EOG activities for later ocular correction Hand movement was recorded using a Polaris Vicra system (Northern Digital

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Inc) at a sampling rate of 20 Hz. Both data streams were synchronized by a control computer for future analysis.

B. Data processing

Hand movements were visually inspected to reject trials with unexpected movement. The continuous EEG data was preprocessed to remove the effect caused by eye blinks and movements [10] and the common average of all electrodes was removed from each electrode. The EEG data were then filtered between 0.05 and 70 Hz and resampled at a rate of 200 Hz. These EEG preprocessing procedures were accomplished using Analyzer 2 software (Brain Products). Baseline periods were chosen as the time when the fixation screen was presented. To reduce the effect caused by the baseline drift, the mean of the baseline period of each trial was subtracted from the EEG of that trial.

C. Decoding model

A linear multiple regression model was used to decode the relation between velocity and EEG [11][12]. The model is described in equations (1) ~ (3).

$$V_x(t) = a_x + \sum_{i=1}^{21}\sum_{k=0}^{19} b_{xik} S_i(t-k) \quad (1)$$

$$V_y(t) = a_y + \sum_{i=1}^{21}\sum_{k=0}^{19} b_{yik} S_i(t-k) \quad (2)$$

$$V_z(t) = a_z + \sum_{i=1}^{21}\sum_{k=0}^{19} b_{zik} S_i(t-k) \quad (3)$$

Here, $V_x(t)$, $V_y(t)$ and $V_z(t)$ are the velocities at time t in the X-, Y- and Z- directions, respectively, calculated as the difference between the hand position at t and t-1; a_x, a_y and a_z are constants; b_{xik}, b_{yik} and b_{zik} are the regression coefficients of electrode i at time lag k for the X-, Y- and Z-directions, respectively; $S_i(t)$ is the EEG potential of electrode i at time t (potentials with a time lag between 0 and 19 were used for decoding); the number 21 is the number of electrodes used here which cover the motor area (Fig. 1B).

D. Data analysis

To prevent an overfitting of the model, we carried out a 10-fold cross-validation in which the data were divided into 10 "folds." For each turn, nine folds were used as the training set for calculating the model coefficients while the remaining fold was used as a testing set. The decoded velocity and actual velocity in the testing set were compared by their squared correlation coefficients (r^2). Higher r^2 values were interpreted as better decoding performances.

We induced two control groups of EEG data to strengthen the conclusion made from the values of r^2. The first group was defined as "trial-shuffled EEG" in which the original EEG data from different trials were shuffled. The second group was defined as "phase-shuffled EEG" and was formed by shuffling the phase of each Fourier component within the trials. Comparing the r^2 between the actual EEG and control EEG allowed us to evaluate the decoding capability of the data.

The EEG was filtered using a zero-phase shift filter in several frequency bands: the lower δ band (<2 Hz), upper δ band (2~4 Hz), θ band (4~7 Hz), α band (8~12 Hz), β band (12~30 Hz) and γ band (> 30 Hz). Decoding was performed on the EEG signal in these bands to evaluate the decoding capability separately.

We aligned the EEG according to the onset of hand movement and averaged out those with the same target in the frequency band with the highest r^2. We compared the trial-averaged EEG signal with the time profile of speed in each direction to discover whether there were any temporal patterns phase-locked to that of speed.

III. Results

A. Decoding of velocity in different frequency bands

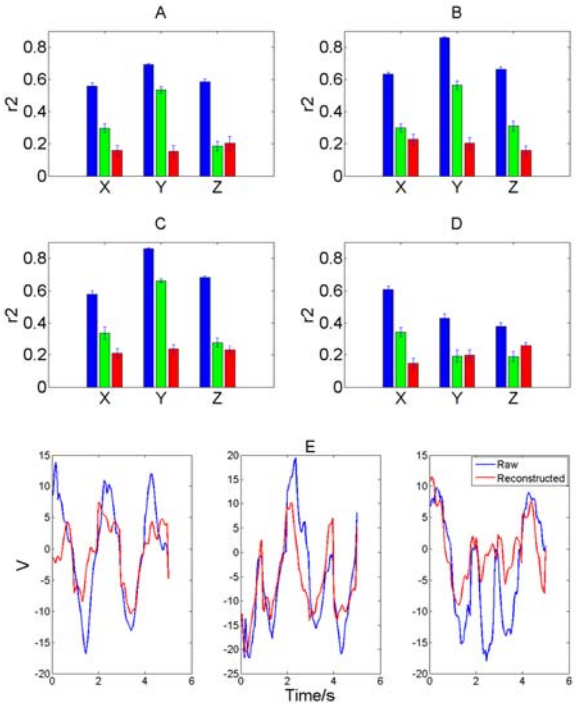

Figure 2. Comparison of the decoding perfomance between the actual EEG data and the shuffled EEG in the lower δ band (<2 Hz). (A)~(D) The squared correlation coefficients of four subjects in the X-, Y- and Z-directions: original EEG (blue), phase-shuffled EEG (green) and trial-shuffled EEG (red). Error bar: the standard deviation of the correlation coefficient across folds of the cross-validation. (E) The comparison between the raw velocity and the reconstructed velocity of the subject shown in panel (B) decoded using the lower δ band EEG. Velocities of X-, Y- and Z-directions are from the left to the right, respectively.

In all four subjects, the lower δ band EEG signal contributed significantly to the decoding of velocity. The r^2 in the X-, Y- and Z-directions were all significantly higher than those of the trial-shuffled decoding ($p<10^{-8}$; Fig. 2). For subjects A-C, the Y-direction, i.e. the left-right direction, displayed higher r^2 than the other two directions. The highest observed r^2 was 0.76.

The higher frequency bands, from upper δ to γ, exhibited poor decoding ability. The absolute ranges of r^2 were low compared to those of the lower δ band. Most did not show a significant difference from the trial-shuffled control group (Fig. 3).

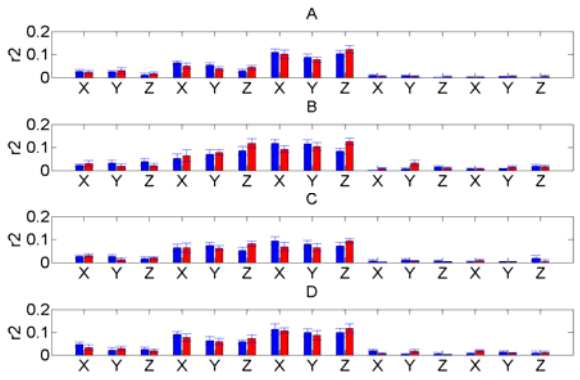

Figure 3. Comparison of the decoding perfomance between the actual EEG data and the trial-shuffled EEG in the upper δ, θ, α, β and γ bands. (A)~(D) The squared correlation coefficients of four subjects in the X-, Y- and Z-directions: original EEG (blue) and trial-shuffled EEG (red). The bar graph repeats in the order from upper δ to γ bands for each subject. Error bar: the standard deviation of the correlation coefficient across folds of the cross-validation.

B. Phase-locking pattern in the lower δ band

As shown in Fig. 2, the phase-shuffled EEG group significantly reduced the r^2 in all directions of all subjects in the lower δ band ($p<10^{-11}$). This suggests that the phase information within the lower δ band EEG is important for decoding velocity. We did not provide the phase-shuffled group for other frequency bands (Fig. 3) because of the correspondingly poor decoding of the original EEG.

IV. Discussion

A significant correlation and phase locking between the velocity time course and lower δ band EEG signal (<2 Hz) are revealed in this paper. In the current study, the spectral power of hand velocity was within the range of the lower δ band. Moran et al. [1] has reported that the speed profile is highly correlated with the averaged firing rate of neuronal populations using the method of single-neuron recording in nonhuman primates. More recently it has been reported by Jerbi et al. [13] that the low frequency MEG is phase-locked to hand kinematics. These findings raise the hypothesis that the lower δ EEG is the equivalence of the summation of related motor cortex activities.

Event-related desynchronization or synchronization (ERD/ERS) [14][15] has been widely accepted as the indication of motor activation or deactivation and has been used in BCI applications. Although the spatio-temporal patterns of this low frequency EEG signal resemble ERD/ERS and both convey limb kinematics [16], it is not clear whether they originate from the same neuronal substrate since ERD/ERS is the change in frequency spectrum primarily found in α and β bands and no evidence has directly linked them together. Moreover, the low frequency EEG carries more information than the contralaterality-related brain function as shown by the X- and Z-direction decoding.

In summary, our findings suggest that limb kinematics may be decoded in the temporal processes of the low frequency EEG signal as an integrative representation of lower level neuronal activities. This may extend our understanding of the control signal used in BCI applications.

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