Journal of Zhejiang University-SCIENCE C (Computers & Electronics)
ISSN 1869-1951 (Print); ISSN 1869-196X (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

A hybrid brain-computer interface control strategy in a virtual environment*

Yu SU[1,2], Yu QI[1,2], Jian-xun LUO[1,2], Bian WU[1,3,4], Fan YANG[1,2], Yi LI[1,2], Yue-ting ZHUANG[1,2], Xiao-xiang ZHENG[1,3,4], Wei-dong CHEN[†‡1,2]

([1]*Qiushi Academy for Advanced Studies, Zhejiang University, Hangzhou 310027, China*)
([2]*School of Computer Science and Technology, Zhejiang University, Hangzhou 310027, China*)
([3]*Department of Biomedical Engineering, Zhejiang University, Hangzhou 310027, China*)
([4]*Key Laboratory of Biomedical Engineering of the Ministry of Education, Hangzhou 310027, China*)
[†]E-mail: qaas@zju.edu.cn

Received June 18, 2010; Revision accepted Nov. 10, 2010; Crosschecked Mar. 15, 2011

Abstract: This paper presents a hybrid brain-computer interface (BCI) control strategy, the goal of which is to expand control functions of a conventional motor imagery or a P300 potential based BCI in a virtual environment. The hybrid control strategy utilizes P300 potential to control virtual devices and motor imagery related sensorimotor rhythms to navigate in the virtual world. The two electroencephalography (EEG) patterns serve as source signals for different control functions in their corresponding system states, and state switch is achieved in a sequential manner. In the current system, imagination of left/right hand movement was translated into turning left/right in the virtual apartment continuously, while P300 potentials were mapped to discrete virtual device control commands using a five-oddball paradigm. The combination of motor imagery and P300 patterns in one BCI system for virtual environment control was tested and the results were compared with those of a single motor imagery or P300-based BCI. Subjects obtained similar performances in the hybrid and single control tasks, which indicates the hybrid control strategy works well in the virtual environment.

Key words: Hybrid brain-computer interface (BCI) control strategy, P300 potential, Sensorimotor rhythms, Virtual environment
doi:10.1631/jzus.C1000208 **Document code:** A **CLC number:** TP399; R318

1 Introduction

Brain-computer interfaces (BCIs) can provide a direct communication and control channel between the brain and external devices, independent of the brain's normal output pathways of peripheral nerves and muscles (Wolpaw *et al*., 2000). Non-invasive BCIs work by detecting and translating electroencephalography (EEG) signals into machine commands. There are two main types of EEG signals used in BCI: spontaneous signals generated by mental tasks and evoked signals resulting from stereotyped sensory stimulation (Wolpaw *et al*., 2002). Motor imagery (MI) related sensorimotor rhythms fall into the former type (Pfurtscheller and Neuper, 2001), while P300 event-related potential and steady-state visual evoked potential (ssVEP) belong to the latter (Farwell and Donchin, 1988; Middendorf *et al*., 2000).

Recent research tends to combine virtual reality (VR) with BCI systems. VR can provide safe, complex, and controllable experimental environments for BCI training and testing (Bayliss, 2003; Velasco-Álvarez and Ron-Angevin, 2009). Also, the variety of VR designs makes an interesting environment

‡ Corresponding author
* Project supported by the National Natural Science Foundation of China (Nos. 30800287, 60703038, 60873125, 61001172, and 61031002), the Zhejiang Provincial Natural Science Foundation of China (No. Y2090707), and the Fundamental Research Funds for the Central Universities of China

possible (Bayliss and Ballard, 2000), which may motivate the user and serve as a good feedback medium (Ron-Angevin and Diaz-Estrella, 2009).

Several EEG controlled navigation paradigms in virtual environments by MI have been developed. Early navigation was realized by mapping imagination of hand/foot movements to stop/forward commands in one direction (Leeb and Pfurtscheller, 2004). Later, a self-paced paradigm was proposed (Leeb *et al*., 2007b), and three-class MI-based BCIs with self-paced operations were further developed, where the system could detect MI-related brain activities and discriminate amongst different MI tasks (Scherer *et al*., 2008; Zhao *et al*., 2009). However, due to the complex dynamics of sensorimotor rhythms related to hand/foot movements and other mental tasks, several studies have reported that the best classification accuracy is achieved when only two tasks are discriminated (Obermaier *et al*., 2001; Kronegg *et al*., 2007). Recently, a system allowing subjects to move freely in three directions by the use of only one mental task was developed (Velasco-Álvarez and Ron-Angevin, 2009). Nevertheless, commands were selected by controlling a rotating bar, which is not a natural and direct way.

Since MI-based BCIs provide relatively low degrees of freedom, in applications with a large number of discrete commands such as spelling or remote control, P300-based BCIs are more efficient. Bayliss (2003) first used the P300 potential to control several objects or commands in a virtual apartment. Other P300-based virtual environment control systems were also developed, such as the smart home with different control elements (Edlinger *et al*., 2008) and four-directional control of a wheelchair (Piccione *et al*., 2008). Chen *et al*. (2010) used the P300 to select different movements of a virtual hand.

Most recently, several hybrid BCI systems combining MI and ssVEP signals have been reported. They detected the two EEG signals in a simultaneous (Allison *et al*., 2010; Brunner *et al*., 2010) or a sequential (Pfurtscheller *et al*., 2010b) manner, and both MI-based and ssVEP-based systems achieved performance improvements. Another hybrid BCI system detects P300 and MI signals simultaneously and independently to control a 2D cursor (Chen *et al*., 2010). With the use of two or more source signals, hybrid BCIs should achieve specific goals better than the conventional BCI systems (Pfurtscheller *et al*., 2010a).

This paper combines P300 and MI signals to create a hybrid BCI control strategy, the goal of which is to augment control functions of a single MI or P300 BCI in the virtual environment. MI and P300 potentials are detected in a sequential manner according to the control state of the virtual environment. Highlighting the advantages of two EEG patterns under specific scenarios, the control strategy uses P300 signals to operate the control panel of virtual devices with discrete commands, and MI signals to continuously navigate in the virtual environment.

2 Materials and methods

The system consists of a virtual apartment environment running on a standard computer, an EEG amplifier (Neuroscan SynAmps, USA), a system controller, and a signal processing module for MI and P300 detection running on another computer. The virtual 3D apartment environment is built up by OpenSceneGraph (OSG), which is an open source graphic engine based on Open Graphics Library (OpenGL). The controller implemented in C# determines the onset and offset of operation or system state, and transfers commands amongst different system components. The signal processing module is based on a Microsoft Foundation Classes (MFC) application which calls Matlab engine to handle the EEG signal. It detects signal patterns and sends decoded commands to the virtual environment via the controller. Communication between the components is realized by sockets, so the system can be distributed on different computers like the BCI2000 platform (Schalk *et al*., 2004).

2.1 Hybrid control strategy

A hybrid BCI control strategy in the virtual environment is proposed to expand the application scope of single MI- or P300-based BCI by using the two patterns as control signals in different system states. With the proposed control strategy, subjects can finish more complex tasks in the virtual environment than by a single pattern BCI. This goal is different from the recently reported hybrid BCI studies, which combined MI and ssVEP to improve the system performance (Allison *et al*., 2010; Brunner *et al*., 2010; Pfurtscheller *et al*., 2010b).

In the current study, the virtual environment has two states: device control and navigation. The former requires a large number of discrete control commands, which can be realized by implementation of the P300 oddball paradigm. Commands in the navigation state can be translated from the detection of continuous MI signals. By highlighting the advantages of MI and P300 patterns under specific scenarios, the proposed control strategy provides a natural and effective interaction with the virtual environment. Also, detection of the two EEG patterns is in a sequential manner depending on the system states where either MI or P300 detector is active in either system state.

Areas in the virtual environment are divided into two types representing device control and navigation states. The system is initialized in the navigation state, where MI patterns are detected and translated into navigation commands continuously. The navigation commands result in position updates in the virtual environment, and every update triggers a detector. The detector checks whether the current position falls into areas corresponding to the device control state and if it reaches this type of area, the controller stops MI detection and switches to a system state. The system switches to the device control state, and the control panel of the virtual device in the current area is presented to the subject as P300 oddball paradigm. The system reverts to the navigation state when the subject selects ‘quit’ command in the control panel. Fig. 1 shows this hybrid BCI control strategy in the virtual environment.

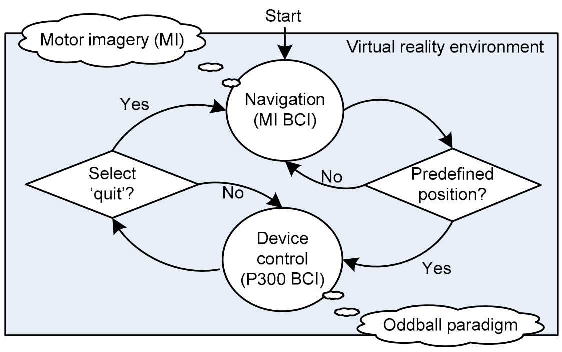


Fig. 1 Hybrid brain-computer interface (BCI) control strategy in the virtual environment

2.2 Hybird BCI control system

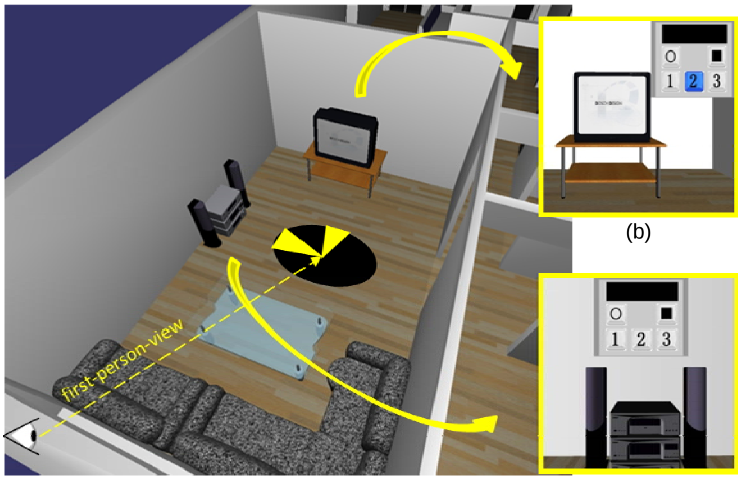
The virtual apartment consists of several rooms and each room contains certain devices and furniture. Navigation commands such as turning left/right and moving forward/backward are provided by the virtual environment. Besides, virtual devices like television (TV) and stereo are designed with a control panel, which is presented to the user in the P300 controlling phase. With the above functions integrated in the virtual apartment, the hybrid BCI control system simulates natural interaction in the real world. Subjects can be trained by this system to walk and to operate device panels in the virtual apartment, and later to control real world applications such as a wheelchair or phone panel by MI and P300 signals.

In the current study, sensorimotor rhythms related to imagery of left/right hand movements are detected, which provide two navigation commands in the virtual apartment. Although a specially designed virtual environment can provide navigation through a predefined path by imagery of left/right hand movements (Leeb *et al*., 2007a), it is limited and unnatural. Our system maps left/right hand imagery to turning left/right in the apartment, and the forward command by imagery of foot movement is to be added in further work.

Due to the above system implementation, subjects are restricted to the living room with a TV, a stereo, and other furniture in it (Fig. 2a). The participant ‘stands’ in the center of the living room and can have a view around the room by rotation (turning left or right). The TV or stereo control panel will pump out when the subject turns direction into a 10° angle where the TV or stereo lies. The pumped out panel serves as the P300 oddball paradigm where control commands flash as the stimuli to elicit the subject’s P300 potential (Figs. 2b and 2c). In the prototype, the control panels are implemented with a simplified design, with only five commands (operations of ‘stop’ and ‘quit’, and choices of three TV channels or songs) available. The selected TV channel or song will be played by its device and ‘stop’ will stop the current channel or song.

2.3 Signal processing

MI and P300 detectors were designed independently of each other because of the different



(a) (c)

Fig. 2 Parts of the virtual apartment
(a) Living room (up-down view); (b) TV control panel as the P300 oddball paradigm (first-person view); (c) Stereo control panel as the P300 oddball paradigm (first-person view). '1', '2', and '3' correspond to three TV channels or songs. The white button above '1' represents 'quit' and the black button above '3' is 'stop'

analyzing procedures of the two EEG patterns. The analysis methods are separately described below.

2.3.1 P300 potential detection

P300 potential is elicited under an oddball paradigm, where rare target stimulus is presented to the subject dotted in a sequence of non-target stimuli (Farwell and Donchin, 1988). In order to obtain stable and recognizable P300 patterns, averaging over trials is generally adopted (Donchin *et al*., 2000). In our experiment, one target selection consisted of 10 trials and each trial contained five stimuli with every command on the control panel intensified once. Therefore, the detection of the target command was conducted with 10 trials' data of the same stimulus averaged.

1. Preprocessing and feature extraction

In both online and offline preprocessing and feature extraction, a method based on regression (Croft and Barry, 2000) was first used to remove ocular artifacts in the EEG data. Then, drift correction was conducted by a piecewise cubic spline interpolation, followed by a low-pass filter (Butterworth filter of order 5, cutoff frequency of 15 Hz). Finally, the continuous data were divided into several epochs according to different stimuli, and epochs presenting the same stimulus were averaged. Each epoch included data samples between 100 and 800 ms posterior to the stimulus event onset.

2. Classification

A support vector machine (SVM) classifier was trained and used as the online P300 detector. SVM proves to be superior under certain circumstances. In typical two-class problems, SVM works by finding the largest margin between classes, which in essence is a quadratic programming optimization problem (Cristianini and Shawe-Taylor, 2000). It takes the mathematical form as follows:

$$\min\left(\frac{1}{2}\|\boldsymbol{w}\|^2+C\sum_{i=1}^{N}\xi_i\right) \tag{1}$$
$$\text{s.t. } y_i(<\boldsymbol{w},\boldsymbol{x}_i>+w_0)\geq 1-\xi_i,\ \xi_i\geq 0\ (i=1,2,\ldots,N),$$

where $\boldsymbol{w}$ and w_0 determine the hyper-plane, C is a positive constant reflecting penalty, ξ_i is known as a slack variable, $\boldsymbol{x}_i$, y_i, and N are input vectors, labels, and the number of samples, respectively. After solving the problem of Eq. (1) and obtaining Lagrange multipliers λ_i and kernel function $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$, where $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ represents the inner product of two samples in the feature space, the final classifier is given by

$$g(\boldsymbol{x})=\boldsymbol{wx}+w_0=\sum_{i=1}^{N_s}\lambda_i y_i K(\boldsymbol{x}_i,\boldsymbol{x})+w_0>(<)0, \tag{2}$$

where N_s is the number of support vectors. The input feature $\boldsymbol{x}$ is the averaged epoch data.

In each target selection, one out of M stimuli corresponded to an epoch containing P300 wave (M is the stimulus number in the oddball paradigm), while the rest of the stimuli were labeled with non-P300 wave epochs. The training samples consisted of epoch data labeled as P300 and non-P300 (two classes), not labeled as M stimuli. Thus, one SVM classifier for a two-class problem was trained for each subject. In P300 recognition, averaged epoch data of M stimuli were handled via Eq. (2). Since there might be more than one epoch satisfying $g(\boldsymbol{x})>0$, the epoch with the largest $g(\boldsymbol{x})$ was assigned as the target event. Stimulus command representing the target epoch was returned to the virtual environment in real time, causing the corresponding operation on the control panel (like switching to the selected TV channel) to be executed.

2.3.2 Motor imagery detection

In the current system, imagination of left/right hand movements is detected and classified to index rotations (turning left/right) in the virtual apartment. The procedure for detecting MI signals is shown in Fig. 3. It is based on analysis of multiple band-pass filtered signals.

An epoch with n EEG channels was the input to the MI detector. Preprocessing contained ocular artifact removal and drift correction, the same as the method used in P300 detection. Then, the signal was band-pass filtered into multiple frequency bands (F-bands) (m bands) and spatial filtering was applied to each band, after which k ($k\le n$) channels were left. Finally, the log band power $P_j^i=\log\left(\mathrm{var}(x_j^i)\right)$ was extracted, where $\mathrm{var}(x_j^i)$ is the variance of signal from the jth channel of the ith F-band. P_j^i (i=1, 2, ..., m; j=1, 2, …, k) formed the signal features, which were further transformed with Fisher's linear discriminant analysis (FLDA) into a control command by mapping negative/positive output to left/right turning.

Before the online experiment (with feedback), spatial filtering and FLDA parameters were trained and the F-bands were specified for each subject to accommodate his/her EEG characteristics. Data collected in the training experiment (without feedback) were split into training and testing samples.

1. Spatial filtering and FLDA classifier training

Training samples were used to determine spatial filtering and FLDA parameters. The spatial filtering was undertaken by a common spatial pattern (CSP). CSP finds a transition matrix $\boldsymbol{W}^{\mathrm{T}}$ that linearly transforms the data matrix $\boldsymbol{S}$ of each F-band to another matrix $\boldsymbol{X}$, where differences between power features of left/right MI are maximized in $\boldsymbol{X}$ and $\boldsymbol{X}=\boldsymbol{W}^{\mathrm{T}}\boldsymbol{S}$. Details of CSP can be found in Blankertz *et al*. (2008).

After obtaining a transformed signal $\boldsymbol{X}$ and features extracted from $\boldsymbol{X}$, an FLDA classifier was trained to distinguish between imagination of left and right hand movements. FLDA is a common linear classifier by projecting original samples into one dimension that maximizes the ratio of between-class variance to within-class variance (Bishop, 2006).

2. Frequency band selection

The F-bands used in the experiment are decided by the following steps:

(1) The testing samples were preprocessed and filtered (Chebyshev I filter of order 4) into 17 overlapping F-bands (1–5, 3–7, …, 33–37 Hz, with a width of 4 Hz and overlap of 2 Hz) between 1 and 37 Hz.

(2) For each F-band, procedures of spatial filtering, signal power extraction, and FLDA classifier in Fig. 3 were applied. The FLDA outputs were used to compute both classification accuracies and Fisher's linear discriminant criteria (FDC). Accuracy depicts significance of each F-band contributing to final classification, while FDC reflects the separability of outputs. These two indexes evaluate the fitness of an F-band for classification.

FDC is the ratio of between-class distance to within-class distance, which is defined as follows:

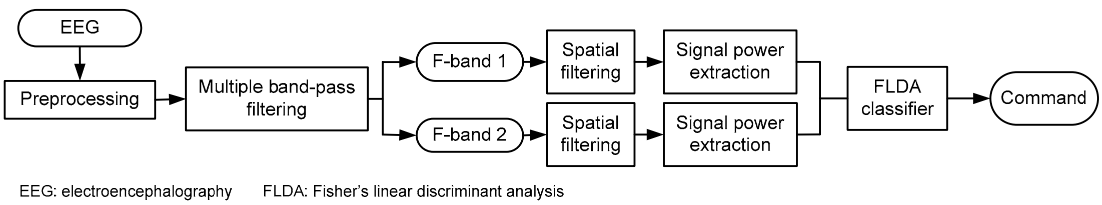


Fig. 3 Sensorimotor rhythms detecting procedure

$$\mathrm{FDC}=\frac{(m_1-m_2)^2}{\sigma_1^2+\sigma_2^2}, \tag{3}$$

where m_1 and m_2 are means of samples from the two motor tasks, and σ_1^2 and σ_2^2 are their corresponding variations.

The computation of accuracy and FDC was five-fold cross validated in this study.

(3) The 17 F-bands were sorted by their FDC in descending order: FDC_1, FDC_2, …, FDC_{17}, and the number of selected bands, t, was determined by

$$t=\arg\min\left\{l \mid \sum_{i=1}^{l}\mathrm{FDC}_i \geq 70\% \times \sum_{i=1}^{17}\mathrm{FDC}_i\right\}. \tag{4}$$

It is the minimum number of F-bands whose sum reached at least 70% of the overall FDC sum.

Therefore, t F-bands were selected for each subject and those with accuracies lower than 75% were discarded. The thresholds of 70% and 75% were determined empirically. Finally, selected bands were merged if they overlapped.

2.4 Experiments

2.4.1 Experimental setup and data acquisition

Four healthy adults (one male and three female, aged 25, 24, 23, and 23) voluntarily took part in this study. All of them had some experiences with a P300-based Chinese typewriter (Su *et al*., 2008), and three of them were familiar with MI BCIs. The subjects were sitting 0.8 m in front of a 22-inch computer screen and 26 channels of EEG signals were recorded by the NeuroScan SynAmps amplifier. Fourteen channels (Fz, FC3, FCz, FC4, C5, C3, Cz, C4, C6, CP3, CPz, CP4, Pz, and Oz) were used for P300 detection, and 22 channels (Cz, Fz, FC3, FC4, C3, C4, CP3, CP4, C5, C6, F1, F2, F3, FC1, FC2, F4, C1, C2, CP5, CP1, CP2, and CP6) were used in MI. All EEG signals were low-pass filtered at 40 Hz and digitized at a sampling rate of 250 Hz. All channels were referenced to the nose, and grounded to the forehead. During the P300 control phase, the subjects were asked to count silently in their minds when the target stimuli flashed, while in the navigation state, the subjects imagined left/right hand movements according to the instructions.

All subjects went through an experimental session with one training run for MI and 22 testing runs for both hybrid and single pattern BCIs.

The training run at the beginning of the session was conducted to train detector parameters of MI. This run consisted of 80 trials, and each trial started with a left or right cue on the screen and lasted 2 s. The 80 trials were presented to the subject consecutively, with 40 left cues for left hand movement imagination and 40 right cues for right hand movement imagination. The personal parameters were computed from the training run data and implemented into the system for later online use.

For P300 detector training, datasets collected in four sessions under a P300 Chinese typewriter from previous P300 BCI studies were used. Runs in the first session were without feedback and the data were used to train a template matching classifier. Then in the next three sessions, template matching served as the online classifier and feedbacks were given in real time. Around 200 target selection data with feedback for each subject were collected and used to train the SVM classifier. A 10-fold cross validation was conducted and accuracies between 92%–98% were achieved offline. The trained SVM classifier for each subject was integrated into the current system for online P300 detection.

2.4.2 Experimental tasks

The 22 testing runs were divided into three blocks. Block 1 contained eight runs for the hybrid control testing, block 2 consisted of eight runs for testing MI-based navigation, and block 3 was made up of six runs for testing P300-based device control.

In the experimental runs with online feedback, inter-stimulus interval (ISI) of the P300 oddball paradigm was 200 ms, with every stimulus on the device control panel intensified for 50 ms and 150 ms between intensifications. Every command selection required 10 trials, and in every trial each command on the control panel was intensified once. During the navigation state, feedback was given every second and each feedback caused a 7.5° turning to the left/right. A quicker update (2 updates/s) was tested but all subjects reported that it was too quick and unstable. Classification results of FLDA were translated into navigation commands by mapping the class affiliation of FLDA to left/right (negative number represented ‘left’ and positive number represented ‘right’). Unlike the training run, no cues were given to the subject for instructions of MI in the testing runs, so the movements were continuously presented. Each subject needed to decide what command to generate or select in real time according to the current outputs and the clearly predefined task given by the operator.

Before block 1 began, a free testing run of MI (10 min) was given to the subjects, so that they could try and test initial imagination of left/right hand in the virtual apartment with online feedback. Results of this testing run were not included.

Tasks in block 1 for testing the hybrid control strategy in the virtual apartment are described as follows:

Task 1: start from the initial position, turn left for 90° to reach the TV control panel, select one TV channel by P300, and then turn right back to the initial position.

Task 2: start from the initial position, turn right for 180° to reach the stereo, select a song to play by P300, and then turn left back to the initial position.

Task 3: start from the initial position, turn left/right for a circle (360°), and select one channel or song when the virtual devices (TV and stereo) are presented.

Tasks 1 and 2 were repeated three times and Task 3 was completed twice with a turning left run and a turning right run. After selecting a TV channel or a song, the subject needed to select ‘quit’ to switch the system back to the navigation state. Since switch to P300 control occurred whenever the position fell into areas corresponding to device control state, there were unintentional switches from misclassification of MI in the critical region of the two states.

Tasks in block 2 were the same as tasks in block 1, except that the virtual device control panels were not evoked when the subject turned into its corresponding position, only MI signals were detected. Runs in block 3 tested only P300 performance, where no navigation was available and the control panel of the virtual device (TV or stereo) was presented to the subject. Task 1 (runs 1 to 3, same task repeated three times) was to select each command on the TV control panel once whilst task 2 (runs 4 to 6, also repeated the same task) was with the stereo control panel. Thus, a total of 30 selections of control commands were made in block 3 (6 runs×5 selections/run).

3 Results

Table 1 summarizes the selected F-bands and the offline classifier accuracy from the cued training run of MI for each subject (subject sx had no experience with MI before the experiment). The offline analysis achieved high accuracies for all four subjects, and the selected F-bands vary. For comparison, classification results by a common F-band between 8 and 30 Hz (Ramoser *et al*., 2000) were also computed and were listed in Table 1.

Table 1 Offline analysis of motor imagery training data

Sub.	Selected F-band (Hz)	Classifier accuracy (%)	
		Selected F-band	Common F-band*
sq	9–17, 21–29	100.00	97.50
sg	9–17, 19–29	100.00	100.00
sx	9–17, 23–35	96.25	92.50
sz	13–31	100.00	100.00

* Common F-band: 8–30 Hz. Sub.: subject. F-band: frequency band

Since the subject needs to select ‘quit’ command to switch the system back into the navigation state, we set a threshold at the device control state that after six continuous selections of non-‘quit’ commands, the controller would automatically switch the system state. In the experiments, although some of the ‘quit’ selections were mistakenly recognized, all subjects succeeded in selecting ‘quit’ before the automatic state switch in all the tasks.

Table 2 summarizes all performance measures in the hybrid BCI control (eight runs in block 1). Time cost for both MI and P300 in each task and the number of unintentional switches in each run are also listed (time for P300 includes several P300 selections in each task). In this study, unintentional switches counted only the number of erroneous switches from the navigation state into the device control state. For MI, accuracies are computed as the ratio of the number of correctly executed commands to the total number of executed commands.

Table 2 Online hybrid control testing results

Sub.	Run	Task 1					Task 2					Task 3				
		Accuracy (%)		Time (s)		US	Accuracy (%)		Time (s)		US	Accuracy (%)		Time (s)		US
		MI	P300	MI	P300	(No.)	MI	P300	MI	P300	(No.)	MI	P300	MI	P300	(No.)
sq	1	87.50	75.00	32	60	1	87.50	85.71	64	105	1	100.00	80.00	48	75	0
	2	90.00	100.00	30	30	0	91.38	100.00	58	30	0	87.50	75.00	64	120	2
	3	76.09	100.00	46	60	1	100.00	66.67	48	45	0					
	Mean	83.33	90.00	36	50	0.67	92.35	83.33	56.7	60	0.33	92.86	76.92	56	97.5	1
sg	1	92.86	66.67	28	45	0	92.86	66.67	56	45	0	98.00	80.00	50	75	0
	2	90.00	100.00	30	30	0	91.38	66.67	58	45	0	91.38	83.33	58	90	1
	3	90.00	75.00	30	60	1	79.27	100.00	82	30	0					
	Mean	90.91	77.78	29.3	45	0.33	86.73	75.00	65.3	40	0	94.44	81.82	54	82.5	0.5
sx	1	70.00	66.67	60	90	2	77.27	50.00	88	60	0	91.38	80.00	58	75	0
	2	81.58	100.00	38	30	0	82.43	66.67	74	45	0	79.27	100.00	82	60	0
	3	78.57	100.00	42	30	0	78.57	100.00	84	30	0					
	Mean	75.71	80.00	46.7	50	0.67	79.27	66.67	82	45	0	84.29	88.89	70	67.5	0
sz	1	76.09	100.00	46	60	2	81.58	100.00	76	30	0	81.58	100.00	76	75	3
	2	74.00	100.00	50	30	0	77.27	80.00	88	75	3	80.00	75.00	80	60	1
	3	73.08	80.00	52	75	2	80.00	66.67	80	45	0					
	Mean	74.32	90.91	49.3	55	1.33	79.51	80.00	81.3	50	1	80.77	88.89	78	67.5	2
Mean		81.07	84.67	40.3	50	0.75	84.47	76.25	71.3	48.8	0.33	88.09	84.13	64.5	78.8	0.88

Sub.: subject; MI: motor imagery; US: unintentional switch; No.: number of unintentional switches

Table 3 Online accuracies of hybrid and single BCI controls

Sub.	Block	Online accuracy (%)*			
		Task 1 (3 runs)	Task 2 (3 runs)	Task 3 (2 runs)	Mean
sq	1, hybrid/MI	83.33	92.35	92.86	90.00
	1, hybrid/P300	90.00	83.33	76.92	82.86
	2, MI	68.56	79.27	94.44	78.47
	3, P300	86.67	80.00		83.33
sg	1, hybrid/MI	90.91	86.73	94.44	89.80
	1, hybrid/P300	77.78	75.00	81.82	78.57
	2, MI	90.91	87.50	100.00	91.49
	3, P300	86.67	86.67		86.67
sx	1, hybrid/MI	75.71	79.27	84.29	79.66
	1, hybrid/P300	80.00	66.67	88.89	78.57
	2, MI	81.58	86.73	80.38	83.33
	3, P300	80.00	80.00		80.00
sz	1, hybrid/MI	74.32	79.51	80.77	78.47
	1, hybrid/P300	90.91	80.00	88.89	86.67
	2, MI	68.37	69.46	78.24	71.20
	3, P300	86.67	93.33		90.00

* Online accuracies are averaged over the same task runs. Sub.: subject; MI: motor imagery

Blocks 2 and 3 were conducted for comparison with the hybrid control strategy. Experimental results are summarized in Table 3, and they are the averaged accuracies over the same task runs. Results obtained in the hybrid control block are relatively close to the results in the single BCI testing, which indicates the combination of P300 and MI in the proposed hybrid BCI strategy for the virtual environment control is practical for further development.

4 Discussion

This paper addresses a hybrid BCI control strategy in a virtual environment, which utilizes MI to navigate and P300 potential to control virtual devices. Preliminary testing results show that subjects can achieve simplified navigation and device control in the virtual apartment. Comparison results between hybrid and single BCI controls demonstrate that the use of the hybrid control strategy with MI and P300 in the virtual environment did not bring any notable decrease of single EEG pattern recognition. Therefore, more complex tasks can be carried out efficiently with the hybrid control strategy. However, all subjects reported that hybrid control tasks were more complicated because of the shifting between motor attention and P300 visual attention. Aiming to expand virtual environment control functions, the proposed hybrid BCI control strategy is different from the recently reported hybrid BCI combining ssVEP and MI, where either simultaneous detection of MI and ssVEP (Allison *et al*., 2010; Brunner *et al*., 2010) or sequential detection (Pfurtscheller *et al*., 2010b) improved system performance. It also differs from the 2D cursor control system that detects P300 and MI signals independently and simultaneously (Chen *et al*., 2010).

In the offline results of MI training in Table 1, subject sx with no prior experience showed a slightly lower accuracy than the other three subjects. However, in the following testing runs, she achieved a better online performance than subject sz in both the hybrid and the single control paradigms (Table 3). The offline comparison of selected and common F-bands in Table 1 indicates that a user-specific F-band selection can improve classification accuracy. Due to the variant sensorimotor rhythm patterns among different subjects, it is useful to optimize channels and F-bands for each individual.

In the hybrid testing runs, subjects sq and sg achieved relatively high performances in MI. Both of them had undertaken MI-based BCI experiments before the current study, and they reported that after training, the imagination of left/right hand movement evolved into a more natural imagination of turning left/right in the virtual environment. This user-based learning may explain the better accuracies they achieved than the other two subjects. Subject sq also reported difficulty in single MI tasks which required shifting between imaginations of left/right hand movements; this explains the relatively poor performance in Tasks 1 and 2 of block 2. In addition, results in Table 3 show that accuracy of MI in Task 3 with a single left or right turning is higher than in Tasks 1 and 2 where shifting between left and right turning was required.

The relatively large difference between offline training and online testing results for both MI and P300 detections may be due to two reasons. One is that online feedbacks evoke extra brain activities for context updating and thus may lead to the decrease in pattern recognition. The other reason may be that training and testing paradigms for both the EEG patterns are different, where data for P300 classifier training was from a P300 Chinese typewriter and the training run for MI was cue-based.

The hybrid control strategy proposed in this paper attempts to realize a natural and effective interaction with the virtual environment, by using MI of left/right hand movement to turn left/right and P300 oddball paradigm to control the virtual devices. Although other methods like P300 navigation (Edlinger *et al*., 2008) or one mental task based navigation (Velasco-Álvarez and Ron-Angevin, 2009) can provide a similar function, mapping left/right hand movement to turning left/right may be the most natural way. However, several factors of the current system can be improved. The unintentional switch numbers in Table 2 reflect the rate in each task by which the subject unintentionally changes to the device control state (an erroneous state switch). A better mechanism should be adopted to overcome this problem, which can be solved either by introducing a classifier to distinguish intentional control (IC) from non-control state (NC) as in Scherer *et al*. (2008), or by designing a better protocol to handle the system state switch. Also, EEG patterns corresponding to moving forward command and self-paced operation are necessary to fulfill the free and real navigation in the virtual environment (Scherer *et al*., 2008).

5 Conclusions

This paper presents a hybrid BCI control prototype where MI and P300 patterns are combined into one BCI system and the characteristic of each pattern is utilized to constitute a better control strategy for the virtual apartment environment. MI patterns are translated into virtual navigation commands while P300 potentials are mapped to device control commands. The two EEG patterns are detected in different system control states in a sequential manner. Preliminary results show that such combination of sensorimotor rhythms and P300 potentials can work well in a virtual environment.

Despite the great promises shown in research combining BCI and VR, much work is needed to further the current hybrid BCI control for a virtual environment. Three-class recognition for MI of left/right hand and foot movements as well as the NC and IC classification are required to simulate a more realistic virtual apartment navigation and device control. Further tests with a head mounted display (HMD) or cave-like environment are meaningful, since these techniques may achieve better feedback effects. Finally, more factors should be taken into account when transfer from a virtual to a real world environment occurs, where EEG patterns may not be generated stably.

References

Allison, B.Z., Brunner, C., Kaiser, V., Müller-Putz, G.R., Neuper, C., Pfurtscheller, G., 2010. Toward a hybrid brain-computer interface based on imagined movement and visual attention. *J. Neural Eng.*, **7**(2):026007. [doi:10.1088/1741-2560/7/2/026007]

Bayliss, J.D., 2003. Use of the evoked potential P3 component for control in a virtual apartment. *IEEE Trans. Neural Syst. Rehabil. Eng.*, **11**(2):113-116. [doi:10.1109/TNSRE.2003.814438]

Bayliss, J.D., Ballard, D.H., 2000. A virtual reality testbed for brain-computer interface research. *IEEE Trans. Rehabil. Eng.*, **8**(2):188-190. [doi:10.1109/86.847811]

Bishop, C.M., 2006. Pattern Recognition and Machine Learning. Springer, USA, p.179-192.

Blankertz, B., Tomioka, R., Lemm, S., Kawanabe, M., Müller, K.R., 2008. Optimizing spatial filters for robust EEG single-trial analysis. *IEEE Signal Process. Mag.*, **25**(1):41-56. [doi:10.1109/MSP.2008.4408441]

Brunner, C., Allison, B.Z., Krusienski, D.J., Kaiser, V., Müller-Putz, G.R., Pfurtscheller, G., Neuper, C., 2010. Improved signal processing approaches in an offline simulation of a hybrid brain-computer interface. *J. Neurosci. Meth.*, **188**(1):165-173. [doi:10.1016/j.jneumeth.2010.02.002]

Chen, W.D., Zhang, J.H., Zhang, J.C., Li, Y., Qi, Y., Su, Y., Wu, B., Zhang, S.M., Dai, J.H., Zheng, X.X., *et al.*, 2010. A P300 based online brain-computer interface system for virtual hand control. *J. Zhejiang Univ.-Sci. C (Comput. & Electron.)*, **11**(8):587-597. [doi:10.1631/jzus.C0910530]

Cristianini, N., Shawe-Taylor, J., 2000. An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods. Cambridge University Press, Cambridge, UK, p.103-131.

Croft, R.J., Barry, R.J., 2000. Removal of ocular artifact from the EEG: a review. *Clin. Neurophysiol.*, **30**(1):5-19. [doi:10.1016/S0987-7053(00)00055-1]

Donchin, E., Spencer, K.M., Wijesinghe, R., 2000. The mental prosthesis: assessing the speed of a P300-based brain-computer interface. *IEEE Trans. Rehabil. Eng.*, **8**(2):174-179. [doi:10.1109/86.847808]

Edlinger, G., Krausz, G., Groenegress, C., Holzner, C., Guger, C., Slater, M., 2008. Brain-Computer Interfaces for Virtual Environment Control. Proc. 13th Int. Conf. on Biomedical Engineering, p.366-369. [doi:10.1007/978-3-540-92841-6_90]

Farwell, L.A., Donchin, E., 1988. Taking off the top of your head-toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr. Clin. Neurophysiol.*, **70**(6):510-523.

Kronegg, J., Chanel, G., Voloshynovskiy, S., Pun, T., 2007. EEG-based synchronized brain-computer interfaces: a model for optimizing the number of mental tasks. *IEEE Trans. Neural Syst. Rehabil. Eng.*, **15**(1):50-58. [doi:10.1109/tnsre.2007.891389]

Leeb, R., Pfurtscheller, G., 2004. Walking Through a Virtual City by Thought. Proc. 26th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society, p.4503-4506. [doi:10.1109/IEMBS.2004.1404251]

Leeb, R., Lee, F., Keinrath, C., Scherer, R., Bischof, H., Pfurtscheller, G., 2007a. Brain-computer communication: motivation, aim, and impact of exploring a virtual apartment. *IEEE Trans. Neural Syst. Rehabil. Eng.*, **15**(4):473-482. [doi:10.1109/tnsre.2007.906956]

Leeb, R., Friedman, D., Müller-Putz, G.R., Scherer, R., Slater, M., Pfurtscheller, G., 2007b. Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: a case study with a tetraplegic. *Comput. Intell. Neurosci.*, **2007**:79642. [doi:10.1155/2007/79642]

Middendorf, M., McMillan, G., Calhoun, G., Jones, K.S., 2000. Brain-computer interfaces based on the steady-state visual-evoked response. *IEEE Trans. Rehabil. Eng.*, **8**(2):211-214. [doi:10.1109/86.847819]

Obermaier, B., Neuper, C., Guger, C., Pfurtscheller, G., 2001. Information transfer rate in a five-classes brain-computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.*, **9**(3):283-288. [doi:10.1109/7333.948456]

Pfurtscheller, G., Neuper, C., 2001. Motor imagery and direct brain-computer communication. *Proc. IEEE*, **89**(7):1123-1134. [doi:10.1109/5.939829]

Pfurtscheller, G., Allison, B.Z., Brunner, C., Bauernfeind, G., Solis-Escalante, T., Scherer, R., Zander, T.O., Müller-Putz, G.R., Neuper, C., Birbaumer, N., 2010a. The hybrid BCI. *Front. Neurosci.*, **4**:30. [doi:10.3389/fnpro.2010.00003]

Pfurtscheller, G., Solis-Escalante, T., Ortner, R., Linortner, P., Müller-Putz, G.R., 2010b. Self-paced operation of an SSVEP-based orthosis with and without an imagery-based “brain switch”: a feasibility study towards a hybrid BCI. *IEEE Trans. Neural Syst. Rehabil. Eng.*, **18**(4):409-414. [doi:10.1109/TNSRE.2010.2040837]

Piccione, F., Priftis, K., Tonin, P., Vidale, D., Furlan, R., Cavinato, M., Merico, A., Piron, L., 2008. Task and stimulation paradigm effects in a P300 brain computer interface exploitable in a virtual environment: a pilot study. *PsychNol. J.*, **6**(1):99-108.

Ramoser, H., Müller-Gerking, J., Pfurtscheller, G., 2000. Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE Trans. Rehabil. Eng.*, **8**(4):441-446. [doi:10.1109/86.895946]

Ron-Angevin, R., Diaz-Estrella, A., 2009. Brain-computer interface: changes in performance using virtual reality techniques. *Neurosci. Lett.*, **449**(2):123-127. [doi:10.1016/j.neulet.2008.10.099]

Schalk, G., McFarland, D.J., Hinterberger, T., Birbaumer, N., Wolpaw, J.R., 2004. BCI2000: a general-purpose, brain-computer interface (BCI) system. *IEEE Trans. Biomed. Eng.*, **51**(6):1034-1043. [doi:10.1109/tbme.2004.827072]

Scherer, R., Lee, F., Schloegl, A., Leeb, R., Bischof, H., Pfurtscheller, G., 2008. Toward self-paced brain-computer communication: navigation through virtual worlds. *IEEE Trans. Biomed. Eng.*, **55**(2):675-682. [doi:10.1109/tbme.2007.903709]

Su, Y., Wu, B., Chen, W., Zhang, J., Jiang, J., Zhuang, Y., Zheng, X., 2008. P300-based brain computer interface: prototype of a Chinese speller. *J. Comput. Inform. Syst.*, **4**(4):1515-1522.

Velasco-Álvarez, F., Ron-Angevin, R., 2009. Asynchronous brain-computer interface to navigate in virtual environments using one motor imagery. *LNCS*, **5517**:698-705. [doi:10.1007/978-3-642-02478-8_87]

Wolpaw, J.R., Birbaumer, N., Heetderks, W.J., McFarland, D.J., Peckham, P.H., Schalk, G., Donchin, E., Quatrano, L.A., Robinson, C.J., Vaughan, T.M., 2000. Brain-computer interface technology: a review of the first international meeting. *IEEE Trans. Rehabil. Eng.*, **8**(2):164-173. [doi:10.1109/TRE.2000.847807]

Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M., 2002. Brain-computer interfaces for communication and control. *Clin. Neurophysiol.*, **113**(6):767-791. [doi:10.1016/S1388-2457(02)00057-3]

Zhao, Q.B., Zhang, L.Q., Cichockis, A., 2009. EEG-based asynchronous BCI control of a car in 3D virtual reality environments. *Chin. Sci. Bull.*, **54**(1):78-87. [doi:10.1007/s11434-008-0547-3]