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Semi-Asynchronous BCI using Wearable Two-Channel EEG

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***Abstract*—Motor imagery (MI)-based EEG can be modulated voluntarily by users through feedback provided by a brain-computer interface (BCI). In MI-based BCIs, feedback design plays an important role in MI training, especially in BCIs that use a limited number of electrodes. This paper presents a semi-asynchronous MI-based BCI system that uses discrete and continuous feedback together, in order to improve practicability and training efficiency. Results show that the proposed method can reduce command generation time to 3.77 s with the accuracy of 77%, using our proposed continuous feedback with a two-channel MI-based BCI system. Our proposed system is non-invasive and wearable, featuring improvement in the practical utility and operational convenience of a BCI system.**

***Index Terms*— Brain-computer interface (BCI), electroencephalogram (EEG), event-related synchronization and desynchronization (ERD/ERS), motor imagery, semi-asynchronous BCI, neurofeedback.**

I. Introduction

A brain-computer interface (BCI) directly translates brain activity into control commands that provide a direct communication channel between a human and the outside world [1]. One of the most commonly employed methods for BCI control is the use of motor imagery (MI), which can induce event-related de-synchronization (ERD) and event-related synchronization (ERS) of mu rhythm (i.e., frequency range from 8 to 13 Hz) and central beta rhythm (i.e., frequency range from 13 to 30 Hz) [2]. However, current MI-based BCIs have several hurdles that prevent them from obtaining high performance. In particular, some challenges they are facing are extensive training time, low accuracy, or only offline-based analysis [3]. Additionally, the performance of a MI-based BCI is highly dependent on the imagery abilities (i.e., temporal congruency between MI and execution that indicates good imagery ability and vice versa) of the subjects.

To improve the efficiency of MI-based BCI, two main concepts of thought regarding the user's cooperation with the computer are introduced in [4]: (1) "let the machines learn," which focuses on the machine learning algorithms adjusting classification; and (2) "let the users learn," which trains users in order to improve their control abilities. Feedback is an important method utilized in "let the users learn." Feedback improves MI ability by providing subjects with instantaneous information about EEG responses [5]. As in any form of MI-based BCIs, users improve their imagery abilities through feedback training, which can lead to the enhancement of EEG self-regulation skills. Therefore, feedback design is particularly important in improving MI performance. In general, feedback utilized in most BCI systems can be divided into two application-dependent types: discrete feedback and continuous feedback. Discrete feedback presents the performance results of a control attempt to the user after the task has completed [6], whereas continuous feedback is presented to the users during the acquisition of command-related EEG signals throughout the task. Continuous feedback can directly impact the EEG generation process. It has been demonstrated that the training progress can be improved if feedback causes the user to feel a sense of achievement or reward for their attempts [7-8].

Generally, a MI-based BCI system with feedback can be developed via a synchronous or an asynchronous mechanism [9]. The synchronous mechanism is time-locked or trial-based and it allows interaction only in a fixed time window determined by the system [10]. Therefore, it would not be complicated to develop a MI-based BCI system based on synchronous mechanism. However, it could be impractical in real world where one decision (i.e., resulting from a BCI system) can be made at any appropriate time. In an asynchronous BCI, users can interact with a BCI at their leisure in self-paced manner in both idle and mental states, without any concern for a well-defined time window [11]. The subjects, however, need to spend more concentration on the visual feedback in order to continuously interact with the BCI. In general, discrete feedback is usually used with synchronous mechanisms whereas continuous feedback is adopted with asynchronous mechanisms [9].

In order to improve practicability and training efficiency of BCIs, this study proposes a semi-asynchronous MI-based BCI applying discrete and continuous feedback. In semi-asynchronous mode, subjects operate in a trial-based paradigm, but the time of each trial is self-paced. Discrete feedback is provided at the training stage in order to collect data for building a reliable classification model. Continuous feedback is applied at the testing stage and provides the semi-asynchronous mode. In addition, for the purpose of wearability and user convenience, the system requires only two EEG signal detection channels. The highlights of the proposed semi-asynchronous MI-based BCI system are as follows:

(1) Feedback is provided at both training and testing stages to ultimately increase the effect of training.
(2) The continuous feedback is semi-asynchronous and it can improve the flexibility and controllability of the system.

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(3) Strong practical utility and wearability are achieved through low power consumption and rapid online processing by using a portable EEG device with only two channels.

II. Method

A. System Overview

Fig. 1(a) shows the proposed wearable wireless EEG system, which consists of a wireless EEG headset and a PC-based signal processing module. The wireless EEG headset is comprised of a sensory detection module (SDM) and a sensory processing module (SPM). The analog data from the SDM is converted to digital data by a built-in 12-bit analog-to-digital converter (ADC). Then, the digitized data is wirelessly transmitted to the PC via a Bluetooth Low-Energy (BLE) module.

1) Wireless EEG headset

The wireless EEG headset consists of five EEG electrodes which are connected to an EEG bio-potential conditioning circuit to match the ADC voltage range (i.e., 0-3.3 VDC) of the MCU (Microprocessor Control Unit). Among the five electrodes, one ear-clip electrode is mounted on the right earlobe and serves as a ground electrode. The others are used as EEG signal electrodes to compose two bipolar channels. As shown in Fig. 1 (b), two signal electrodes are located on the left (C3) while the other two are placed on the right (C4) central areas of the brain. The Channel C3 is derived as the difference between Electrode 1 (i.e., placed 2.5 cm anterior to C3) and Electrode 2 (i.e., placed 2.5 cm posterior to C3) [12]. The Channel C4 (which consists of Electrodes 3 and 4) is similarly derived. This configuration refers to the standard 10–20 electrode montage system [13].

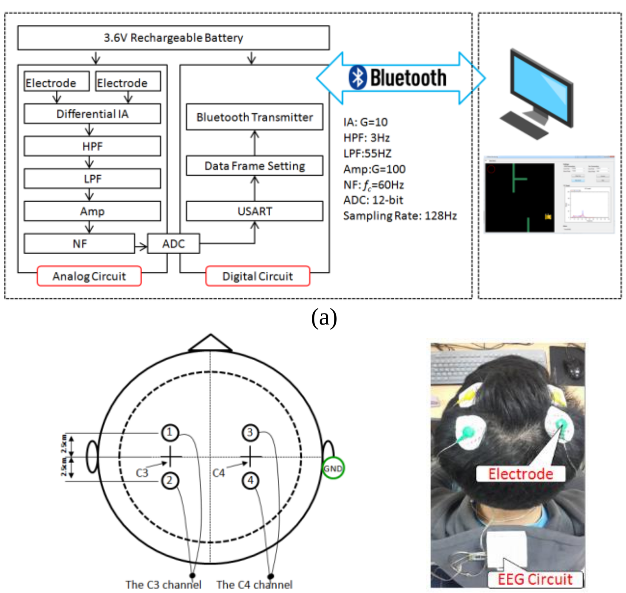

Fig. 1. (a) Proposed wearable wireless EEG system with SDM, SPM, and PC-based signal processing model. (b) Electrode positions of the bipolar EEG device. (C) Setup of wireless EEG device.

The human skin typically provides source impedance on the order of 1–5 Mohm [14]. Thus, the amplifier must match the source impedance to effectively acquire EEG signals. For these reasons, the output of the bipolar electrodes is first amplified by a differential instrument amplifier (IA), which balances the electrode-skin impedance. Additionally, in order to acquire the most useful EEG bands (θ (4–7 Hz), α (8–12 Hz), and β (13–30 Hz)), the IA output signal is transferred to a High Pass Filter (HPF) and then a Low Pass Filter (LPF). The filtered signal is amplified by a main amplifier in order to meet the ADC's input requirement. Finally, digitized data are sent to the PC for further analysis via the BLE.

2) PC-based signal processing module

The signal processing module was implemented using a C#-based user interface, through which signals were processed to extract features and perform classification. A support vector machine (SVM)-based classifier was trained prior to being used in classifying the MI task (left hand or right hand MI task).

B. EEG Signal Analysis and Feature Extraction

In order to extract features, the ERD/ERS in α band (8−12 Hz) was measured. Following the standard ERD/ERS calculation proposed by Pfurtscheller and Aranibar in [15], a short-time Fourier transform (STFT) was used to calculate power values from the amplitude, and then a relative power value (ERD) was measured according to Equation (1), where A is the average power value in the motor imagery interval and R is the average power value in the baseline interval.

$$ERD(\%) = \frac{A-R}{R} \times 100\% \tag{1}$$

The ERD and ERS are defined here as the percentage power decrease and increase, respectively, in relation to the baseline interval (rest state) before the MI task.

C. Experimental paradigms

Discrete and continuous feedbacks were utilized in this study. Based on feedback type, the experiment consists of two main stages:

(1) Discrete feedback training stage: discrete feedback was provided in the execution of MI task (Stage 1).
(2) Continuous feedback testing stage: continuous feedback was provided in the execution of MI task (Stage 2).

Stage 1 is used to collect data for building the SVM model, whereas Stage 2 is used to test it. The following section introduces these two stages separately.

1) Discrete Feedback Training Stage

Subjects were required to perform MI tasks that consisted of imaging grasps with either the left or right hand according to a visual cue shown in the user interface, as illustrated in Fig. 2.

Each discrete feedback training session began with a calibration run. In MI-based BCI systems, the data from the calibration training session is used to construct the classifier model; hence, no feedback is provided. The present experimental procedure differs from previous studies in that visual feedback is included at the end of each MI calibration trial in the training session (shown in Fig. 2).

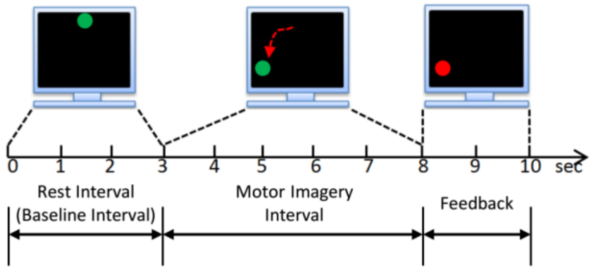

Fig. 2. Timing calibration training trial with delayed feedback. The subject was instructed to imagine the movement of either his/her left or right hand during the motor imagery interval. After 8 s, a red ball appears as feedback on the center, left, or right side of the screen.

Each calibration trial started with a green ball displayed at the top center of the user interface for 3 s (Fig. 2). The green ball then moved downward to either the left or right side of the screen for an additional 5 s. Depending on the direction in which the ball had moved (left or right), the subject was instructed to imagine a hand-grasp motion with the corresponding hand to catch the green ball. After 8 s, features were extracted by calculating the ERD/ERS values according to Equation (1) as described in Section II (B). Then, feedback (a red ball) was displayed on the left, right, at the center of the screen for 2s (i.e., 8^{th}-10^{th} s), indicating the decision of the threshold-based classifier.

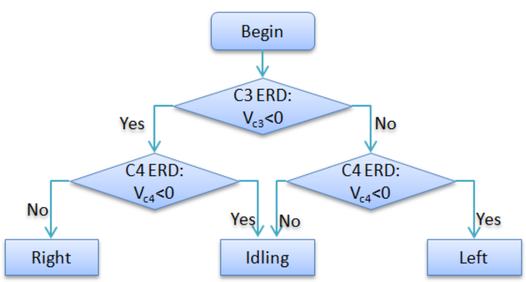

Fig. 3. Binary tree classifier in the model training stage.

A special classifier was used to classify the different MI tasks and feedback was delivered at the end of each trial. The classifier (Fig. 3) has two inputs: the ERD values of Channel C3 and Channel C4 (i.e., V_{c3} and V_{c4}, respectively). The algorithm to generate feedback at the end of each trial can be expressed as follows, where V_{c3} is the ERD (calculated by Equation (1)) of Channel C3 and V_{c4} is the ERD of Channel C4:

(a) If only $V_{c3} < 0$, then the feedback is "Right";
(b) If only $V_{c4} < 0$, then the feedback is "Left";
(c) Otherwise, the feedback is "idling".

After the training stage, data was collected for the initialization of the subject-specific SVM classifier, which was used to classify the subject's EEG signals in the following continuous feedback testing stage while he or she imagined the required types of hand movement.

2) *Continuous feedback testing stage*

The continuous feedback testing stage operates semi-asynchronously, such that the time of a single trial is flexible. The user interface with the green ball at the screen center indicates the start of the trial, and its end depends on the user's control ability. As shown at the top of Fig. 4, subjects were instructed to imagine grasping with their left or right hands to control the red bar to catch the falling green ball.

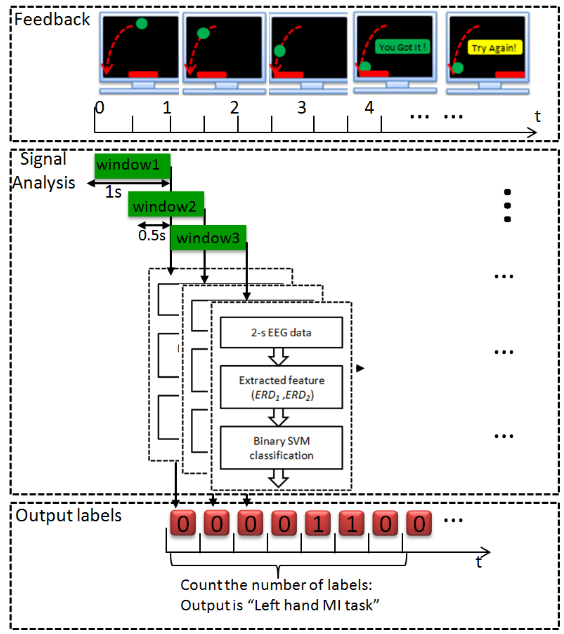

Fig. 4. Semi-asynchronous trial with continuous feedback. Subjects were instructed to imagine their either left- or right-hand grasps to control the movement of the red bar to the left or right, until the red bar caught the falling green ball.

From the beginning of each trial, feedback of the classification result was visually displayed to the user every 0.5 s. Features were extracted from a 1-s window of data every 0.5 s from the two channels, where the overlapping window was 0.5 s. The red bar moves one step to the left or right as feedback, representing the result of a single classification. The single classification of user action and feedback were performed continuously. The SVM model was used to classify and to output the predicted label: "0" (left-hand MI) or "1" (right-hand MI). Two counters track the number of each classification result. An MI command is generated only when the desired number of labels are obtained. In other words, if the counter for label "0" is equal to a pre-defined number, the left-hand MI command is generated; otherwise, if the counter for label "1" is equal to the pre-defined number, the-right hand MI command is generated. When the generated command matches the one suggested by the interface, the message "You Got It" is displayed (hit trial). Otherwise, the message "Try Again" appears (failed trial).

In this experiment, the desired number was set to 5, because the minimum time to detect the ERD/ERS is 2–3 s after the baseline interval [16]. The processing time window was set to 0.5 s, so the system would receive 4–6

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classification results in 2–3 s; therefore, the control number was 5 on average. Fig. 4 shows the semi-asynchronous trial procedure with continuous feedback.

As described in Section II (B), feature extraction is based on ERD/ERS, which is defined as the percentage power (A) decrease or increase in relation to the baseline interval (E, rest state) before the MI task. Therefore, A is the average power value of data over 1 s. In order to decrease the time of one trial and speed up MI command generation, baseline data E was recorded in the discrete feedback training stage.

D. *Subjects*

A total of ten right-handed healthy male subjects were selected for this study. Each subject was trained in the discrete feedback training stage and then tested in the continuous feedback testing stage. Each stage consisted of six sessions, with three sessions per week. Each session, lasting for approximately an hour, consisted of three calibration runs. The interval between two contiguous runs was 5 m. Each run consisted of 10 left-hand and 10 right-hand MI grasp trials.

III. Result

A. *Discrete Feedback Training*

Classification results of the discrete feedback training study were generated by a threshold-based classifier. The accuracy in this stage was defined as the percentage of hit trials divided by the total number of trials (i.e., both hit and failed trials). A trial is considered to be failed when feedback does not appear in the desired position; in other words, feedback for the left-hand MI task is displayed on the right or at the center of the screen, and vice versa. Fig. 5 shows the learning curves for each subject during six discrete feedback training sessions. It is obviously seen that subjects can increase their accuracy after six training sessions and that the intersubjective differences are considerable. As mentioned earlier, the main purpose of the discrete feedback training stage is to collect data for the construction of the classification model. Discrete feedback contains some information about the quality of the training data. Therefore, for building the SVM model, only hit trials were selected as input for the classifier.

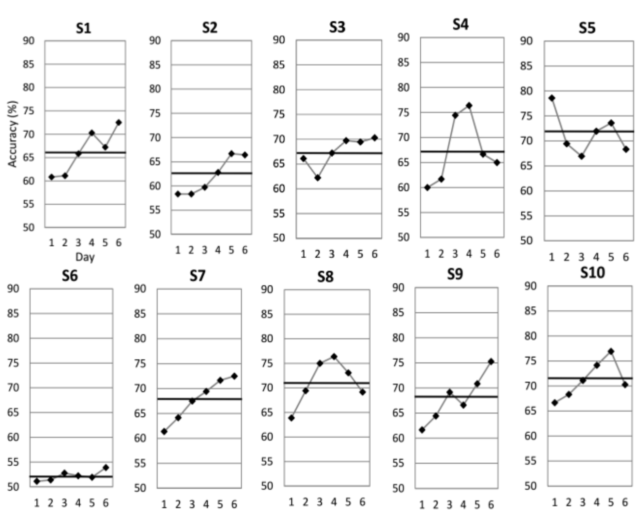

Fig. 5. Mean accuracy for each subject over the course of six discrete feedback training sessions.

B. *Continuous Feedback Testing*

The learning curves for each subject during six continuous feedback testing sessions are shown in Fig. 6. Classification accuracies increased compared with those of discrete feedback training for most subjects as the number of testing sessions increased. Each subject obtained the highest accuracy among six sessions. In addition, the mean control time and the average classification accuracy (hits/trials) across these six sessions were used to evaluate the performance of the continuous feedback. As shown in Table I, subjects achieved a mean accuracy of 77.00% during MI tasks in the best session in terms of accuracy. The time subjects spent on each movement task was 3.77 s on average.

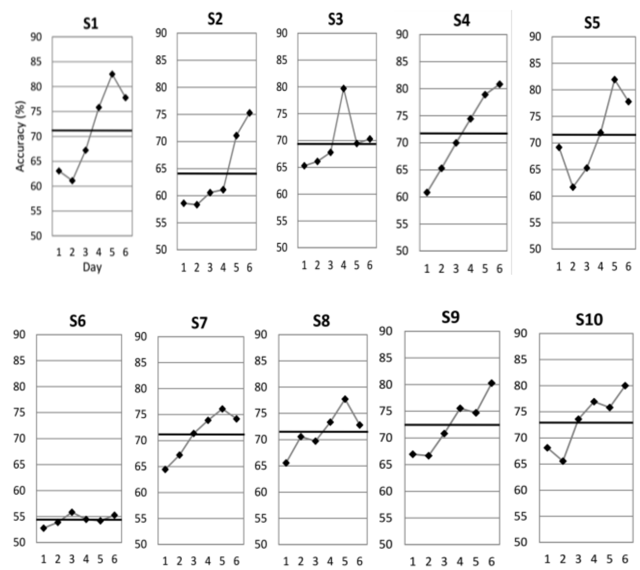

Fig. 6. Mean accuracy for each subject in the course of six continuous feedback tesing sessions.

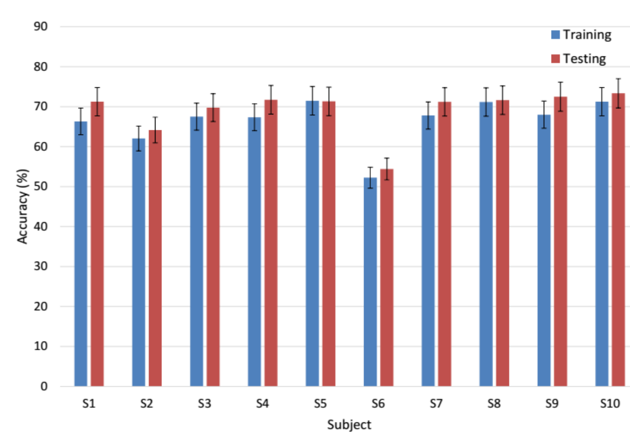

Fig. 7. Average training and testing accuracies from ten subjects. Error bars indicate standard deviation.

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TABLE I
Result of the best session in continuous feedback testing stage

Subjects	Acc (%)			Mean Control time (s)
	LH *(hits/trials)*	RL *(hits/trials)*	Mean	
S01	80.56 *(145/180)*	84.44 *(152/180)*	82.50	3.69
S02	72.22 *(130/180)*	78.33 *(141/180)*	75.28	3.68
S03	79.44 *(143/180)*	80.00 *(144/180)*	79.72	3.66
S04	82.78 *(149/180)*	78.89 *(142/180)*	80.83	4.00
S05	82.22 *(148/180)*	81.66 *(147/180)*	81.94	3.56
S06	56.67 (102/180)	55 (99/180)	55.83	3.65
S07	75 (135/180)	77.22 (139/180)	76.11	3.83
S08	78.89 (142/180)	76.11 (137/180)	77.5	3.75
S09	79.44 (143/180)	81.11 (146/180)	80.28	3.70
S10	78.89 (142/180)	81.11 (146/180)	80.00	4.17
Mean	**76.61**	**77.39**	**77.00**	**3.77**

Fig. 7 shows a comparison in accuracies from 10 subjects between training and testing stages. In general, the accuracy was improved in the testing stage in most cases except for subject 5 (i.e., 72% in training stage vs. 71% in testing stage). Subject 10 obtained his highest accuracy (i.e., 71% in training stage vs. 74% in testing stage) compared with others.

IV. Discussion

A. Accuracy

Compared with other studies, the accuracy in our study (i.e., 69% on average) indicates no significant difference. For instance, there is 74.84% accuracy on average obtained according to [4], whereas 65% accuracy (i.e., left vs. right hand) obtained according to [9]. Several reasons that may explain this result are:

(1) The quantity of EEG channels can affect the accuracy. For the purpose of wearability, practicability, and rapid signal processing, we utilized a two-channel-based EEG device. However, it would achieve better accuracy using multi-channel EEG devices in comparison with those of only one or two channels [4].

(2) The training period is insufficient. The length of the experiment was 1 month—2 weeks for each of the discrete and continuous feedback testing stages. Average training time is several months, as mentioned in [3]. Taken in this sense, reaching this level of accuracy with a one-month training period is valuable.

(3) The results indicated no significant difference in terms of accuracy between left hand and right hand motor imagery (i.e., p = ~0.4 in training session and p = ~0.34 in testing session). Moreover, the accuracy in the testing stage was calculated to be 69.1 ± 5.7% on average which was higher (i.e., 4%) than that in the training stage (i.e., 66.5 ± 4.1, p<0.001).

B. Self-paced command generation time

A prominent result of our proposed study is the effect of self-paced control. In order to enhance MI classification accuracy in the MI detection module, most studies [5, 17] adopt a synchronization mechanism, which means that the subjects' behavior should be synchronous with cues from the system. The calibration run in the discrete feedback stage is an example of a synchronization mechanism. The time interval of one trial is fixed (usually 8 s), and consists of a 3-s rest interval and 5-s MI interval. The subject should keep relax in rest interval for 3s and followed by MI interval for 5s. This type of synchronization mechanism has been widely utilized in many BCI studies [18-19], which required a total of 8-s time window. However, for a real-time control system, 8 s is too long to be useful. In this study, a semi-asynchronous mechanism ensures the flexibility of the time interval of a single trial. The system only prompts subjects with the start of the trial. Additionally, the rest interval is removed from the continuous feedback trial. Our proposed method can issue a command at a control time of 3.77 s on average, making the system more practical compared with those in other studies. For instance, the subjects need to spend on each correct movement command 8.81s on average according to [4]. In another work [20], in most cases, the subjects need to spend longer than 4s in order to generate a command with peak performance.

C. Continuous feedback

Experimental results show that continuous feedback is an effective method to improve imagery ability as well as to decrease the control time of a two-channel MI-based BCI system. As [12] introduced, there are several approaches to improve the accuracy of an EEG-based BCI system. In cases of less-channel applications (i.e., one or two channels), advanced algorithms for feature extraction, and various classifiers are needed in order to obtain a higher accuracy. Our study results confirm that continuous feedback is also an important method to improve MI performance.

V. Conclusion

This study presents a two-channel semi-asynchronous MI-based BCI system with discrete and continuous feedbacks. The experiment can be divided into the discrete feedback training stage, which is used to collect data for building a classifier, and the continuous feedback testing stage, which adopts real-time feedback as a self-paced control for improving imagery ability and decreasing control time. The experimental results show that continuous feedback successfully improves imagery ability as well as decreases the control time of one trial in a two-channel MI-based BCI system. Our proposed method can reduce command generation time to ~3.77 s while maintaining ~69.1% accuracy. Our proposed system is a non-invasive and wearable BCI which improves the practicability and operational convenience of recent BCIs.

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