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EVENT-RELATED DESYNCHRONIZATION/SYNCHRONIZATION-BASED VOLITIONAL CURSOR CONTROL IN A TWO-DIMENSIONAL CENTER-OUT PARADIGM

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Abstract

To achieve a reliable two-dimensional control by noninvasive EEG-based brain-computer interface (BCI), users are typically required to receive long-term training to learn effective regulation of their brain rhythmic activities, and to maintain sustained attention during the operation. We proposed a two-dimensional BCI using event-related desynchronization and event-related synchronization associated with human natural behavior so that users need neither long-term training nor high mental loads to maintain concentration. In this study, we intended to further investigate the performance of the proposed BCI associated with either physical movement or motor imagery with an online two-dimensional center-out cursor control paradigm. Model adaptation method was employed for better decoding of human movement intention from EEG activities. The results demonstrated an effective center-out cursor control: as high as 77.1% during online control with physical movement and 57.3% with motor imagery. It suggests that two-dimensional BCI control can be achieved without long-term training.

1 Introduction

The brain-computer interface (BCI) can decode people's intention bypassing peripheral nerves and muscles to achieve direct control of external devices (Wolpaw, 2007). It provides a new communication pathway to the people with severe motor disabilities. Performance of the BCI system is highly depended on the signal-to-noise ratio (SNR) of the brain signal.

Invasive and semi-invasive BCIs may provide better SNR than non-invasive BCI as invasive BCI detects signal by implanting electrodes into the motor cortex such as local field potential recorded from individual or small population of motor neurons (Kubanek et al., 2009), and semi-invasive BCI pastes electrodes under dura (ECoG) (Leuthardt et al., 2004; Miller et al., 2007b; Schalk et al., 2007; Leuthardt et al., 2007; Miller et al., 2007a; Schalk et al., 2008a). However, the widespread of clinical use of invasive or semi-invasive BCIs in human being is impeded by the high risk of surgical procedures and the problems in achieving robust and stable long-term recordings (Kipke et al., 2008).

Electroencephalography (EEG) is the most commonly used non-invasive method, which detects signal from the scalp (Wolpaw et al., 2002; Wolpaw and McFarland, 2004; McFarland et al., 2008; Bai et al., 2008; Huang et al., 2009; Morash et al., 2008). The critical challenge of EEG-based BCI is how to keep good and robust performance while the variation of EEG signal is large. Studies in recent years show that EEG-based BCI has great potential in achieving two-dimensional or multi-dimensional cursor control (McFarland et al., 2008; Wolpaw and McFarland, 2004). However, these systems usually require long-term training in regulating brain rhythm, and the performance in long-term use is often not robust (Kubanek et al., 2009).

The discovery of event-related desynchronization (ERD) or power decrease and event-related synchronization (ERS) or power increase casts a light on the development of brain-computer interface (Birbaumer et al., 2006). Recent studies developed a paradigm to achieve two-dimensional cursor control using ERD/ERS method, directly decoding movement intention without long-term training (Bai et al., 2008; Huang et al., 2009). Human limbs are controlled by contralateral brain hemispheres, which has been confirmed by many studies (Bai et al., 2005; Rao et al., 1993; Salenius et al., 1996). During physical and motor imagery of right and left hand movements, beta band brain activation (15-30 Hz) ERD occurs predominantly over the contralateral left and right motor areas. The post movement ERS associated with ceasing to move, 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 of ERD and ERS may potentially provide four reliable features for a two-dimensional control, e.g. left-hand ERD to command move to the left, left-hand ERS to command move up, right-hand ERD to command move to the right, and right-hand ERS to command move down.

In this study, we further investigated the performance of the BCI, which was done online using a two-dimensional center-out cursor control paradigm with an improved model adaptation method for better decoding of human movement intention from EEG activities.

2 Method

2.1 Human subjects

Three healthy subjects: a female at age 24 (S1), a male at age 26 (S2) and a female at age 25 (**??**) were the BCI users in this study. They were right-handed according to the Edinburgh inventory (Oldfield, 1971), and they had no prior BCI experience. The protocol was approved by the Institutional Review Board, and each user gave the informed consent before the study.

2.2 Study protocol

Each subject participated in two parts of study in a single visit: motor execution with physical movement and motor imagery. Each part consisted of a first 6-min calibration period, containing 48 trials, followed by five to six 3-min blocks of online cursor control separated by 1-min breaks, 16 trials each block. Subjects finished 128 to 144 trials for each part and it took around 2.5 hours to complete both parts in a single visit.

During BCI operation, subjects were seated in a chair facing a computer screen, which was place about 1.5 meters in front of the subject. EEG activity was recorded from 27 (tin) surface electrodes (F3, F7, FC3, C1, C3, C5, T7, CP3, P3, P7, F4, F8, FC4, C2, C4, C6, T8, CP4, P4, P8, FPZ, FZ, FCZ, CZ, CPZ, PZ and OZ) (shown in figure 1) attached on an elastic cap (Electro-Cap International, Inc., Eaton, OH, U.S.A.) according to the international 10-20 system (Jasper and Andrews, 1938), with reference from the right ear and ground from the forehead. Surface electromyography (EMG) and electrooculogram (EOG) signals were also recorded for monitoring the muscle and eye movements. For surface EMG, two electrodes were taped over the right and left wrist extensors. Electrodes for bipolar EOG were pasted above left eye and below right eye. Subjects were instructed to keep all muscles relaxed and have the forearms semi-flexed, supported by a pillow. They were also instructed to avoid body movement during the BCI operation. The investigator was monitoring the EMG activity continuously; once EMG activity was observed during motor imagery, subjects were reminded to relax the muscles. Trials with EMG contamination were excluded based on visual inspection for further offline ERD and ERS analysis and classification. Signals from all the channels were amplified (g.tec GmgH, placeCitySchiedlberg, country-regionAustria), filtered (0.1-100 Hz) and digitized (sampling frequency was 250 Hz). The digital signal was then sent to a HP PC workstation and was online processed using a home-made MATLAB (MathWorks, Natick, MA) Toolbox: brain-computer interface to virtual reality or BCI2VR (Bai et al., 2008). The BCI2VR programs provided both the visual stimulus for the calibration and the two-dimensional cursor-control testing, as well as online processing of the EEG signal.

2.3 Volitional cursor control in a two-dimensional center-out paradigm

Similar experimental paradigms for calibration and two-dimensional center-out cursor control were adopted and modified to perform an improved control in this study. Figure 2 was used to demonstrate the procedures for both calibration and online test.

2.3.1 Calibration

A trial began when a target (in red) appeared at one of the four locations on the periphery of the screen, together with three non-target objects (in green) on the other three sides (Fig. 2a). A target location was pseudo-randomized (i.e. each occurred the same times in one block). In both parts (physical movement and motor imagery), there were four hint words in the task paradigm (a), 'RYes', 'RNo', 'LYes', and 'LNo' ('R' indicating right hand task, and 'L' for left hand task) on the four directions of the central cursor, which was set in green initially. Subjects were instructed to begin real or imagined repetitive wrist extensions of the right arm, if the target was on the direction of 'RYes' or 'RNo'; if the target was on the direction of 'LYes' or 'LNo', they performed real or imagined repetitive wrist extensions of the left arm. After a period of 1s, the central cursor changed color to blue (b), when the subject was instructed to continue real or imagined movement with the 'Yes' case or abruptly relax and stop moving with the 'No' case. After displaying for a period of 1.5s, the configuration disappeared, indicating that subject needed to stop the task, and the screen was blank for 4.5s (f). Next trial began from (a).

2.3.2 Two-dimensional center-out cursor control paradigm

Sustained movement is usually associated with a persistent event-related desynchronization (ERD), while cessation of movement is followed by a beta band rebound above baseline power levels, i.e. event-related synchronization (ERS). Since we intended to discriminate ERD from ERS, which occurs only after cessation of movement in the T2 window, we only extracted EEG signal in the T2 time window to classify 'Yes' or 'No' intention determined from ERD and ERS. Successfully classifying the four kinds of movements in motor execution or motor imagery was the basis of realization of 2D control.

In a 2D plane, the cursor can move to four directions: up, down, right and left, each of which was linked to one of the four movements. We intended to decode movement intentions to determine the subject's control of cursor direction. As human movement intention is associated with spatial ERD and ERS (on either left or right hemisphere), we applied the detection strategy as shown in Figure 3. 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 to develop an ERD pattern on the left hemisphere. When the associated ERD on the left hemisphere was detected in the T2 time window, the cursor would move to the right direction; similar for controls on the other directions.

The initial calibration step determined the optimal frequency band and spatial channels. The selected features and generated model were then used to test an online two-dimensional center-out cursor control. Similar to what the subjects did in calibration step, they performed real or imagined hand movement in T1 window (figure 2a), and in T2 window (b) continued in if 'Yes' case or stopped if 'No' case. Until the hint words disappeared (c), they stopped the task. Cursor moved to the classified direction in 2s with a constant speed (d). If the target was hit, it flashed for 1s as a reward (e); if the cursor failed to reach the target, the configuration simply disappeared. The screen went blank for 1.5s and then next trial began.

2.4 Signal processing method and the model adaptation

Figure 4 illustrates the procedures for online calibration and online test using two-dimensional center-out paradigm. In calibration step, data was first spatially filtered using surface Laplacian derivation (SLD), which referenced the EEG signal from each electrode to the averaged potentials from the nearby four orthogonal electrodes (Hjorth, 1975), in order to improve the localization of sources and thus enhanced the EEG feature of local synchrony, i.e., frequency power changes, making the spatial difference due to different hand movements more distinguishable. And then data was temporally filtered by estimation of the power spectral density. Through offline neurophysiological analysis, 0.5s-1.5s after T2 window started was selected to obtain strongest ERD/ERS. We applied Welch method with Hamming window, and kept the frequency resolution 4 Hz, the same as previous study, with 50% overlap of the segments. For either physical movement or motor imagery, there were 48 trials for training data, making the data pool. Parameters and features were determined from the training data, for decoding the movement intention in online test. We performed empirical feature reduction by reducing the channel number from 29 to 14, which covered the area of left and right motor cortex; restricting the frequency band from 8 to 32 Hz, which included alpha and beta bands. Since the previous study (Huang et al., 2009) showed that genetic algorithm based Mahalanobis linear discrimination classifier (GA-MLD) and decision tree classifier (DTC) gave similar classification performances in this two-dimensional control, we used both of them in the current study to generate models, and during the online games, each time we selected the one giving the higher result for classification in the next trial. Specifically, in online test, either physical movement or motor imagery, there were 5 or 6 blocks, each containing 16 trials. The new data also went through spatial filtering, temporal filtering, channels and frequency bands restriction. In classification, either GA-MLD or DTC would be used to classify the movement intention. The cursor was then moved to the classified direction. The trial was then combined with the old trials, keeping the data pool updated. New models would be generated using MLD and DTC, the one with higher accuracy would be used as the classifier in next trial. If the block was completed, the features would be re-selected by genetic algorithm, and new models were generated by GA-MLD and DTC. Next block began with the same procedures.

The procedures above in the online test illustrate how the adaptive algorithm was applied. The control accuracy was determined by the model, which was generated initially by GA-MLD and DTC in the calibration step. From then on, after each trial, the model was automatically adapted on the basis of past trials to optimize, for subsequent trials, the translation of subject's movement intention into cursor movement control.

2.5 Offline neurophysiological analysis

To investigate the neurophysiology following the tasks of 'Yes' and 'No' using the right or left hands, we epoched the data from -1s to 4s with respect to the first cue onset. Epochs with artifacts were rejected. ERD and ERS were calculated for each case. Epochs were linearly de-trended and divided into 0.256s segments. The power spectrum of each segment was calculated using FFT with Hamming window resulting in a bandwidth of about 4 Hz. ERD and ERS were obtained by averaging the log power spectrum across epochs and baseline corrected with respect to -1s to 0s.

3 Result

3.1 Neurophysiological analysis of ERD/ERS

For each subject, all the calibration data and testing data were included to do the spatiotemporal analysis. The study differentiated the ERD and ERS patterns in two hemispheres following hands movement or motor imagery using the period after the 'No' cue onset. Figure 5 shows the time-frequency plots, head topographies of ERD and ERS for all the three subjects, with physical movement (left half of each sub-figure) and motor imagery (right half of each sub-figure). For S1 and S3, channel C3 over the left sensorimotor cortex and C4 over the right hemisphere were selected to illustrate the strongest ERD and ERS patterns, containing each of the four situations: 'RYes', 'RNo', 'LYes', and 'LNo'. For S2, channel C1 on left hemisphere and channel C2 on right hemisphere were used for the same purpose. ERD was observed from around 0.2 – 0.5s after the cue onset. For S1 and S3, ERD centered around 15Hz (lower beta band); for S2, ERD centered around 22Hz. ERD was observed on both hemispheres for all the subjects during physical movement, but more on one side. ERS was observed around 20 Hz, over the contralateral motor areas for S1 and S3, but also appeared slightly ipsilateral for S2 on the central channels C2 or C1. Compared with ERD patterns, ERS was more focal on the contralateral hemisphere. Therefore, the ERD and ERS on either left or right hemisphere provided four spatial patterns to detect 'RYes', 'RNo', 'LYes', and 'LNo' intentions. For motor imagery, ERD and ERS have similar patterns as for physical movement, although the amplitudes were smaller. ERD and ERS patterns were not clear to observe for S3.

3.2 Classification

Figure 6 gives out the online cursor control test results for the three subjects, with physical movement (Block 1 to Block 6) and motor imagery (Block 1' to Block 6'). All the subjects finished 6 blocks in physical part, containing 16 trials in each block, with four tasks evenly assigned. Either DTC or GA-MLD was used each time for the intention detection, depending on which one created a better model after model adaptation. Average online performances for each subject in physical part were 77.1%±8.54%, 70.8%±5.10%, and 57.0%±6.85%. We observed a trend that the overall performances increased across blocks, although correlation did not show significant difference (r=0.19, p-value=0.4468). In motor imagery online test, S1 and S2 had 6 blocks and S3 had 5. Average online performances for each subject in motor imagery part were 57.3%±13.35%, 46.9%±8.62%, and 42.5%±5.23%. We also observed a trend that the overall performances increased across blocks, and the correlation showed a significant relationship between motor imagery performances and blocks (r=0.62, p-value=0.0057).

Offline analysis using 10-fold cross-validation was done for each subject. All the calibration data and test data (total 128-144 trials per subject per part) were used. Table 1 listed the results, evaluated by DTC and GA-MLD classifiers, for physical and motor imagery parts. The two classifiers provided similar results in each part.

4 Discussion

4.1 Center-out paradigm

In the previous study, we used a goal oriented paradigm in the online two dimensional cursor control test, where the target randomly appeared in the 2D plane. The subject was supposed to control the cursor moving to it and avoid being trapped by a randomly assigned obstacle (Huang et al., 2009). Most subjects found the paradigm interesting and easy to learn, requiring little mental load. As we discussed before, in motor imagery where no EMG was involved, subjects could determine the route in each step moving the cursor to the target by themselves, so, it was difficult for the computer to tell whether the cursor really moved to the desired direction without feedback, and therefore we did not report the accuracy for motor imagery in the previous study, instead, we reported overall target reaching rate. In this study, we adopted the commonly used center-out paradigm (Wolpaw and McFarland, 2004; Schalk et al., 2008b; Vaughan et al., 2006) to further investigate the performance of our proposed BCI with motor imagery, where four tasks were evenly assigned in each block and the calculation of control accuracy was straightforward. The four-target center-out paradigm can be generalized to eight or more target paradigm, which would be more ideal for testing further improved 2D control, for example, continuous 2D control.

4.2 Decoding rate and accuracy

Information transfer rate (ITR) in bits per minute (bpm) has been introduced by Wolpaw et al. to evaluate the performance of BCI system; both control accuracy and control speed determine the BCI performance (Wolpaw et al., 2000; Wolpaw et al., 2002). In this study, we used the classification accuracy given by the best subject to calculate the ITR. For physical movement, the classification accuracy was 83%, and for motor imagery 56.8%. For a four class task, ITR was 1.34 bits per trial for physical movement and 1.01 bits per trial for motor imagery. The cuing period T1 was set to 2.5s before, which left enough time for subjects to pre-

Table 1. 10-fold Cross-Validation Accuracy. DTC: decision tree classifier; GA-MLD: genetic algorithm-based Mahalanobis linear discrimination.

	Physical		Motor imagery	
Subject	DTC(%)	GA-MLD(%)	DTC(%)	GA-MLD(%)
S1	78.5 ± 4.28	83.0 ± 4.59	52.4 ± 3.04	56.8 ± 2.76
S2	74.7 ± 3.15	78.2 ± 3.90	38.4 ± 4.02	49.1 ± 2.57
S3	59.1 ± 5.47	63.2 ± 4.83	40.8 ± 5.73	39.7 ± 4.88
Average	70.7 ± 10.28	74.8 ± 10.33	43.9 ± 7.49	48.5 ± 8.56

pare for the movement. In current study, we shortened it to 1s. Although the variance was larger than before, subjects reported good attention level, and from the neurophysiological analysis we observed clear ERD/ERS patterns and even shorter response delay than before. Since in either part, the total duration for T1 and T2 windows has been shortened to 2.5s, i.e. 24 trials per minute. Therefore, ITR was 32.16 bits per minute for physical movement and 24.24 bits per minute for motor imagery. Compared with the results given in previous study (Huang et al., 2009), ITR was greatly improved.

4.3 Decoding accuracies changing with time

To achieve four-directional classification for a two-dimensional control associated with human natural behavior, the BCI in this study was expected to show stable and robust performance without subject's intensive training. As the results showed, a trend could be observed that the overall performance for the three subjects improved across blocks, in either physical part or motor imagery part. Since model adaptation was used for each trial and the features were re-selected for each new block, classification accuracy was supposed to increase or stabilize when the tasks were done consistently, although the increase may be insignificant. We expect that in further study, with the model adaptation, the accuracy can increase or at least stabilize in multiple visits, with stable performances across blocks in each single visit. If that is the case, the proposed BCI would be able to achieve reliable control in both short time use and long-term use.

4.4 Spatiotemporal features of ERD and ERS

As was expected for physical movement, we observed clear ERD and ERS in beta band over the contralateral motor cortex associated with the moving hand, ERD during the sustained movement and ERS after the movement stopped. We also observed ERD appeared on ipsilateral hemisphere and even stronger than that on contralateral hemisphere. We considered the reason might be that during the hand moving, although the other hand was not moving, the automatic urging of the movement also generated ERD activity, on the contralateral motor cortex, which was the ipsilateral side of the moving hand. Similar patterns appeared for motor imagery. In this case, the discrimination between 'RYes' and 'LYes' could be difficult, since the movement of either hand would generate ERD over both hemispheres, especially when its variance was large. Although in this study, genetic algorithm combined with adaptive method provided multiple features for the classifier, which greatly helped with the classification, 'RYes' and 'LYes' was still the most difficult pair to distinguish compared with others. Further improvement on this issue could be either adding another feature to enhance classification or improving the paradigm to avoid direct comparison of 'RYes' and 'LYes'.

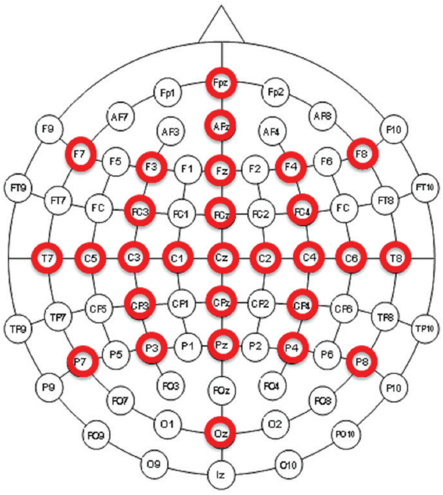

Figure 1. Locations of the 27 EEG surface electrodes (F3, F7, FC3, C1, C3, C5, T7, CP3, P3, P7, F4, F8, FC4, C2, C4, C6, T8, CP4, P4, P8, FPZ, FZ, FCZ, CZ, CPZ, PZ and OZ, marked by red circles) and the ground (AFz).

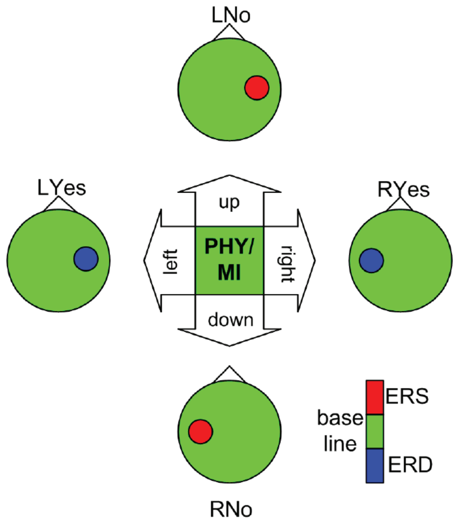

Figure 3. Scheme of 2D center-out cursor control. Four directions control by spatial detection of ERD/ERS on right/left hemisphere associated with intention to move or cease to move of left/right hand. In order to control cursor moving to left ('LYes' direction), subjects may perform sustained physical movement/motor imagery so that ERD on the right hemisphere can be detected. It is similar for other direction controls.

The present study further confirms the results presented in our previous study, which demonstrated that EEG activity associated with human natural behavior deliver information from which human volitional movement intention can be decoded. This preliminary study provides evidence that EEG based natural BCI support 2D control, with a competitive information transfer rate in terms of control accuracy and control speed. In particular, the 2D control can be easily achieved within 3 hours in the experiment by imaging the movement, where long time training is no longer needed. Successfully decoding of movement intention is highly depended on the experimental design and optimization of parameters in experiment and computational procedures. Further research is needed to explore the reliability and applicability of the natural BCI on larger population, including healthy subjects and patients, in multiple visits, and the how well it can be generalized to achieve fast continuous control . We anticipate that such studies will further demonstrate that EEG is highly capable of realizing continuous multi-dimensional control with human natural behavior or thinking, which will eventually benefit people in their daily life.

List of figure captions.

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2. Online 2D center-out cursor control paradigm. (a) A trial begins. The target (red) is pseudorandomly chosen from the four positions along the edges; the cursor is in green. Subject starts motor task for 1 s. (b) The cursor turns to cyan, at which point subject stops and relaxes in 'No' case, or performs sustained movement in 'Yes' case for 1.5s. (c) The hint words disappears. Subject stops the task. (d) The cursor moves steadily towards the classified direction for 2 s. (e) The target flashes for 1 s when it is hit by the cursor. If the cursor misses the target, the screen is blank for 1 s. (f) The screen is blank for a 1.5s interval before next trail starts.

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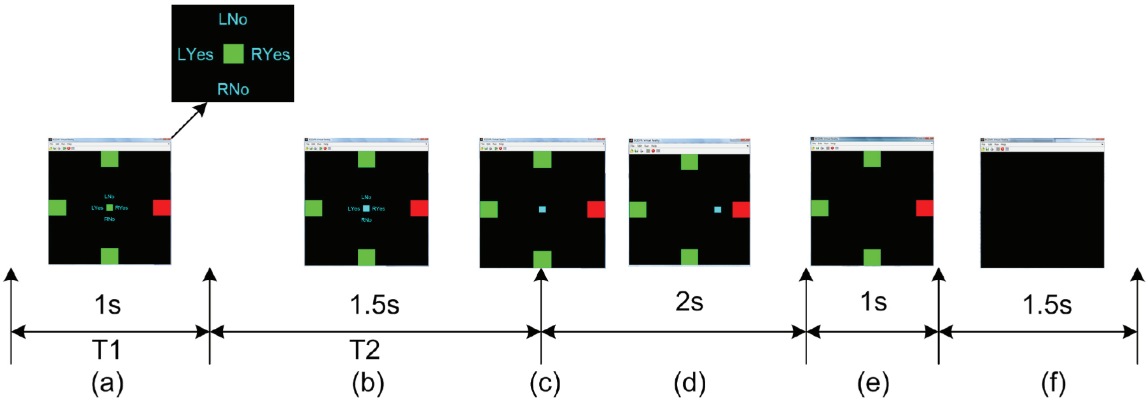

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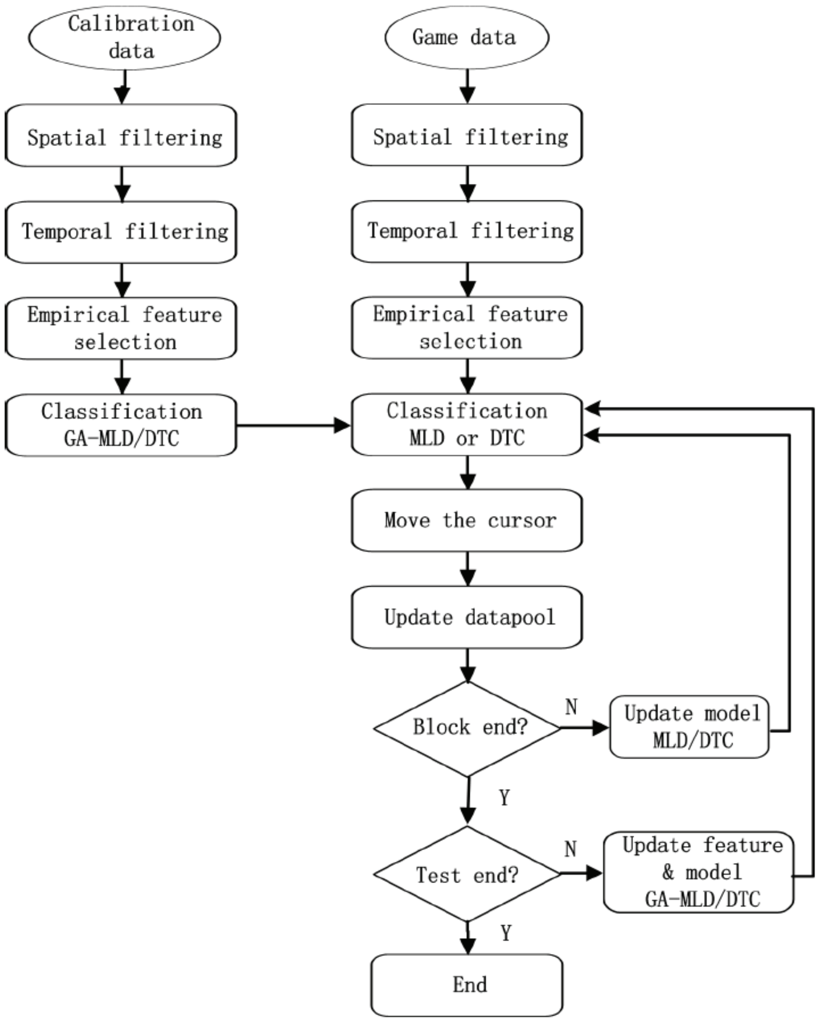
4. Flow chart of online calibration and two-dimensional cursor control. Calibration data went through spatially filtering, temporally filtering and empirical feature selection. In classification, genetic-algorithm based Mahalanobis linear discrimination (MLD) classifier and decision tree classifier (DTC) were used to generate models for online game. During the online test, data was spatially filtered, temporal filtered, and empirical features were selected. Then the model generated in calibration step, giving a better prediction result was used to classify the movement intention, and the cursor was moved. After data pool was updated, the model would be updated too, using MLD and DTC, and the one gave a higher result was used as the model for classification in next trial; if the block ended, features would be re-selected by genetic algorithm and then generated model by GA-MLD and DTC, providing it for next trial. If all the blocks were completed, the procedure ended.

5. Time-course and topography of ERD and ERS for S1, S2 and S3. For each subject, the left part is plotted for motor execution and the right part for motor imagery. The blue color stands for ERD; the red stands for ERS. T1 window is from 0 s to 1s and T2 window from 1 s to 2.5 s. For S1and S2, ERD and ERS were clear for physical movement and motor imagery. For S3, ERD and ERS can only be clearly observed for physical movement.

6. Online two-dimensional cursor control accuracies of physical movement (Block 1 to Block 6) and motor imagery (Block 1' to Block 6') for S1, S2 and S3.



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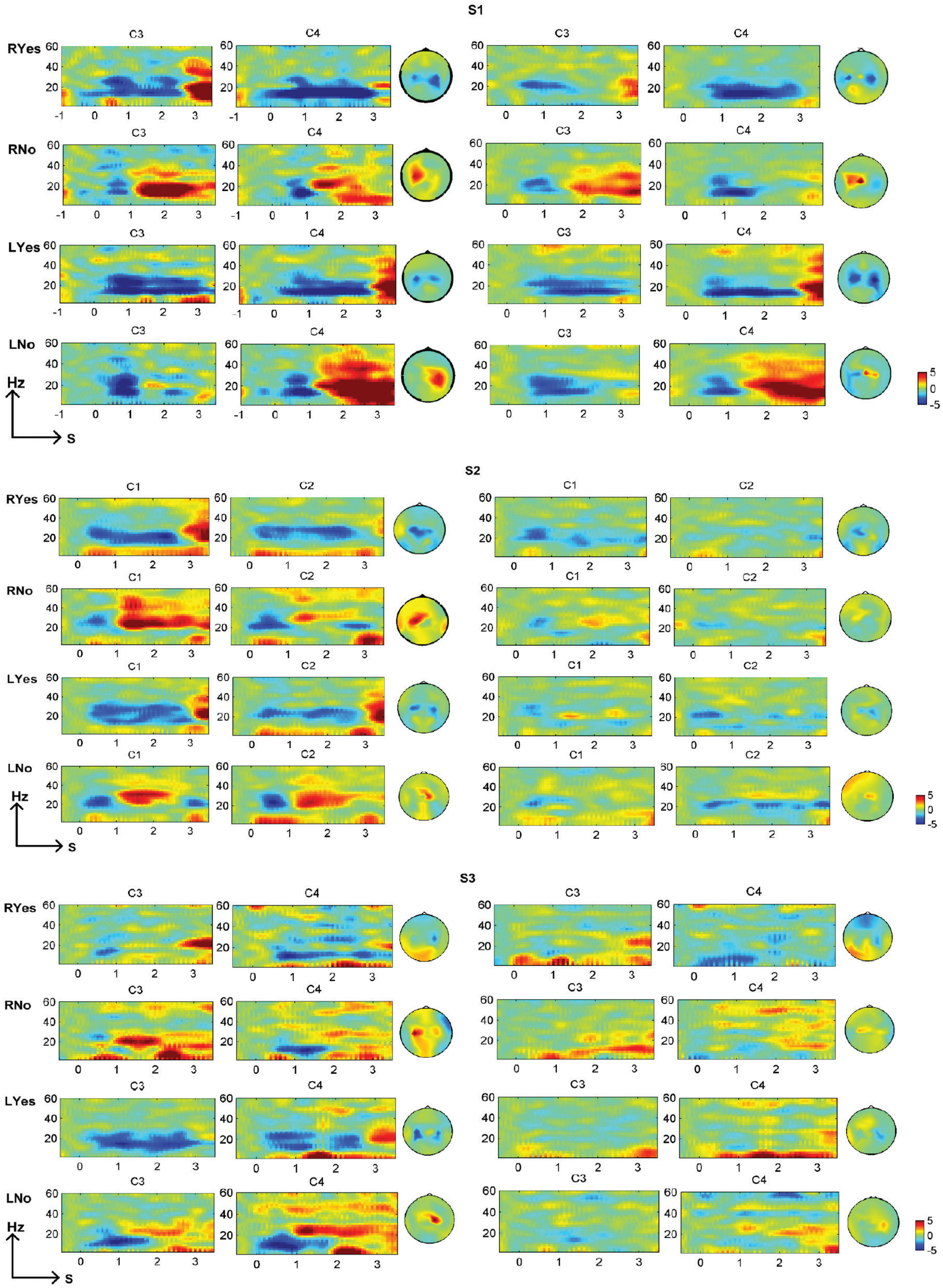

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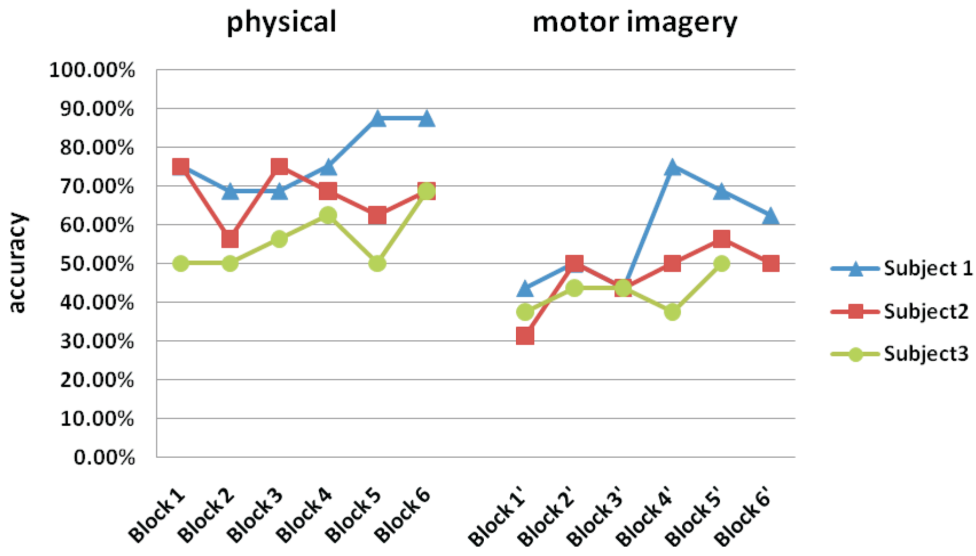

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