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EEG-Based Online Two-Dimensional Cursor Control

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***Abstract*— This study aims to explore whether human intentions to move or cease to move right and left hands can provide four spatiotemporal patterns in single-trial non-invasive EEG signals to achieve a two-dimensional cursor control. Subjects performed motor tasks by either physical movement or motor imagery. Spatial filtering, temporal filtering, feature selection and classification methods were explored to support accurate computer pattern recognition. The performance was evaluated by both offline classification and online two-dimensional cursor control. Event-related desynchronization (ERD) and post-movement event-related synchronization (ERS) were observed on the contralateral hemisphere to the moving hand for both physical movement and motor imagery. The offline classification of four motor tasks provided 10-fold cross-validation accuracy as high as 88% for physical movement and 73% for motor imagery. Subjects participating in experiments with physical movement were able to complete the online game with the average accuracy of 85.5±4.65%; Subjects participating in motor imagery study also completed the game successfully. The proposed brain-computer interface (BCI) provided a new practical multi-dimensional method by noninvasive EEG signal associated with human natural behavior, which does not need long-term training.**

I. Introduction

THE brain-computer interface (BCI) enables direct brain communication with the external environment for patients who partly or entirely lose voluntary muscle contraction, i.e. in the 'locked-in' state [1]. Most BCI applications need multidimensional control, which is highly promising using invasive methods [2, 3], or semi-invasive methods using electrocorticography (ECoG) [4]. However, the noninvasive methods, in particular, electroencephalography (EEG), mainly support one dimensional (binary) control [5, 6]. Successful two-dimensional BCI using noninvasive EEG signals [7] required long-term training for the subjects before attaining reliable two-dimensional control. Sequential combination of one-dimensional control may achieve two-dimensional control [8, 9], however, direct two-dimensional control will be more effective and convenient for patients with movement disorders.

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Human limbs are controlled by contralateral brain hemispheres [10-12]. During physical movement or motor imagery of right and left hand movements, beta band brain activation (15-30 Hz), i.e. event-related desynchronization (ERD) occurs predominantly over the contralateral hemispheres; the brain activity associated with ceasing to move, event-related synchronization (ERS) can also be found over the contralateral motor areas. Therefore, reliably decoding the movement intention of right and left hand, which are associated with different spatiotemporal patterns, may potentially provide four reliable features for two-dimensional control.

The aim of this study is to introduce a novel BCI paradigm/method: decoding ERD and ERS associated with natural motor behavior so that the subjects can control cursor movement in a two-dimensional plane with minimal training. We have tested whether the decoding of multiple movement intentions is reliable enough to control a two-dimensional computer cursor for a possible multi-dimensional brain-computer interface (BCI). The robustness of two-dimensional cursor control has been tested with an online virtual computer game.

II. METHOD

A. Subjects

Five right-handed healthy volunteers participated in this study. All subjects gave informed consent. The protocol was approved by the Institutional Review Board.

B. Experimental paradigm

All subjects participated in the first session, i.e. motor execution with physical movement. Two subjects (S1 and S2) also participated in the second session, i.e. motor imagery. During the recording, subjects were seated in a chair with the forearms semi-flexed and supported by a pillow. They were asked to keep relaxed during the experiment. During motor imagery, one of the authors monitored EMG activity and remind subjects to relax their muscle when EMG presented. Trials with EMG contamination were excluded from further analysis. Each of the motor execution with physical movement and motor imagery sessions contained an initial calibration step to determine the optimal frequency band and spatial channels. The selected features and generated model were then used to test an online two-dimensional-cursor-control game. Duration of calibration session was about 1 hour, where about 3 to 4 datasets were recorded, each of which contained 48 trials of movements.

During calibration, visual stimuli were periodically presented on a computer screen. In the first session (physical movement), there were four cues in the task paradigm, 'RYes', 'RNo', 'LYes', and 'LNo' ('R' indicating right hand task, and 'L' for left hand task). The visual cue was displayed for a T1 period in green color, followed by a color change of the cue to blue color. The second cue was displayed for a T2 period, after which the cue disappeared. T1 and T2 window were set to 2.5 s initially. Subjects were instructed to begin repetitive wrist extensions of the right arm at the onset of the initial cue 'RYes' or 'RNo'. At the time of color change, the subject was instructed to continue movement with the 'Yes' cue or abruptly relax and stop moving with the 'No' cue. The task was similar for 'LYes' and 'LNo', where subjects used left hand instead. In the second session, subjects imagined the tasks following the corresponding cues onsets.

In a 2D plane, the cursor may move to four directions: up, down, right and left, each of which was linked to one of the four movement tasks. We intended to decode movement intentions to determine the subject's control of cursor direction. The detection strategy was shown in Fig. 1. For example, if the subject wanted to move the cursor to the right, he needed to perform the 'RYes' task, either physical or motor imagery so as to develop an ERD pattern on the left hemisphere.

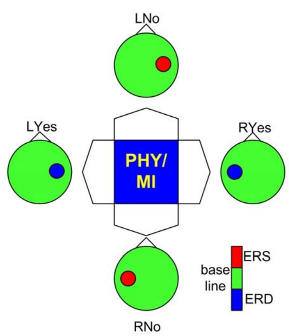

Figure 1. Scheme of 2D cursor control. Four directions control by spatial detection of ERD/ERS on right/left hemisphere associated with intention to move or cease to move of left/right hand. In order to control cursor moving to left ('LYes' direction), subjects may perform sustained physical movement/motor imagery so that ERD on the right hemisphere can be detected. It is similar for other direction controls.

Upon successfully decoding movement intentions in the offline analysis, the subjects played a game of two-dimensional control of cursor movement on a computer monitor. A brief description of the 2D cursor-control game is given here since the detailed design of the online game was similar to the one given for binary cursor-control game [9]. Subjects were instructed to move the cursor to the target and avoid a designated 'trap'. Cues were presented with the same duration as that in the calibration session. Classification of 'Yes' and 'No' trials of right and left hands were used to direct 2D control correlated with cursor movement. As illustrated in Fig. 1, the detection of 'LYes' will direct the cursor move to the left, and similar with the other directions.

In the 2D game, subjects determined the path to reach the target using their own game strategy. From the example shown in Fig. 2(a), the subject may choose to move to the right instead of downward in that situation. It was also possible that the subject would choose to move up to the margin of the grid and then move along the margin to the target. Due to the various strategies, it was difficult to determine the cursor-control accuracy from the path of the cursor movement. In the case of physical movement, we used the EMG activity in the detection window to interpret whether the subjects desired to move to one of four directions, and as a result, the control accuracy could be determined from the actual cursor movement from the EEG derived results. However, as there was no EMG activity in the sessions of motor imagery, we were unable to calculate the control accuracy. We evaluated the success of the two-dimensional cursor control with motor imagery by whether the subjects could control the cursor to reach the target.

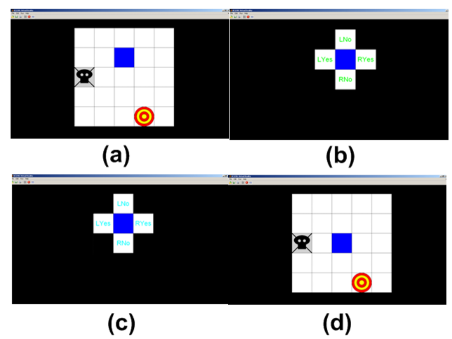

Figure 2. Paradigm of two-dimensional cursor-control game. (a) A game grid is displayed for 2-3 s showing a cursor (blue), target (red) and trap (black). (b) All squares except those adjacent to the cursor are masked and green prompts are displayed in the adjacent squares. (c) After a T1 delay, these prompts turn blue and remain for a period of T2. (d) The subject's response uniquely determines the cursor movement direction, which the cursor slides to. The entire process (a)-(d) then repeats for the next cursor move, and so on until the target is obtained, the trap is hit or too many moves have been made.

C. Recording and data processing system

EEG was recorded from 27 (tin) surface electrodes (F3, F7, C3A, C1, C3, C5, T3, C3P, P3, T5, F4, F8, C4A, C2, C4, C6, T4, C4P, P4, T6, FPZ, FZ, FCZ, CZ, CZP, PZ and OZ) attached on an elastic cap (Electro-Cap International, Inc., Eaton, OH, U.S.A.) according to the international 10-20 system [13]. Surface electromyography (EMG) was used to monitor the movement and electrodes for bipolar electrooculogram (EOG) were also pasted. Signals from all the channels were amplified (g.tec GmgH, Schiedlberg, Austria), filtered (0.1-100 Hz) and digitized (sampling frequency was 250 Hz). The digital signal was online processed using a home-made MATLAB (MathWorks, Natick, MA) Toolbox: brain-computer interface to virtual reality or BCI2VR [8, 9].

D. Computational methods for decoding movement intention

We employed intensive computational methods . The online signal processing to decode movement intention consists of four steps: (1) spatial filtering, where surface laplacian derivation (SLD) was applied. (2) temporal filtering: the power spectral density was estimated from the T2 window to distinguish ERD/ERS. Welch method was applied. We found that 4 Hz band-width under 50% overlapping segments provided a better ERD and ERS estimation for accurate 2D cursor control. (3) feature extraction: we reduced the channel number from 29 to 14, which covered both left and right motor area, and only alpha and beta band (8-30 Hz) activities were extracted for modeling and classification. Genetic algorithm with Mahalanobis linear distance (MLD) classifier was applied for feature evaluation. (4) classification: GA-MLD, Decision tree classifier (DTC), and Support vector machine (SVM) were employed and compared to determine a better performance of multi-classification.

E. Neurophysiological analysis

Offline data analysis was performed to investigate the neurophysiology following the tasks of 'Yes' and 'No' using the right or left hands. Epoching was done with windows of -2s to 7s and were linearly de-trended and divided into 0.256s segments. ERD and ERS were obtained by averaging the log power spectrum across epochs and baseline corrected with respect to -2s to 0s.

III. RESULTS

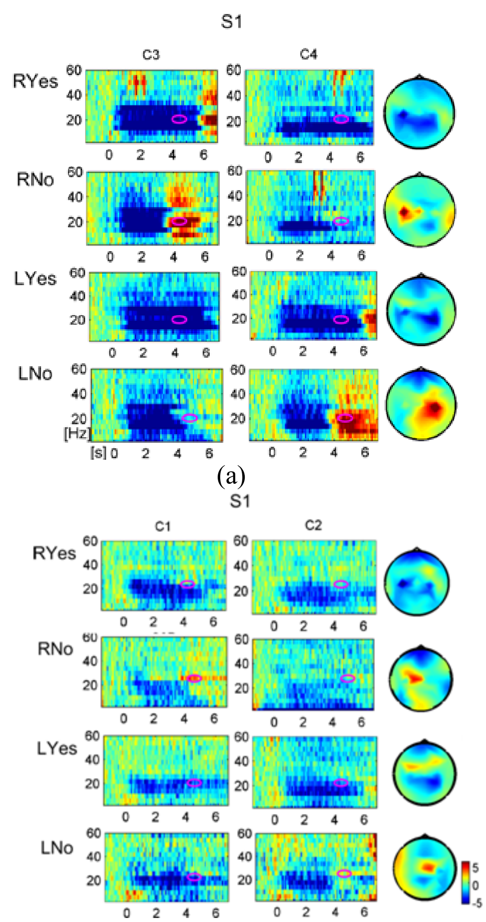

Figure 3. Time-course and topography of ERD and ERS during physical movement (a) and motor imagery (b) following the calibration paradigm for subject1. Blue color stands for ERD; red color stands for ERS. T1 window is from 0s to 2.5s and T2 window from 2.5s to 5s. ERD was observed in T2 window on left hemisphere during sustained right hand movement and ERS was observed in T2 window on left hemisphere with ceasing to move right hand. For left hand movement, similar patterns were observed on right hemisphere.

Fig. 3 shows an example of time-frequency plots and head topographies of ERD or ERS for physical movement (a) and motor imagery (b) for subject 1. Channel C3 over left sensorimotor cortex and C4 over the right hemisphere were used for time-frequency plots. For physical movement, ERD in both alpha and beta bands from 10-30 Hz was observed over motor area contralateral to the hand moved. ERS was mainly observed in the beta band centered around 20 Hz over the contralateral motor area. Compared with ERD patterns, ERS was short-lasting in time but highly distinguishable. For motor imagery (b), ERD was observed in both alpha and beta band on the contralateral hemisphere with the hand moved, although ERD amplitude was smaller than that of physical movement. ERS in the T2 window was observed on the contralateral hemisphere in beta band (13-24 Hz) only, and its amplitude was smaller than that of physical movement. The ERD and ERS associated with motor imagery also provided four spatially differentiable patterns, however, the smaller amplitudes of ERD and ERS with motor imagery may result less effective detection in single-trials. The patterns were similar for other subjects, except subject 4 didn't show clear patterns, and we exclude data from subject 4 from further analysis.

The comparison of 10-fold cross-validation accuracies using GA-MLD, DTC and SVM methods for S1, S2, S3 and S5 during physical movement is shown in Table 1.

Table 1. 10-fold Cross-Validation Accuracy

Subject	GA-MLD(%)	DTC(%)	SVM(%)
S1	87.7 ± 1.29	87.8 ± 1.47	87.8 ± 1.31
S2	93.0 ± 1.97	85.5 ± 3.87	90.0 ± 3.12
S3	85.2 ± 0.95	84.5 ± 2.30	88.9 ± 1.04
S5	87.2 ± 0.58	87.7 ± 1.75	85.8 ± 2.13
Average	88.3 ± 3.33	86.4 ± 1.64	88.1 ± 1.79

There was no significant difference among these three methods through one-way analysis of variance (AVONA), $F(1,2)=5.7$, p-value<0.39, alpha=0.05.

Since there was no significant difference among the intensive methods, DTC method was employed for the online 2D cursor control game. Except for S4, all the other four subjects were successful to control the cursor moving to the target by physical movement and the average online game performances for S1, S2, S3, and S5 were 92%, 85%, 81%, and 84%, with the overall performance of 85.5%±4.65%. S1 and S2 participated in the second session performing motor imagery tasks. Offline classification accuracy for S1 was 73%±5.97%, and for S2 was 59.2%±3.63%, which were lower than those of physical movement with physical movement. The two subjects both reported good concentration throughout the recording.

Online 2D cursor control game using motor imagery was performed by S1 and S2. S1 was able to move the cursor to the target; However, S2 performed less well than S1. The performance was consistent with the classification results for motor imagery.

IV. DISCUSSION

Throughout the experiment, EMG signal was monitored for all subjects, to make sure correct movements were performed and no EMG occurred during motor imagery. Further, feature analysis showed that beta activities restricted to motor areas were used for classification. Therefore, the EMG contamination was not a concern in this study.

Wolpaw et al. introduced the information transfer rate (ITR) for a BCI as bits per minute (bpm) as a good measurement for both decoding rate and accuracy [14]. In our study of 2D control for a four-class mental task, the total duration of T1 and T2 windows was 5 s, i.e. 12 trials per minute. Therefore, the ITR was 13.9 to 16.5; the average was 15.5 bits per minute. Similarly, for motor imagery, the ITR was 4.15 bits per minutes to 8.03 bits per minutes. The results were comparable in terms of decoding rate and accuracy with previous studies (see review in [15]).

The two-dimensional BCI control in this study shows that robustness or accuracy was less with motor imagery than with physical movement. However, only two subjects have been studied with motor imagery so that further study with more subjects should be addressed. For patients who are not in a 'locked-in' state but cannot produce reliable muscle contraction due to muscle weakness or spasticity, we would expect more reliable two-dimensional control with their limited motor output as this study demonstrates a highly reliable control with simple physical movement.

In summary, ERD/ERS using our 2D natural paradigm present four distinguishable patterns as we expected, both in physical movement and motor imagery. Although variability might lead to considerable challenges in the classification process, the intensive methods we applied exhibit satisfying properties and robust results, making 2D control more reliable. It is worthwhile to pursue this potential system. If the design and signal processing methods can be further improved, BCI products will eventually offer those who have totally lost muscle control with convenient, fast and reliable control of mechanical devices. This will largely reduce the reliance on continuous support from others, and thus enhance their quality of life.

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