An EEG-based BCI System for 2D Cursor Control

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Abstract— In this paper, an electroencephalogram (EEG)-based brain computer interface (BCI) is proposed for two dimensional cursor control. The horizontal and vertical movements of the cursor are controlled by mu/beta rhythm and P300 potential respectively. The main advantages of this system are: (i) two almost independent control signals are produced simultaneously; (ii) the cursor can be moved from a random position to another random position in a screen. These advantages have been demonstrated in our experiment and data analysis.

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

I. Introduction

As a communication interface to translate brain activities into computer control signals, brain-computer interfaces (BCIs) have received more and more attention in recent years [1]-[3]. BCIs provide an alternative communications and control method for people with severe motor disabilities [4]. An important issue in BCI research is cursor control, where the objective is to map the EEG signal to movements of a cursor on a computer screen. It has many potential applications, not only in the control of computer cursors, but also in other devices like robotic arms or neuroprostheses. In the past, several studies have been devoted to one dimensional (1D) cursor control via EEG-based BCIs [6], [7], [8]. 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 the imagination of left- and right-hand movements. The biological background is that imagination of movements leads to short-lasting and circumscribed attenuation (or accentuation) in mu and beta rhythm activities in EEG signals, known as event-related desynchronization (or synchronization) (ERD/ERS) [9]. However, usually with a 1D cursor control system, the user is only allowed to control either the vertical or the horizontal movement of a cursor at a time. It's easy to see that, compared with 1D cursor control, multidimensional cursor control would provide stronger interface between the user and the machine, and allow a much wider range of applications.

EEG-based 2D continuous cursor control BCI was reported and proven effective in [10]. The BCI in [10] relies on two independent control signals extracted from two particular EEG rhythms, mu and beta, respectively. One may take a classification methodology for multidimensional control, such as in [11], [12], which is based on the detection of the steady-state visual evoked potential (SSVEP) or P300 potential, a late positive component occurring in response to task-relevant stimuli. Obviously, the control in [11], [12] is not analogue since the cursor takes only one of the four directions anytime. It can be seen that the classification methodology would be suitable for discrete control rather than for the continuous control of interest in this work.

In this paper, we propose a method for 2D 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. Three subjects attended our experiments. After a short term of training in 2D cursor control, all three subjects succeeded in using this system and obtained satisfactory accuracy rates (average accuracy rate: 89.5%) for moving the cursor to targets. Besides relatively short training time, our experiments and further data analysis results show two other advantages of our method and BCI system: first, two almost independent control signals for 2D cursor control are obtained, second, the cursor can move from one randomly given point to another randomly given point.

II. Methods

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

A. Graphical user interface

A 40-channel electronic EEG cap LT 37 from Compumetics is used to collect EEG data from subjects. The collected EEG signals are sent to a portable amplifier Nuamps also from Compumetics. It amplifies the analog EEG signals, digitalizes them with sampling rate 250 Hz and sends the data to a notebook computer for processing. The computer receives EEG data from the amplifier through a USB port, and also sends synchronous stimulus code through parallel port to the amplifier.

Our GUI is shown in Fig. 1, in which the circle represents a cursor and the square represents a target. The initial position of the cursor and the position of the target are randomly generated in the screen. There are 8 buttons around the window, with 3 buttons labelled "up" at the top, 3 buttons labelled "down" at the bottom, and two buttons labelled "stop" in the middle. These button will flash in a random order during 2D control. The subjects will attempt to move the cursor to hit the target. The ratio of the diameter of the cursor, the width of the target and the width of the screen is $0.026 : 0.049 : 1$.

The horizontal movement of the cursor is controlled by beta rhythm (or mu rhythm), while the vertical movement of

the cursor is controlled by P300 potential. The method for horizontal movement control is similar to that in [8]. If the user wants to move the cursor right, then he needs to imagine his right hand, and vice versa. The vertical movement of the cursor is controlled by P300 potential. If the user wants to move the cursor up, then he needs to focus on one of the three "up" buttons. If the user wants to move the cursor down, then he needs to focus on one of the three "down" buttons. Finally, if he does not want to move the cursor in vertical direction, then he can focus on one of the two "stop" buttons.
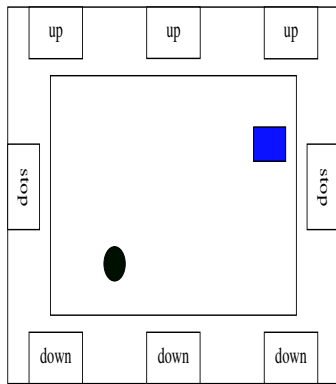

Fig. 1.   The GUI for 2D cursor control

B. Models and algorithms for 2D 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 corresponding algorithms.

A. Control of vertical movement based on P300 potential

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

$$y(k + 1) = y(k) + cv_0, \quad (1)$$

where $c \in \{1, -1, 0\}$ 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, k represents the kth update of the position of the cursor. In this study, $v_0 = 20$, i.e. the cursor moves 20 pixels vertically every update.

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

(i) Feature extraction;
(ii) Train a SVM classifier;
(iii) Classification and P300 detection;

(iv) Determine the direction of vertical movement of the cursor. If P300 happens at one of the three "up" buttons, set $c = -1$ (The cursor will go up); If P300 happens at one of the three "down" buttons, set $c = 1$ (The cursor will go down); If P300 happens at one of the two "stop" buttons, set $c = 0$ (The cursor will have no vertical movement. See the GUI in Fig. 1).

Remark 1: Note that P300 detection is performed every round, then the direction of vertical movement of the cursor is judged every round (each round lasts 1.6 seconds).

B. Control of the horizontal movement of the cursor based on mu or beta rhythm

In our system, the horizontal movement of the cursor is controlled by beta rhythm (limited in the band of 19-23Hz) over the right and left sensorimotor cortices. In fact, mu rhythm also can be used for horizontal movement control. From our experiments, we found that the efficiency of using mu rhythm is similar.

The control model is

$$x(k+1) = x(k) + \frac{1}{3}\mathbf{a}^T(\mathbf{p}(k-2) + \mathbf{p}(k-1) + \mathbf{p}(k)) + b, \quad (2)$$

where $x(k)$ is the horizontal coordinate of the cursor, $\mathbf{p}(k)$ is a n dimensional power difference vector calculated from $2n$ EEG channel signals, $\mathbf{a}$ is n dimensional constant vector, b is a constant, k represents the kth update of the position of the cursor. $\mathbf{p}(k)$, $\mathbf{a}$ and b will be defined in the following. We introduce delays into the control model (2) to make the cursor move smoothly.

We now show the method for calculating the power difference vector $\mathbf{p}(k)$. As stated before, the position of the cursor is updated every 200 ms. Therefore, the time point for the kth update is $200k$ ms. First, we perform preprocessing, common average reference (CAR) spatial filtering to the selected $2n$ channel EEG signals in the time interval $[200k - 199, 200k]$. The obtained signals are then filtered in the range $19 - 23Hz$ (beta band). The power vector for the filtered EEG signals is denoted as $[p_{k,1}, \cdots, p_{k,n}, p_{k,n+1}, \cdots, p_{k,2n}]$, where $p_{k,1}, \cdots, p_{k,n}$ are from the n channels over the left sensorimotor cortex, while $p_{k,n+1}, \cdots, p_{k,2n}$ are from the n channels over the right sensorimotor cortex. Set $\mathbf{p}(k) = [p_{k,1}, \cdots, p_{k,n}]^T - [p_{k,n+1}, \cdots, p_{k,2n}]^T$. In this paper, the EEG signals from 6 electrodes distributed in the sensorimotor cortex are used, i.e. $n = 3$.

Next, we calibrate the parameters $\mathbf{a}$ and b. Suppose that the EEG data in the time interval from 0 to $200N$ms is used for calibration (during this period, the subject is idle). According to the method described in the previous paragraph, we calculate the power vector $[p_{k,1}, \cdots, p_{k,n}, p_{k,n+1}, \cdots, p_{k,2n}]$ using the EEG signals in the time interval from $200k - 199$ to $200k$ ms, where $k = 1, \cdots, N$.

Set

$$
\begin{aligned}
m_i &= \frac{1}{N}\sum_{k=1}^{N}(p_{k,i} - p_{k,i+n}), \\
mi_i &= \min\{p_{k,i} - p_{k,i+n}, k = 1, \cdots, N\}, \\
ma_i &= max\{p_{k,i} - p_{k,i+n}, k = 1, \cdots, N\}, \quad (3)
\end{aligned}
$$

where $i = 1, \cdots, n$.

Then we calculate $\mathbf{a} = [a_1, \cdots, a_n]^T$ and b,

$$a_i = \frac{h}{max\{ma_i - m_i, m_i - mi_i\}}, \quad b = -a_1 m_1 - \cdots - a_n m_n. \tag{4}$$

In the above calibration, the parameter h in (4) is used for adjust the horizontal movement velocity of the cursor. It may have different settings for different subjects, however h is fixed to 5 for the 3 subjects in our experiments. This calibration method will allow the user to control the cursor using beta rhythm, while it also ensures that the cursor does not deviate from its horizontal position if the user is idle.

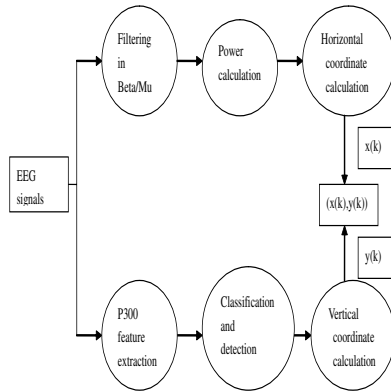Fig. 2 shows the diagram of our algorithm for 2D cursor control.

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

III. EXPERIMENTS AND DATA ANALYSIS

In this section, we present two experiments and corresponding data analysis. In the first experiment, we will validate our approach for 2D cursor control, while in the second experiment, we will prove that visual stimulus evoked P300 potential and motor imagining related beta rhythm can happen and work simultaneously. Furthermore, from our data analysis, it will show that the two control inputs used in our system are almost independent.

A. Experiment 1

The three male people are of age 31, 41 and 40 respectively. The first two have some experience in using a P300-based BCI speller and in using a 1D cursor control BCI system, which is based on mu or beta rhythm. However, they have no experience in using our 2D cursor control system. The third subject has no experience in using P300, mu or beta rhythm to control BCI systems.

During BCI operation, the subject sat facing a video screen. EEG activity was recorded from 15 electrodes, of which the distribution on the scalp was shown in Fig. 3 (we only used the 15 electrodes although the cap was 40

channel). All channels were referenced to the right ear, the signals were digitized at 250 Hz. A trial began when a target and the cursor appeared simultaneously at two random positions on the screen. 100 ms later, the 8 buttons flashed in a random order. Each flash lasted 100 ms, while the time interval between two consecutive flashes was 100 ms. From the beginning of one flash, the subject started to move the cursor to the target. The trial ended once the cursor touched the target or one of the four edges of the GUI. A new trial would start after 2 seconds.
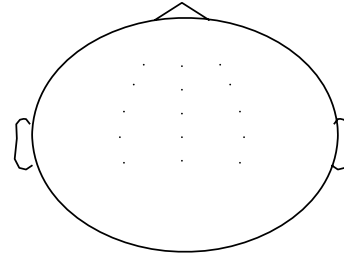

Fig. 3.   The scalp map of 15 EEG electrodes used in this study

Before every subject controlled the cursor, we set the parameters of our system using the approach in Section 2.2. A SVM classifier for detecting P300 potential was first trained. During this training phase, the subject needed to look at 8 buttons one by one according to a random order produced by the system. For each button, the clue given by the system lasted 2 seconds; the subject looked at the button for 12.8 seconds. Therefore the total training time for establishing the SVM model was $118.4 (= (12.8 + 2) \times 8)$ seconds. Next, the parameters of the control model based on beta rhythm were calibrated. During the calibration period of about 100 seconds, the subject was relaxed.

After two sessions conducted on 2 consecutive days, the three subjects completed 205, 159 and 197 trials respectively. In each session, they had a break of about 5 minutes every 20 trials.

Table I shows the experimental results including the numbers of trials, accuracy rates for hitting the target and average time of a trial for the three subjects.

TABLE I
RESULTS IN EXPERIMENT 1

	Trial number	Accuracy (%)	Average time (s)
Subject A	205	94.2	23.1
Subject B	159	88.1	19.7
Subject C	197	86.3	18

From Table I, we can find that the accuracy rates for the three subjects are satisfactory. However, the control time for each trial is not short (about 20 s in average). The main reason is that triggering and detecting $P300$ are time consuming to some degree. To reduce the time for processing P300 and improve the speed of our system are our future work.

TABLE II

TRAINING SESSIONS FOR SUBJECT C

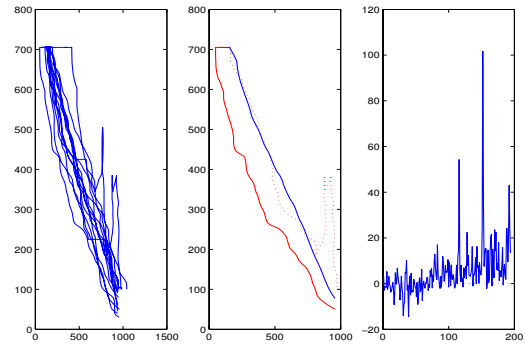|	Trial number	Accuracy (%)	Average time (s)
Session 1	51	55.2	20.7
Session 2	58	59.1	22
Session 3	75	75	16.1
Session 4	76	85.5	17.2

Fig. 4. Results in Experiment 2 in which the starting position of the cursor and the position of the target are fixed. Left: traces of the cursor in 61 trials; Middle: the blue curve is the average of all tracks shown in the left subplot. The red solid curve and the red dotted curve are two traces of the cursor obtained in two trials; Right: the power difference curve of two beta rhythms extracted from the left sphere and the right sphere of the brain respectively.

However, we would like to emphasize that our system is relatively convenient for new users. In the 2D cursor control system shown in [10], initial sessions were designed for all users. In these initial sessions, the transition from 1D to 2D control was accomplished by gradually increasing the magnitude of movement in the second dimension and/or by alternating between 1D runs in the vertical and horizontal dimensions and then switching to 2D runs. In this work, there need not such special initial sessions for new users' training. Among the three subjects, the first two had some experience in using P300- and mu/beta-based BCI systems, the third had no experience in using BCI systems. About two hours were sufficient for the first two subjects to be familiar with our system. For the third subject, four sessions of training were arranged in four consecutive days. The details of these four training sessions are shown in Table II. Note that the trials shown in Table I for Subject C were carried out after these four training sessions. From Table II, we can see that even for a subject who had no experience in BCI control, it was not difficult to be familiar with and using our system.

B. Experiment 2

In this experiment, we prove that visual stimulus evoked P300 potential and motor imaginary related beta rhythm can work simultaneously in our system. We use a new GUI which is similar as in Fig. 1 except that the initial position of the cursor is fixed in the upper left corner, and the target position is fixed at the lower right corner. Only Subject A attended this experiment, and 61 trials of data were collected. The traces of the cursor are shown in Fig. 4.

From the left and middle subplots in Fig. 4, we can see that the horizontal and vertical movements of the cursor are simultaneously controlled by beta rhythm and P300 potential in each trial. Furthermore, from the right subplot, it can be found that the horizontal movement of the cursor is continuously controlled by beta rhythm. During this period, the vertical movement direction is still controlled by P300. Therefore, P300 potential and beta rhythm can exists simultaneously in our system.

C. Data analysis

As shown in previous sections, we use P300 potential and beta rhythm as two control signals in our 2D cursor control system. For efficient 2D control, the two control signals need to be independent. In the following, we will analyze the data collected from the first experiment and prove the independence of P300 potential and mu/beta rhythm.

As an example, we present the details of our data analysis for Subject A. For the other two subjects, we had the same data analysis but only present the results here.

Suppose that $(x_{c,j}, y_{c,j})$ are the coordinates of the initial position of the cursor, and $(x_{t,j}, y_{t,j})$ are the coordinates of the position of the target at time point t in the jth trial, $j = 1, \cdots, N$ (the number of trials N equals to 205 for Subject A). Denote $\mathbf{x}_c = [x_{c,1}, \cdots, x_{c,N}]$, $\mathbf{y}_c = [y_{c,1}, \cdots, y_{c,N}]$, $\mathbf{x}_t = [x_{t,1}, \cdots, x_{t,N}]$ and $\mathbf{y}_t = [y_{t,1}, \cdots, y_{t,N}]$. Furthermore, define $\mathbf{x} = \mathbf{x}_c - \mathbf{x}_t$, $\mathbf{y} = \mathbf{y}_c - \mathbf{y}_t$.

Using the EEG data from the ith channel and the jth trial, we calculate the power values in mu rhythm frequency band. The power values in mu band are denoted as $P_\mu(i,j)$, $i = 1, \cdots, 15$, $j = 1, \cdots, N$. Now we calculate the power differences of three pairs of channels, FC3 and FC4, C3 and C4, CP3 and CP4, which are used for the horizontal movement control of the cursor in this study (the channel number of FC3, FC4, C3, C4, CP3 and CP4 are $4, 6, 7, 9, 10$ and 12 respectively),

$$Dp_{\mu,1}(j) = P_\mu(4,j) - P_\mu(6,j), \tag{5}$$

$$Dp_{\mu,2}(j) = P_\mu(7,j) - P_\mu(9,j), \tag{6}$$

$$Dp_{\mu,3}(j) = P_\mu(10,j) - P_\mu(12,j), \tag{7}$$

where $j = 1, \cdots, N$.

In the following, we calculate the average correlation coefficient between these power difference vectors defined above and $\mathbf{x}$, and the average correlation coefficient between these power difference vectors and $\mathbf{y}$,

$$C_{\mu,x} = \frac{1}{3} \sum_{k=1}^{3} |Cor(Dp_{\mu,k}, \mathbf{x})|, \tag{8}$$

$$C_{\mu,y} = \frac{1}{3} \sum_{k=1}^{3} |Cor(Dp_{\mu,k}, \mathbf{y})|, \tag{9}$$

where $|Cor(\cdot, \cdot)|$ represents the absolute value of the correlation coefficient of two vectors.

The average correlation coefficients $C_{\mu,x}$, $C_{\mu,y}$ for Subject A are shown in the second row in Table III.

Next, we analyze the correlation between $P300$ potentials and $\mathbf{x}$, and the correlation between $P300$ potentials and $\mathbf{y}$. Similarly as in Section 2.2, we cut the segment of each channel signal from 150 ms to 500 ms after a button flashes. Furthermore, down sample the segment with rate 0.2. The obtained data vector is denoted as $Pb_{i,k,q,j}$, where i, k, q, j represents the ith channel, the kth button corresponding to a flash, the qth round and the jth trial respectively.

During the jth trial, suppose that there are L_j outputs of P300 detection, the corresponding L_j button numbers are denoted as $k_1, \cdots, k_{L_j}$. For the output k_l, we calculate the average P300 potential,

$$\bar{P}b_{i,k_l,j} = \frac{1}{8} \sum_{q=l-7}^{l} Pb_{i,k_l,q,j}. \tag{10}$$

Define

$$\tilde{P}b_{i,k_l,j} = \begin{cases} \bar{P}b_{i,k_l,j}, & \text{if } k_l \in \{1,2,3\}, \\ -\bar{P}b_{i,k_l,j}, & \text{if } k_l \in \{4,5,6\}, \\ \mathbf{0}, & \text{if } k_l \in \{7,8\}, \end{cases} \tag{11}$$

where $\{1,2,3\}$ are the numbers of three "up" buttons, $\{4,5,6\}$ are the numbers of three "down" buttons, $\{7,8\}$ are the numbers of two "stop" buttons. We add signs to $\bar{P}b_{i,k_l,j}$ in (11) such that $\tilde{P}b_{i,k_l,j}$ contain the information of the vertical movement direction of the cursor.

Note that $\tilde{P}b_{i,k_l,j}$ and $\frac{1}{L_j} \sum_{l=1}^{L_j} \tilde{P}b_{i,k_l,j}$ are vectors with the same dimension as $Pb_{i,k,q,j}$. Next, we calculate an average value representing the average P300 potential for the ith channel and the jth trial,

$$P_{i,j} = mean(\frac{1}{L_j} \sum_{l=1}^{L_j} \tilde{P}b_{i,k_l,j}), \tag{12}$$

where $i = 1, \cdots, L$, $j = 1, \cdots, N$.

In the following, we calculate the average correlation coefficients,

$$C_{P300,x} = \frac{1}{L} \sum_{i=1}^{L} |Cor([P_{i,1}, \cdots, P_{i,N}], \mathbf{x})|, \tag{13}$$

$$C_{P300,y} = \frac{1}{L} \sum_{i=1}^{L} |Cor([P_{i,1}, \cdots, P_{i,N}], \mathbf{y})|. \tag{14}$$

Furthermore, we calculate the average correlation coefficient between $p300$ and mu rhythm,

$$C_{P300,\mu} = \frac{1}{L} \sum_{i=1}^{L} |Cor([P_{i,1}, \cdots, P_{i,N}], [P\mu_{i,1}, \cdots, P\mu_{i,N}])|, \tag{15}$$

where $P\mu_{i,j}$ and $P\beta_{i,j}$ denote the average power value in mu band and the average power value in beta band respectively, which are extracted from the EEG signal of the ith channel and jth trial.

The average correlation coefficients $C_{P300,x}$, $C_{P300,y}$, $C_{P300,\mu}$ for Subject "A" are shown in the last 3 columns in the second row of Table III.

Through similar data analysis as above, we obtain the results for the other two subjects, which are shown in the third and forth rows of Table III respectively.

TABLE III
DATA ANALYSIS RESULTS

	$C_{\mu,x}$	$C_{\mu,y}$	$C_{P300,x}$	$C_{P300,y}$	$C_{P300,\mu}$
Sub. A	0.54	0.06	0.04	0.35	0.03
Sub. B	0.38	0.02	0.02	0.58	0.05
Sub. C	0.18	0.02	0.07	0.41	0.054

From Table III, we can see that the correlation between beta (or mu) and $\mathbf{x}$ is big, while the correlation between beta (or mu) and $\mathbf{y}$ is small. The correlation between P300 potential and $\mathbf{x}$ is small, while the correlation between P300 and $\mathbf{y}$ is big. This is reasonable because the horizontal and vertical movements of the cursor are controlled by beta rhythm and P300 potentials respectively. Furthermore, we find that the correlation between $P300$ potentials and beta (mu) rhythm is very small. Our data analysis results show that we can use beta (or mu) rhythm and $P300$ potential to control the horizontal and vertical movements of a cursor respectively, and the two control signals are almost independent.

IV. CONCLUSIONS

In this paper, we presented an approach and its system implementation for 2D movement control of a cursor, in which the horizontal and vertical movements of the cursor are controlled by P300 potentials and beta rhythm respectively. Our experimental results show the validity of our approach. It follows from our data analysis that the two dimensional movements of the cursor can be independently controlled by $P300$ and beta (or mu) rhythm respectively. In our system, the user can move the cursor from a random position to the target also located in a random position. For new users (without any experience in using our system), it is easy to be familiar with our system and corresponding control skill. Our main task in the future is to optimize the parameter settings and algorithms to improve the speed of the system.

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