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Control of a Simulated Wheelchair Based on A Hybrid Brain Computer Interface

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***Abstract*— In this paper, a hybrid BCI system was described for the control of a simulated wheelchair. This hybrid BCI was based on the motor imagery-based mu rhythm and the P300 potential. With our paradigm, the user may perform left- or right-hand imagery to control the direction (left or right turn) of the simulated wheelchair. Furthermore, a hybrid manner was used for speed control: e.g., foot imagery without button attention for deceleration and a specific button attention without any motor imagery for acceleration. An experiment based on a simulated wheelchair in virtual environment was conducted to assess the BCI control. Subjects effectively steered the simulated wheelchairs by controlling the direction and speed with our hybrid BCI system. Data analysis validated that our hybrid BCI system can be used to control the direction and speed of a simulated wheelchair.**

Keywords: Hybrid brain-computer interface (BCI), motor imagery, P300, wheelchair, direction, speed.

I. Introduction

One important application of Electroencephalogram (EEG)-based brain-computer interfaces (BCIs) is for wheelchair control, which is valuable for improving the quality of life and self-independence of disabled users [1], [2]. Until now, two types of protocols, synchronous and asynchronous, have been used for EEG based wheelchair control. The EEG signals used for synchronous control depend on the potentials evoked by visual stimuli, including the P300 potential and SSVEP [1], [3]. When using this synchronous protocol, the direction or the route of the wheelchair cannot be changed by the user as the wheelchair moves to the destination. These synchronous prototypes exhibit high accuracy but suffer from a low response speed; an effective control command is generally obtained after 4 seconds [1]. The brain signals used for asynchronous control protocols are generally derived from motor imageries, allowing users to send an appropriate command (e.g., a change in direction) to a moving wheelchair [2], [4].

Multi-degree control is essential for an operational wheelchair. For instance, two control signals are required for both directional control (left and right) and speed control (acceleration and deceleration). Furthermore, these control commands must be accurately and quickly generated. Multiple independent control signals based on BCIs have been discussed in several studies [5], [6]. A common characteristic for these BCI systems is that the control signals were from a single modality of motor imageries. Additionally, hybrid BCIs that combine different brain signals are appealing in their ability to simultaneously or sequentially provide multiple control commands [7], [8], [9]. For example, Allison et al. demonstrated that by combining multiple brain signals, such as motor imagery and SSVEP, BCI accuracy can be improved, especially for BCI-blind subjects [7].

This paper proposes a hybrid BCI paradigm to provide directional and speed control commands to a simulated wheelchair. In our system, left and right direction commands are based on the user's left- and right-hand imageries, respectively. Furthermore, a hybrid paradigm is used to control speed. In order to decelerate, the user performs a third motor imagery (e.g. the foot) while ignoring any flashing buttons on the GUI. If the user wishes to accelerate, he/she pays attention to a specific flashing button without any motor imagery. An experiment of a simulated wheelchair driven in a virtual-environment was conducted to assess the performance of our proposed hybrid BCI. Our experimental results and data analysis demonstrated the efficiency of our method.

II. Graphical User Interface And Control Methods

In this section, we present the graphical user interface (GUI), and the algorithms of our system. The GUI, similar to that used in [8], [9], is illustrated in Fig. 1. A rectangular workspace and 8 flashing buttons are included. The workspace is 1166×721 $pixels$. There are 8 buttons on the GUI which flash in a random order to induce P300 potentials.

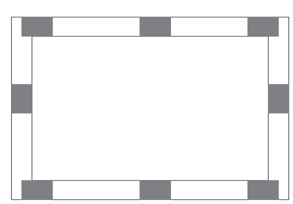

Fig. 1. The GUI for brain-actuated control of a wheelchair. Eight flashing buttons are included for evoking P300 potentials.

In addition, we propose a hierarchical decision method for simulated wheelchair steering (Fig. 2) to detect directional and speed control commands from the user's EEG signals.

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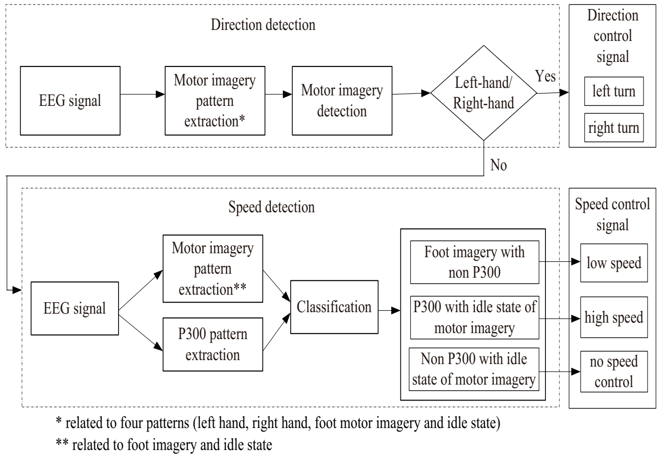

Fig. 2. Algorithm diagram for the detection of directional and speed control signals. In this paradigm, the user imagines left- or right-hand to produce a control command for a left or right turn, respectively. Moreover, the user performs foot motor imagery with ignoring the flashing buttons and focuses on a specific button without any motor imagery to send a deceleration or an acceleration control command, respectively.

First, the motor imagery patterns are extracted for identifying the directional control commands. If a left- or right-hand motor imagery is detected, then a directional control command for a left or right turn is obtained. Otherwise, speed control commands are identified. Speed control command acceleration/deceleration is determined by discriminating two tasks for the user. The first task corresponding to deceleration command is that the user performs foot imagery without paying attention to the specific flashing button, while the other task corresponding to acceleration command is that the user pays attention to the specific flashing button without any motor imagery. At the end, the user can keep the current moving speed with idle state of both motor imagery and P300.

1) Detection of directional control signals: As described above, left- and right-hand imagery are associated with a left or right turn of the simulated wheelchair. One directional control command triggers a fixed, predefined degree of rotation. Hence, the objective for directional control is to detect left- and right-hand motor imagery from the online EEG signals. The steps of our algorithm for left- or right-hand motor imagery detection is as follows:

(i) EEG signals are spatially filtered with common average reference (CAR) and then bandpass-filtered at 8-32 Hz.

(ii) Spatial patterns are extracted using the method of one versus the rest common spatial patterns (OVR-CSP) proposed in [10]. In this study, there are 4 classes related to motor imagery: left-hand, right-hand, foot and idle state. Thus, we obtain 4 CSP transformation matrices based on the training dataset including 30 trials for each condition. Training data collection is illustrated in Fig. 3. We select the first and last three rows from each CSP transformation matrix (W) to construct a new transformation matrix with 24 rows for feature extraction as in [10].

(iii) Based on the CSP features of the training data set, 4 linear discriminant analysis (LDA) classifiers are trained with the *one-versus-rest* policy for dealing with the multi-class classification problem[11].

(iv) For online testing, the four classifiers trained in the step iii are applied to the feature vector extracted from EEG data in a time interval of 1000 ms before the current time point. Hence four LDA output scores are obtained. Following a loss-based decoding method described in [11], the class label corresponding to the maximal score is given to the feature vector. This detection is performed every 200 ms.

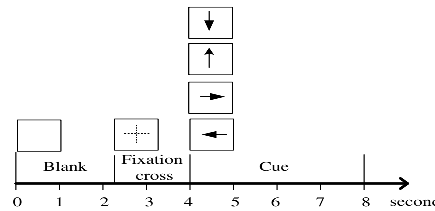

Fig. 3. Paradigm for training data acquisition in a trial. At the beginning (0-2.25 s), the screen is blank. From 2.25 s to 4 s, a cross appears in the screen to capture the subject's visual attention. From 4 s to 8 s, an arrow cue appears. The subject is instructed to implement a mental task according to the following cues: left or right arrows for left- or right-hand motor imagery, an up arrow for foot motor imagery and a down arrow attention to a specific button (the middle up button in our experiment). When an arrow appears on the screen, 8 buttons flash alternately in a random order. Each button is intensified for 100 ms, and the time interval between two consecutive button flashes is 120 ms. Thus, one round of button flashes takes 960 ms and there are 4 rounds (repeats) of button flashes per trial.

The direction of the simulated wheelchair will remain constant if the user performs foot motor imagery or is in the idle state of motor imagery. In this case, the detection of speed control signals is performed as described in the next subsection.

2) Detection of speed control signals: When no directional control signals are detected, speed control signals are detected. There are two features extraction for speed detection (Fig. 2). One is for motor imagery detection and the other is for P300 detection.

First, we describe feature extraction for motor imagery detection using the training data. Here the training data set contains two classes of data corresponding to foot imagery and the idle state of motor imagery (attention to a specific button), respectively. If a trial in the training data corresponds to the idle state of motor imagery, then its label is set to 1. Otherwise, its label is -1. A CSP feature vector x_j for the jth trial of the training data can be constructed with the method similar to the description in section II-.1, where $j = 1, \ldots, N$.

The P300 feature extraction for the jth trial of the training data ($j = 1, \ldots, N$) is similar to that described in [8]. First, we extract a segment (0-600 ms after a button flash) of the filtered EEG signals with frequency band 0.1-20 Hz from each channel for each flash of the specific button (the middle up button in our experiment). Then, the segment is downsampled by a rate of 6 from each channel to obtain a new data vector with 375 dimensions (25 time points $\times$15 channels) by concatenating from all 15 channels. The feature vector (p_j) in each trial is obtained by averaging 4 data vectors corresponding to 4 repeats of the button flash. If the trial corresponds to attention to the specific button, then its label is set to 1. Otherwise, its label is -1.

After extracting the motor imagery feature x_j and the P300 feature p_j ($j = 1, \ldots, N$) based on the training data set, a combination algorithm, PROB, is used to combine these features of two modalities [10]. Specifically, two LDA classifiers, denoted as (w_X, b_X) and (w_P, b_P), are trained using the motor imagery feature vectors with labels and the P300 feature vectors with labels, respectively. For each pair of motor imagery feature vector and P300 feature vector from a trial, two scores are computed using the corresponding classifiers. Next, we calculate the sum of these two scores as,

$$D_j = \frac{1}{2}[w_X^T x_j + b_X] + \frac{1}{2}[w_P^T p_j + b_P], j = 1, \ldots, N. \quad (1)$$

Using D_j, we calculate two thresholds, D^+_{mean} and D^-_{mean}, as follows:

$$D^+_{mean} = \frac{1}{|D^+|}\sum_{j\in D^+} D_j, \quad D^-_{mean} = \frac{1}{|D^-|}\sum_{j\in D^-} D_j, \quad (2)$$

where D^+ and D^- denote the set of indexes of D_j satisfying $D_j > D_{mean}$ and $D_j < D_{mean}$, respectively ($j = 1, \ldots, N$), D_{mean} is the mean of all D_j, and $| * |$ is the cardinality of a set.

In the test phase, a motor imagery feature vector is extracted every 200 ms using EEG data between 0 ms and 1000 ms before the current time point, while a P300 feature vector is extracted every flash of the specific button as above. Specifically, P300 feature extraction is based on the EEG data of 4 repeats of the specific button flash (the current flash and the three before). The speed signal detection is performed every 200 ms based on the motor imagery feature vector updated every 200 ms and the P300 feature vector updated every 960 ms (a round of button flashes).

A score denoted as D is then calculated as in (1). A label $\hat{y}$ for this epoch of EEG data is defined as

$$\hat{y} = \begin{cases} +1, \ \texttt{if}\ D > D^+_{mean} \\ 0, \ \texttt{if}\ D^-_{mean} \leq D \leq D^+_{mean} \\ -1, \ \texttt{if}\ D < D^-_{mean}. \end{cases} \quad (3)$$

In (3), the label $\hat{y} = 1, -1, or\ 0$ are corresponding to an acceleration command, a deceleration command and no speed control command for the simulated wheelchair, respectively.

III. Experimental Results

To validate our proposed hybrid BCI system for detecting directional and speed control commands, an experiment of a simulated wheelchair in a virtual environments was conducted.

In this experiment, the simulated wheelchair and 6 fixed destinations (circles) are shown in Fig. 4. We defined two routes for each user by setting the order of destinations, which are presented in Fig. 4A and Fig. 4B, respectively. The numbers in these circles denote the order in which the simulated wheelchair arrives at each destination. Both routes had the same optimal path length, 2270 $pixels$. The current destination, where the simulated wheelchair was first located, is marked red. When the subject drives the simulated wheelchair through the current destination at low speed, the color of this circle changes to blue and the next circle changes to red. If, however, the simulated wheelchair passes the current destination with high speed, the circle remains red. The user must drive the simulated wheelchair through the missed circle again (at low speed) until the color changes. The working space and control task designs originate from the AUTOMATIC CAR CONTROL event from the BCI competition held in China (2010), which was organized by Tsinghua University. During the competition, the order of destinations was randomly set for each participant. The hybrid BCI system described here won the first place in this competition.

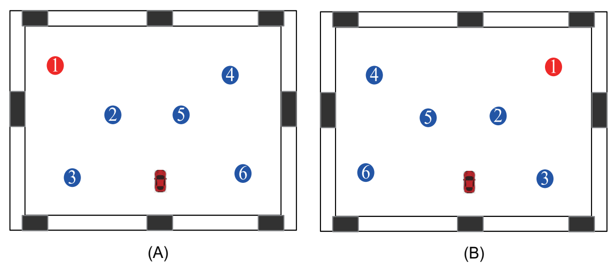

Fig. 4. The simulated wheelchair and two predefined routes.

Five healthy subjects with ages in the range of 22-33 years participated in this experiment. There were three sessions for each subject, and each session held 10 trials. In each trial, one of two predefined routes was randomly selected. The subject was required to drive the simulated wheelchair past the six circles sequentially at low speed while trying to proceed as quickly as possible, similar to the BCI competition in China (2010). Furthermore, if the user did not accomplish this task within 2 minutes, then the trial was considered a failure and was automatically terminated. In this experiment, the high speed and the low speed were set to 40 $pixels/s$ and 20 $pixels/s$, respectively. The rotational speed was set to 6° per directional control command.

The following performance indexes are used to assess our hybrid BCI with respect to directional and speed control in this experiment.

1) Accuracy rate: the percentage of successful navigation tasks.

2) Path length: the distance ($pixels/meters$) traveled to accomplish the task.

3) Path length optimality ratio: the ratio of the path length to the optimal path length. The optimal path length is the

TABLE I

PERFORMANCE INDEXES FOR ASSESSING THE SIMULATED WHEELCHAIR DRIVEN BY OUR HYBRID BCI.

	Accuracy rate (%)	Path length ($pixel$)	Path opt. ratio	Time (s)	Time for low speed (s)	Collisions
S1	100±0	2837.35±66.63	1.25±0.04	82.11±1.62	22.35±1.22	0±0
S2	100±0	2761.13±51.26	1.22±0.03	80.84±1.35	23.63±1.45	0±0
S3	100±0	2919.65±76.42	1.29±0.03	88.39±1.26	30.80±1.76	0±0
S4	100±0	2856.32±73.27	1.26±0.04	85.02±1.19	27.22±1.23	0±0
S5	100±0	2842.32±54.71	1.25±0.02	85.75±1.22	29.38±1.15	0±0
mean±std	100±0	2843.46±105.41	1.25±0.05	84.42±4.63	26.67±4.18	0±0

sum of point-to-point distances between each pair of adjacent destinations.

4) Time: the time ($seconds$) taken to accomplish the task.

5) Time for low speed: the time ($seconds$) that the simulated wheelchair travels at low speed.

6) Collisions: the number of collisions incurring to the edges of the working space for the simulated wheelchair.

The experimental results are summarized in Table I. All of the subjects accomplished each predefined task successfully using the directional and speed control for the simulated wheelchair. The average path optimality ratio was 1.25, indicating that there was a difference between the optimal path length and the actual path length taken by the subjects. This difference was mainly due to the extra distance required to turn sharply around each destination; directional correction occurred in the open space. Furthermore, no collisions occurred during the experiment. Thus, the performance of our proposed hybrid BCI system for directional control was satisfactory. In this experiment, the subjects were required to accomplish the tasks as soon as possible. The average time for low speed was 26.67 s in a trial. This was mainly because the user needed to drive simulated wheelchair to pass these destinations at low speed according to our experimental requirement. The average total time for accomplishing the task of a trial was 84.42 s. Thus, on average, the simulated wheelchair traveled at high speed for $57.75s$ $(84.42 - 26.67 = 57.75s)$ in a trial. This implies that all subjects performed speed control effectively using our hybrid BCI system.

IV. CONCLUSIONS

In this paper, a hybrid BCI that combines mu/beta rhythm from motor imagery and the P300 potentials was presented for directional and speed control of a simulated wheelchair. Four commands, associated with 4 mental tasks respectively, are provided. Specifically, left- or right-hand imagery is used for the left or right movement of the simulated wheelchair, and foot imagery or a specific button attention is used for deceleration or acceleration. An experiment based on a simulated wheelchair in a virtual environment demonstrated the effectiveness of our method and system.

REFERENCES

[1] B. Rebsamen, C. Guan, H. Zhang, C. Wang, C. Teo, M. H. Ang, and E. Burdet, "A brain controlled wheelchair to navigate in familiar environments," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 6, pp. 590–598, 2010.

[2] F. Galán, M. Nuttin, E. Lew, P. W. Ferrez, G. Vanacker, J. Philips, and J. R. Millán, "A brain-actuated wheelchair: asynchronous and non-invasive Brain-computer interfaces for continuous control of robots," *Clinical Neurophysiology*, vol. 119, no. 9, pp. 2159–2169, 2008.

[3] G. R. Müller-Putz, R. Scherer, C. Neuper, and G. Pfurtscheller, "Steady-State Somatosensory Evoked Potentials: Suitable Brain Signals for Brain–Computer Interfaces?" *IEEE transactions on neural systems and rehabilitation engineering*, vol. 14, no. 1, pp. 30–37, 2006.

[4] R. Scherer, F. Lee, A. Schlögl, R. Leeb, H. Bischof, and G. Pfurtscheller, "Toward self-paced brain–computer communication: navigation through virtual worlds," *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 2, pp. 675–682, 2008.

[5] J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proceedings of the National Academy of Sciences*, vol. 101, no. 51, pp. 17 849–17 854, 2004.

[6] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, "Electroencephalographic (eeg) control of three-dimensional movement," *Journal of Neural Engineering*, vol. 7, p. 036007, 2010.

[7] B. Z. Allison, C. Brunner, V. Kaiser, G. R. Müller-Putz, C. Neuper, and G. Pfurtscheller, "Toward a hybrid brain–computer interface based on imagined movement and visual attention," *Journal of Neural Engineering*, vol. 7(2), 2010.

[8] Y. Li, J. Long, T. Yu, Z. Yu, C. Wang, H. Zhang, and C. Guan, "An EEG-based BCI System for 2-D Cursor Control by Combining Mu/Beta Rhythm and P300 Potential," *IEEE Trans. on Biomed. Eng.*, vol. 57, no. 10, pp. 2495 – 2505, 2010.

[9] J. Long, Y. Li, T. Yu, and Z. Gu, "Target selection with hybrid feature for bci-based 2-d cursor control," *IEEE Trans. on Biomed. Eng., accept*, 2011.

[10] G. Dornhege, B. Blankertz, G. Curio, and K. R. Müller, "Boosting bit rates in noninvasive EEG single-trial classifications by feature combination and multiclass paradigms," *IEEE Trans. on Biomed. Eng.*, vol. 51, no. 6, pp. 993–1002, 2004.

[11] E. L. Allwein, R. E. Schapire, and Y. Singer, "Reducing multiclass to binary: A unifying approach for margin classifiers," *The Journal of Machine Learning Research*, vol. 1, pp. 113–141, 2001.