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A Hybrid BCI System for 2-D Asynchronous Cursor Control

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Abstract— **In this paper, a hybrid EEG-based brain computer interface (BCI) is designed for two-dimensional cursor control. In our approach, two brain activity patterns, i.e., motor imagery and P300 potential, are used for controlling the horizontal and the vertical movements of the cursor respectively. A real-time BCI system based on this approach is implemented and evaluated through an online experiment. Six subjects attending this experiment can perform 2-D cursor control effectively. Our experimental results show that the system has the following merits compared with prior systems: 1) it does not rely on intensive user training; 2) it allows cursor movement between arbitrary positions.**

Keywords: Brain-computer interface (BCI), electroencephalogram (EEG), 2-D cursor control, mu rhythm, P300 potential.

I. INTRODUCTION

An important issue in BCI research is cursor control, where the objective is to map brain signals to movements of a cursor on a computer screen. In the EEG-based BCI literature, most studies were focused on one dimensional (1-D) cursor control [1], [2], [3], [4]. This type of BCI is based upon detection and classification of the change of mu (8-12 Hz) or beta (13-28 Hz) rhythm during different motor imagery tasks, such as imagination of left- and right-hand movement. However, a 1-D cursor control system would allow the user to control either the vertical or the horizontal movement of a cursor at a time. Compared with 1-D cursor control, multidimensional cursor control enables a considerably enhanced interface between the user and the machine, with a much wider range of applications. A typical application of 2-D cursor control is computer mouse for web browser. To date, most of the multi-dimensional cursor control BCIs have been invasive [6]. On the other hand, the development of noninvasive 2-D control BCI especially using EEG is impeded by the difficulty in obtaining two independent control signals from the noisy EEG data of poor spatial specificity. Therefore, the first report of a EEG-based 2-D cursor control BCI was remarkable [5]: the authors showed that through guided user training of regulating two particular EEG rhythms (mu and beta), two independent control signals can be derived from combinations of the rhythmic powers. The downside of the approach is the required intensive user training. In recent years, other forms of 2-D BCI were also reported that usually adopted a classification approach: for example using P300 potential in [8] or using steady-state visual evoked potential (SSVEP) in [7]. However, these P300 and SSVEP based techniques produced discrete outputs only: a constant movement speed along a few fixed directions.

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Therefore, there is a need to develop a new BCI method that would be capable of producing two independent control signals while alleviating the necessity of intensive user training. In this paper, we propose a method for 2-D movement control of a cursor. In our approach, the vertical movement of the cursor is controlled by P300 potential, while the horizontal movement is controlled by mu or beta rhythm. A BCI system based on this method has successfully been developed, which is composed of an asynchronous p300 control module and an asynchronous motor imagery control module. Six subjects who attended our experiments are able to effectively control the 2-D cursor. Besides the relatively simple training task, our experiments and further data analysis results show another other advantage of our method and BCI system: the cursor can move from one randomly given point to another randomly given point.

In fact, our system belongs to hybrid BCIs which receive more and more attentions of researchers recently. In [9], [10], an offline simulation of a hybrid BCI was presented in which subjects performed two mental tasks independently and then simultaneously. This hybrid BCI could use two different types of brain signals common in BCIs: event-related desynchronization (ERD) and steady-state evoked potentials (SSEPs). The study in [9] suggested that such a hybrid BCI was feasible and beneficial.

II. GRAPHICAL USER INTERFACE AND CONTROL MODELS

In this section, we present the graphical user interface (GUI), the control models and the algorithms of our system.

Our GUI is shown in Fig. 1, in which the ball and the square represent a cursor and a target respectively. The workspace has a pixel size of 1166×721 pixels. The ratios of the size of the cursor, the size of the target and the workspace are fixed to be $0.00084 : 0.003 : 1$. The initial position of the cursor and the position of the target are randomly generated in the screen. There are 8 buttons distributed at the horizontal and vertical edges of the screen, with 3 buttons labeled "up" at the top, 3 buttons labeled "down" at the bottom, and two buttons labeled "stop" in the middle.

Each trial begins from the time at which the cursor and the target appear on the screen. In each trial, the subject is given a time limit of 60s to direct the movement of the cursor towards a predefined target on the screen. Each trial contains several rounds of button flashes. In a round, each of the 8 buttons flashes once in a random order. Note that the length of each trial is not fixed.

In each trial, the subjects will attempt to move the cursor to the target. The motion of cursor in left/right direction is controlled by imagining left/right hand and up/down direction is controlled by looking at up/down buttons. Finally, if he/she does not want to move the cursor in vertical direction, then he can focus on one of the two "stop" buttons.

In our online system, the detection of P300 and the detection of motor imageries are performed simultaneously. This implies that the control of the cursor's horizontal movement and the control of the cursor's vertical movement are carried out simultaneously. In each trial of cursor control, there are many times of P300 detection. In each round of button flashes, there is a P300 detection. However, the starting point and the end point of the EEG segment for each p300 detection are not fixed. Thus the P300 control is asynchronous. Similarly, there are many times of horizontal movement control in each trial and each control is based on a motor imagery detection. This control is also asynchronous since the starting point of EEG segment for each detection of motor imagery is not fixed.

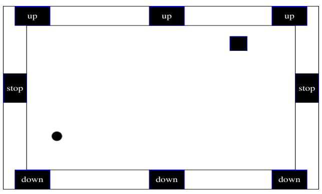

Fig. 1. The GUI for 2-D cursor control

During the period of the cursor's moving, the cursor's positions are updated every 200 ms. Now, we present our control models and their corresponding algorithms.

A. Asynchronous control of vertical movement based on P300 potential

In our system,when the cursor moves, it has a constant speed in the vertical dimension and its direction of vertical movement is determined by the result of P300 potential detection. The following model is used for updating the cursor's vertical position,

$$y(k+1) = y(k) + c(k)v_0, \tag{1}$$

where k represents the kth update of the position of the cursor (the kth movement), $c(k) \in \{1, -1, 0\}$ determines the vertical movement direction of the cursor ($1, -1$ represent the down and up movements respectively; 0 implies no vertical movement), v_0 is a positive constant representing the speed of vertical movement. In this study, $v_0 = 10$, i.e., the cursor moves 10 pixels vertically every update, which can be adjusted according to each subject's control performance.

The steps of our algorithm for detecting P300 potential and determining the vertical movement direction of the cursor are as follows:

(i) Feature extraction: The EEG signals are filtered between 0.1 and 20 Hz. Then a segment (e.g. 600 ms after a button flash) of the EEG data of each channel for every flash is extracted. Furthermore, downsample the segment by a rate of 6 to obtain a data vector and concatenate them by channel for each flash to create a single feature vector corresponding to each button.

(ii) Train a support vector machine (SVM) classifier: The subjects are instructed to focus attention on 6 buttons one by one (3 "up" buttons and 3 "down" buttons). Each attention lasts 64 consecutive rounds, where each round contains 8 flashes from the 8 buttons respectively. Using the feature vectors of the training data set and their corresponding labels, we train an SVM classifier.

(iii) Classification and P300 detection: For the lth round in an update of the cursor's position, we extract feature vectors $Fe_{j,l}$ ($j = 1, \cdots, 8$) and obtain 8 scores denoted as $s_{j,l}$ with the trained SVM model. Then calculate the sum of scores for each button: $ss_j = s_{j,1} + \cdots + s_{j,l}$, $j = 1, \cdots, 8$. Suppose that $ss_{j_0} = \max\{ss_1, \cdots, ss_8\}$, $ss_{j_1} = \max\{\{ss_1, \cdots, ss_8\} \setminus \{ss_{j_0}\}\}$ (the second maximal value). If $1 - \frac{ss_{j_1}}{ss_{j_0}} > \theta_0$, then the system makes a decision that P300 potential occurs at the j_0th button and outputs a direction of the cursor's vertical movement corresponding to the j_0th button, where θ_0 is a predefined positive constant (e.g. 0.3 in this paper). Otherwise, the system has no output and continues P300 detection of the next round. In this case, the system does not change the direction of the cursor's vertical movement.

Remarks 1: (i) If P300 is detected at one of the three "up" buttons, set $c(k) = -1$ (the cursor will go up); If P300 is detected at one of the three "down" buttons, set $c(k) = 1$ (the cursor will go down); If P300 is detected at one of the two "stop" buttons, set $c(k) = 0$ (the cursor will have no vertical movement). See the GUI in Fig. 1. (ii) In Algorithm 1, only when the threshold condition $1 - \frac{ss_{j_1}}{ss_{j_0}} > \theta_0$ is satisfied, there is an output for the direction of the cursor's vertical movement. In our system, we set an upper bound of round as 15. That is, if the threshold condition is not satisfied in 15 rounds, the system will give an output, i.e., the direction of the cursor's vertical movement corresponding to the j_0th button.

B. Asynchronous control of the horizontal movement through motor imagery

In our system, the horizontal movement of the cursor is controlled by subject's motor imageries. The control model is given by

$$x(k+1) = x(k) + \frac{a}{3}(f(k-2) + f(k-1) + f(k)) + b, \tag{2}$$

where k represents the kth update of the position of the cursor (the kth movement), $x(k)$ is the horizontal coordinate of the cursor, $f(k)$ is a SVM score, a and b are two constants. $f(k)$, a and b will be defined later. We introduce delays with the last three time points into the control model (2) to make the cursor move smoothly.

First, we show the method for calculating the SVM score $f(k)$ for the kth update. For every 200 ms, the system outputs an $f(k)$ using the most recent 1200 ms of EEG signals which have been preprocessed. The preprocessing steps include (i) spatial filtering with common average reference (CAR), (ii) band-pass filtering in specific mu rhythm band (8-13Hz), (iii) spatial filtering based on a common spatial pattern (CSP) [1] transformation matrix W determined by a training data set. The pre-acquired training data set contains 60 trials, in each trial the subject performs a motor imagery of left/right hand. Six channels of the preprocessed EEG signals are selected, which correspond to the first three and the last three rows of W. Their logarithm variances are calculated and a 6 dimensional feature vector is constructed. Applying a SVM classifier trained by a training data set, we obtain a SVM score $f(k)$.

Next, we calibrate the parameters a and b using the EEG data when the brain is in idle state (without any motor imagery). The objective is to make the cursor not move left or right when the brain has no motor imagery. This data set contains N time segments of 200ms ($N = 10$ in this paper). According to the method described above, we calculate the SVM scores $f(1), \dots, f(N)$.

Set

$$\begin{aligned} m &= \frac{1}{N}\sum_{k=1}^{N} f(k), \\ mi &= \min\{f(k), k = 1, \cdots, N\}, \\ mx &= \max\{f(k), k = 1, \cdots, N\}, \end{aligned} \quad (3)$$

Then we calculate a and b as

$$a = \frac{h}{\max\{mx - m, m - mi\}}, \quad b = -am. \quad (4)$$

In the above calibration, the parameter h in (4) is used for adjusting the velocity of the cursor's horizontal movement. It may have different settings for different subjects. In our experiments, h is fixed to 8 for all of the subjects.

Considering the model (2) and the above parameter setting of a and b, we can find that the average horizontal movement during the idle state $\frac{1}{N}\sum_{k=1}^{N-1}(x(k+1) - x(k))$ is close to zero. Thus our calibration method has the advantage that the cursor almost does not change its horizontal position if the subject is in the idle state of motor imagery. This has been demonstrated in our online experiments.

Combining the above algorithms for vertical movement control and horizontal movement control, we obtain our algorithm for 2-D cursor control of which the diagram is shown in Fig. 2. It follows from Fig. 2 that for the kth movement of the cursor, the horizontal coordinate $x(k)$ and the vertical coordinate $y(k)$ are determined by motor imagery and p300 potential respectively. Furthermore, the horizontal movement control based on motor imagery and the vertical movement control based on P300 are performed simultaneously in our algorithm as well as in our online BCI system. As will be shown in our data analysis, the two control signals for the horizontal movement and the vertical movement respectively are almost independent to each other.

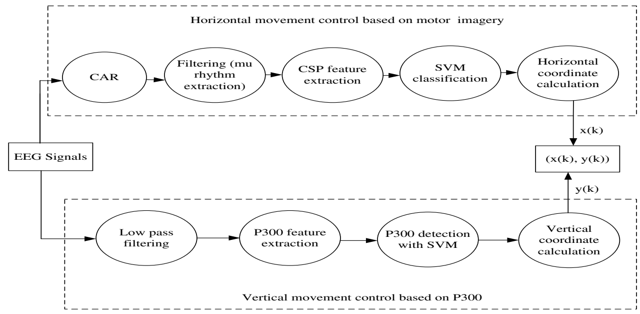

Fig. 2. Diagram of the algorithm for 2-D cursor control.

III. Online experimental results

Six subjects, five males and a female, aged from 22 to 30, attended our online experiments. Before our experiments, two of them had some experience in using our 2-D cursor control system because of the system's set up. The other four subjects had no any experience in using BCI systems. The training time for effectively using our system for the 4 new user was from 2 independent sessions to 8 independent sessions. For all new users, each training session lasted about 2 hours including preparation. All the training sessions for a subject were arranged in several consecutive weeks.

During BCI operation, the subject sat facing a video screen. Scalp electrodes recorded 30 channels (10-20 system) of EEG signals with all channels referenced to the right ear. The signals were digitized at 250 Hz.

Before a subject controlled the cursor, three data sets were collected of which two were used for training P300 control model and motor imagery control model respectively, and the other one was used for calibration. The parameters of our system were set as described in Section 2.

Once the parameters of the system were determined, the subject used our system for 2-D cursor control. A trial began when a target and a cursor appeared simultaneously at two random positions on the screen. 100 ms later, the 8 buttons began to flash in a random order. Each button was intensified for 100 ms, while the time interval between two consecutive button flashes was 120 ms. From the beginning of a trial, the subject started to move the cursor to the target. The trial ended when the cursor hit the target or the control time exceeded a predefined value (60 s in our experiment). The interval between two consecutive trials was 2 seconds.

Table I shows the experimental results including the numbers of trials, accuracy rates for hitting the target and the average time of a trial for the six subjects. Note that for each subject, all the trials were performed in a single session.

TABLE I
RESULTS IN EXPERIMENT 1

	Number of trials	Hit rate (%)	Average time (s)
Subject A	90	95.6	25.1
Subject B	160	90.6	29.3
Subject C	102	83.5	35.6
Subject D	80	82.5	33.6
Subject E	80	92.5	33.9
Subject F	80	92.5	28.2

From Table I, we can find out that the accuracy rates of all the six subjects are satisfactory. However, the control time of each trial was not short (about 30 s in average). There are two main reasons: (i) The relative small size of the cursor and the target. The ratio of the target size and the workspace is just 0.03%. Therefore the subjects need a long time to control the cursor to hit the target. (ii) Triggering and effectively detecting $P300$ are time consuming to some degree. To reduce the time for detecting P300 and improve the speed of our system are our future work.

However, we would like to emphasize that our system is relatively convenient for new users. For instance, in the 2-D cursor control system shown in [5], initial sessions were designed for all users. In these initial sessions, the transition from 1-D to 2-D control was accomplished by gradually increasing the magnitude of movement in the second dimension and/or by alternating between 1-D runs in the vertical and horizontal dimensions and then switching to 2-D runs. In the present work, such special initial sessions are not necessary for new users' training. Generally, if a subject is able to separately use P300-based BCIs and motor imagery-based BCIs, he/she can use our system without difficulty.

In our system, CSP filters are used to produce the control signal for the control of horizontal movement of the cursor. We now show the topographies of CSP filters to the signal band-pass filtered with $8-12Hz$ and the power spectra of two channels of raw EEG signals calculated based on the training data set. For Subjects A and B, two of the selected CSP filters (the first and the last rows of W) are displayed as scalp map on the left of Fig. 3, which are easily related to the motor imageries of right and left hands respectively. Plots on the right of Fig. 3 show the spectra calculated from two channels (C3 and FC4) of raw EEG signals. The discriminability of the brain signals corresponding to the motor imageries of right and left hands is demonstrated.

IV. Conclusions

In this paper, we presented an approach and corresponding system implementation for a 2-D cursor control. The horizontal and the vertical movements of the cursor are controlled by P300 potential and mu rhythm respectively. Six subjects attended our online experiment. The results show that the horizontal and vertical movements of the cursor can be effectively and independently controlled by their $P300$ and mu (or beta) rhythm respectively. Using our system, the user can move the cursor from a random position to the target also located in a random position.

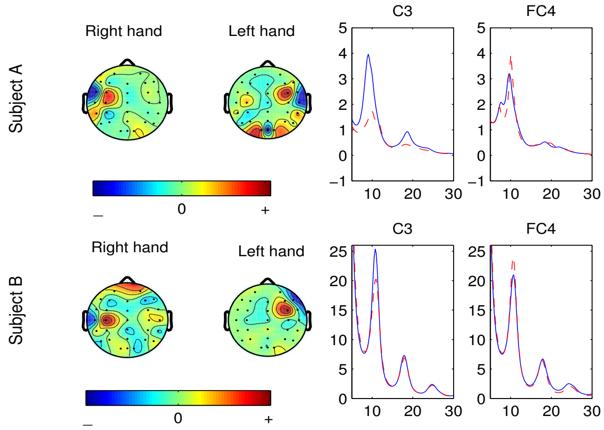

Fig. 3. Topographies of two selected CSP filters and the spectra of two channels of raw EEG signals for two subjects. Left: for each subject, two of the selected CSP filters (the first and the last rows of W) displayed as scalp maps. Right: for each subject, the spectra of two channels of raw EEG signals with blue curves referring to the motor imagery of right hand and red curves referring to the motor imagery of left hand.

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