A Novel Online Action Observation-Based Brain–Computer Interface That Enhances Event-Related Desynchronization

Xin Zhang, Wensheng Hou, Xiaoying Wu, Shuai Feng, and Lin Chen

***Abstract*— Brain-computer interface (BCI)-based stroke rehabilitation is an emerging field in which different studies have reported variable outcomes. Among the BCI paradigms, motor imagery (MI)-based closed-loop BCI is still the main pattern in rehabilitation training. It can estimate a patient' motor intention and provide corresponding feedback. However, the individual difference in the ability to generate event-related desynchronization (ERD) and the low classification accuracy of the multi-class scenario restrict the application of MI-based BCI. In the current study, a novel online action observation (AO)–based BCI was proposed. The visual stimuli of four types of hand movements were designed to simultaneously induce steady-state motion visual evoked potential (SSMVEP) in the occipital region and to activate the sensorimotor region. Task-related component analysis was performed to identify the SSMVEP. Results showed that the amplitude of the induced frequency in the SSMVEP had a negative relationship with the stimulus frequency. The classification accuracy in the four-class scenario reached 72.81 $\pm$ 13.55% within 2.5s. Importantly, the AO-based closed-loop BCI, which provided visual feedback based on the SSMVEP, could enhance ERD compared with AO-alone. The increased attentiveness might be one key factor for the enhancement of the ERD in the designed AO-based BCI. In summary, the proposed AO-based BCI provides a new insight for BCI-based rehabilitation.**

***Index Terms*— Action observation (AO), brain-computer interface (BCI), event-related desynchronization (ERD), steady-state motion visual evoked potential (SSMVEP), rehabilitation after stroke.**

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Xin Zhang and Shuai Feng are with the Bioengineering College, Chongqing University, Chongqing 400044, China (e-mail: zx2929108zx@cqu.edu.cn; fengshuai563100@zmu.edu).

Wensheng Hou, Xiaoying Wu, and Lin Chen are with the Key Laboratory of Biorheological Science and Technology, Ministry of Education, Bioengineering College, Chongqing University, Chongqing 400044, China (e-mail: w.s.hou@cqu.edu.cn; wuxiaoying69@163.com; clxyz@cqu.edu.cn).

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I. Introduction

BRAIN-COMPUTER interface (BCI) is a very appealing therapy in stroke rehabilitation as it can translate brain signals into meaningful outputs [1], [2]. Currently, motor imagery (MI)-based BCI is a novel treatment that can promote motor functional recovery after stroke [3], [4]. Event-related desynchronization (ERD), which is a decrease in the spectrum power of spontaneous oscillatory rhythms over the sensorimotor region, is usually selected as the electrophysiological (EEG) signature of MI [5]. Several studies have reported the efficacy of BCI-based therapies in rehabilitation [6]–[8], such as increasing the functional connectivity between motor areas [9].

In addition, action observation (AO), which is traditionally used in physical training to enhance the rehabilitation effect, can evoke ERD similar to MI [10]. Acting via the mirror neuron system (MNS), AO can subconsciously activate the motor neurons that are responsible for producing the observed action [11]. Mirror therapy is one representative application of AO in rehabilitation. Observing the reflection of a moving body part provides the illusion that its contralateral counterpart with limited motor function seems move normally [12]. In addition, AO has been reported to have a positive impact on stroke patients [13], [14].

Presently, AO is used as the visual guidance along with MI in BCI. Both AO and MI can activate targeted brain regions. As earlier reported, ERD has been used to evaluate sensorimotor cortical activities [15], [16]. An enhancement of sensorimotor cortical activities can lead to functional enhancement and positive rehabilitation outcomes [17]. Recently, several studies have aimed to identify methods that can enhance ERD. Tanaka, *et al*. reported that the participants' own hands could elicit a stronger ERD compared to observing the movement of another person's hand [18]. Sungho, *et al*. compared ERD responses using a virtual reality headset and a monitor display when performing AO. Compared to the monitor display, the ERD showed greater improvement using the virtual reality headset.

However, a number of stroke patients fail to generate the ERD through MI due to their impairment in sensorimotor region or their advanced age [19]. Even in healthy subjects, a significant proportion (estimated at 15% to 30%) of the population fail to generate a clear ERD [20]. Furthermore, MI-based BCIs have limited performance, that

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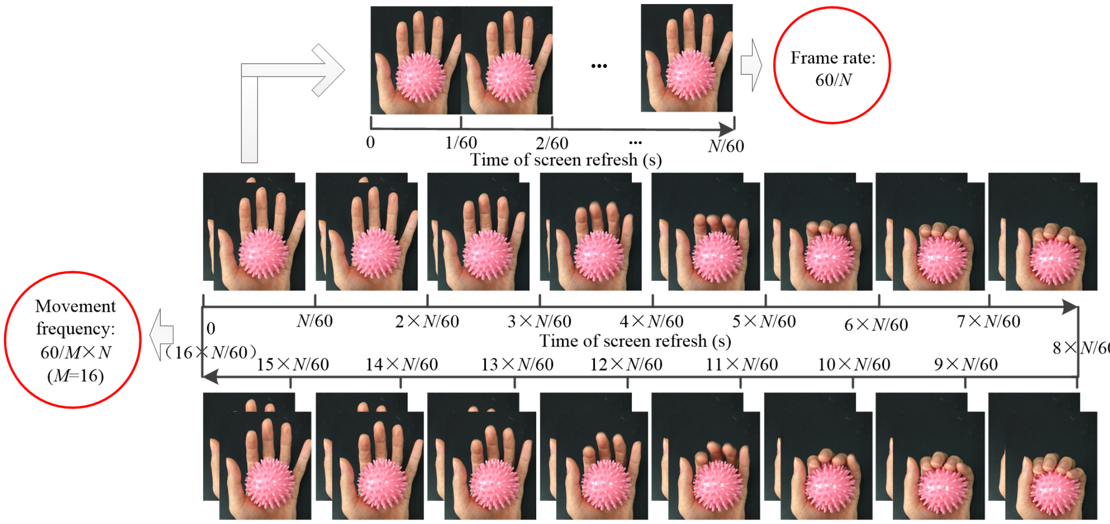

Fig. 1. The method of generating the stimulus.

is, the average classification accuracy was only 59.4% for the four-class scenario [21]. Moreover, few studies have reported fine MI due to the indistinguishable EEG signatures. The existing AO-based BCI studies still utilize the ERD response in the sensorimotor region to generate a closed-loop BCI. As such, its shortcomings are similar to those of MI.

Considering that AO is a visual stimulus, our recent study aimed to classify the EEG features in the occipital region induced by a gaiting stimulus [22]. The results showed that observing the designed gaiting stimulus could simultaneously induce the steady-state motion visual evoked potential (SSMVEP) in the occipital area and activate sensorimotor rhythm (SMR) in the primary sensorimotor area. However, the mechanism of AO-based BCI remains unclear.

In this study, we designed a novel online AO-based BCI, utilizing EEG data from the occipital region for classification, and demonstrated that AO-based BCI could enhance the ERD and attract more attention compared with AO alone. The enhanced sensorimotor cortical activities may benefit those requiring rehabilitation. Our approach was designed to explore the EEG response in different brain regions (occipital region, sensorimotor region, and frontal region) in different motor tasks (AO-alone, AO-based BCI, and AO along with MI). The influence of the stimulus' parameters, such as stimulus frequency and movement type, on the EEG response was further analyzed. The visual stimuli of the four types of hand movements (index finger movement, thumb movement, grasping, and grasping a ball) were designed to build an online AO-based BCI. The task-related component analysis (TRCA) method was utilized to identify the SSMVEPs induced by the designed stimuli. The visual feedback was provided to the participants based on the classification results. Compared with AO-alone and AO along with MI, the ability of the AO-based closed-loop BCI to activate the sensorimotor region (ERD) and the frontal region (the attention level) were evaluated.

II. Methods

A. Participants

Sixteen healthy subjects (6 males and 10 females, 23.3 ± 3.2 years old) with normal or corrected-to-normal vision were recruited in this study. Thirteen of the subjects (except S9, S12 and S14) were naïve to BCI. The study was approved by the ethical committee of Chongqing Cancer Hospital. Written informed consent forms were obtained from the participants before the experiment.

B. The Method to Generate the AO Stimulus

A frame-based stimulation pattern was adopted to present the action observation stimuli on a liquid crystal display monitor. The screen refresh rate was 60Hz, *i.e.* 60 frames per second. The stimulus was generated by the frame rate reduction (FRR) method. The steps of the FRR were as follows. Firstly, we recorded the video of one action, such as thumb movement or grasping. Secondly, M pictures in one cycle of the action were exacted from the video. Thirdly, the Psychophysics Toolbox [23] was utilized to present the M pictures and control the presentation time of each picture. Each picture lasted for $N/60$ s (the refresh rate of the screen is 60 Hz).

Taking the stimulus of grasping a ball as an example, as shown in Figure 1, each frame was extracted from a video. The same image would last for $N/60$ s ($N \geq 4$ in current study), followed by the next different image. Consequently, the frame rate of the designed stimulus decreased to $60/N$ (the frame rate of traditional video was 30Hz). In one cycle of the movement, there were a total of M captured images ($M = 16$ in Figure 1). Thus the frequency of the movement was $60/(M \times N)$. The background of the stimuli was unchanged so that the subject intuitively felt that the finger was moving instead of flicker. The normal speed of the movement ($60/(M \times N) < 1$Hz) was guaranteed by designing M and N.

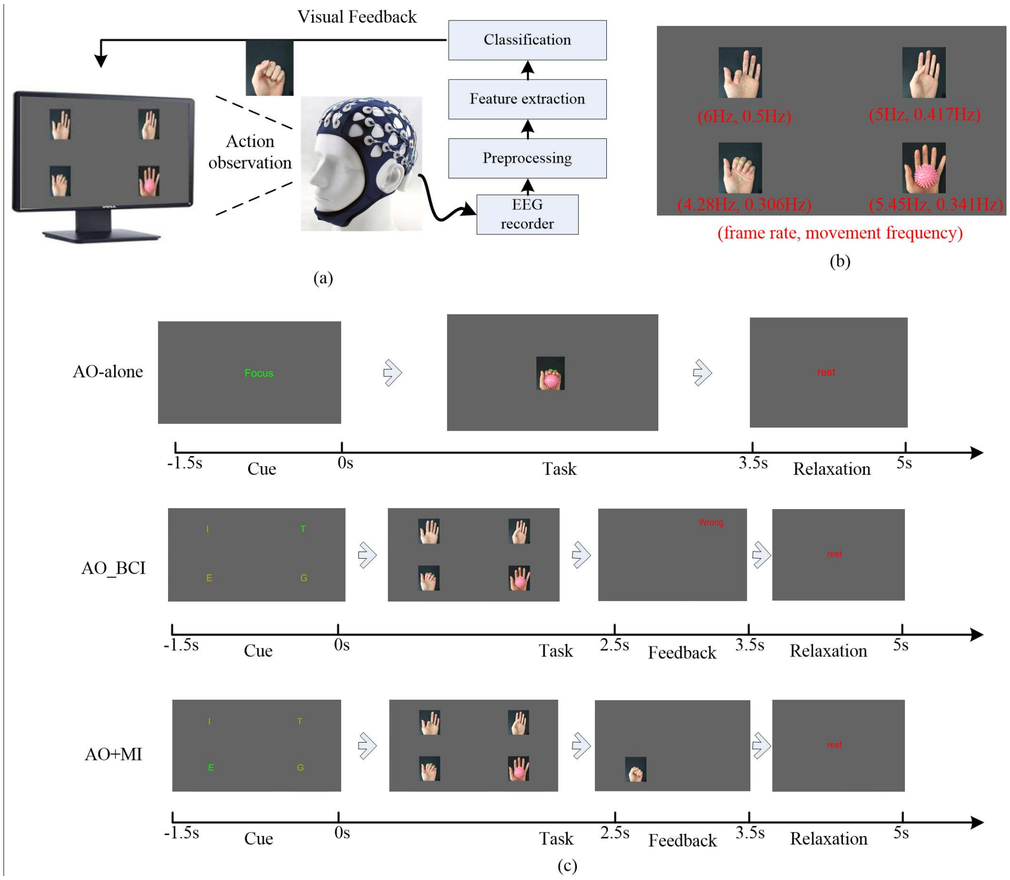

Fig. 2. Experimental design. (a) System diagram of the designed AO-based BCI. (b) Four visual stimuli of left hand movement. (c) The trial sequence in the experiment. Three motor tasks were performed (AO-alone, AO-based BCI (AO_BCI) and AO-based BCI and MI simultaneously (AO + MI)).

C. Experimental Design

To study the parameters' influence on the SSMVEPs induced by the designed action observation stimulus and to compare the ERD responses and the attention level during different motor tasks, we performed an EEG experiment, as shown in Figure 2, consisting of three different conditions: AO-alone, AO-based BCI (AO_BCI) and AO-based BCI and MI simultaneously (AO + MI). In AO-alone conditions, only one action observation stimulus with the movement of grasping a ball was displayed in the middle of the screen. No online classification results were fed back to participants. The frame rate of the stimulus changed from 4Hz to 15Hz (4Hz, 4.29Hz, 4.62Hz, 5Hz, 5.45Hz, 6Hz, 6.67Hz, 7.5Hz, 8.57Hz, 10Hz, 12Hz and 15Hz, *i.e.* $N = 15, 14, \ldots, 4$). There were a total of 16 images in one cycle of the movement, *i.e.* $M = 16$. In AO_BCI and AO + MI conditions, four left hand movement targets (index finger movement, thumb movement, grasping, and grasping a ball) were displayed on the screen as shown in figure 2(b) (https://youtu.be/Vb5tP9XXAwA). The frame rates of these four targets were 6Hz, 5Hz, 4.28Hz and 5.45Hz, respectively ($(M, N) = (12, 10), (12, 12), (14, 14)$, and (16, 11), respectively). Online visual feedback was provided for each participant in these two conditions. Participants aimed to achieve correct identification in each trial in AO_BCI and AO + MI. The only difference of AO_BCI and AO + MI was that participants needed to imagine the action as they stared at the AO + MI condition. The stimulus program was developed with MATLAB using the Psychophysics Toolbox.

During the experiment, the participant was seated in a comfortable chair and was briefed on the tasks to be performed. The participant was asked to watch the LCD screen on which the visual cues, task, feedback and rest information were displayed. Figure 2(c) illustrated the trial sequence in the experiment. Each trial started with the cue phase (from −1.5 to 0 s), where one cue word ('Focus') would appear in the middle of the screen in the AO-alone session or where four letters ('I,' 'T,' 'E,' 'G') would appear on the screen in AO_BCI and AO + MI. The green letter indicated the target stimulus for the current trial, in which the participant would then engage his or her gaze. Immediately after the cue phase, the designed action observation stimuli would replace the word or letters, appearing on the screen for 3.5s in AO-alone or 2.5s in AO_BCI and AO + MI, during which the stimuli were modulated at the frequencies stated above. During the task period, the participants were asked to gaze at the target appearing in the same position as the green letter shown in the cue phase. In AO + MI, participants were asked to imagine the same hand movement they were gazing at. The 1s feedback phase (2.5s to 3.5s) was followed in AO_BCI and AO + MI. The classification result utilizing canonical correlation analysis (CCA) or TRCA (CCA was utilized in the first block and the EEG data in the first block were used as the training data for the TRCA. TRCA was utilized in other blocks) would be displayed at the target position. If the classification results were the same as the target the participant was gazing at, a picture with the corresponding hand movement would appear in the screen lasting 1s. Otherwise, the word 'Wrong' would appear. Participants were asked to avoid blinking and avoid any limb movements during the task period. Thus, a rest phase was set for participant to blink and rest (3.5 to 5s).

The experiment comprised of three sessions, which included five blocks for each session. For each participant, the order of the 15 blocks was randomized. In one experimental block of AO-alone, each frame rate (4Hz to 15Hz) was repeated two times, i.e. a total of 24 trials. In one experimental block of AO_BCI or AO + MI, each of the four targets was repeated seven times in randomized order, i.e. a total of 28 trials. In total, each participant performed 400 trials.

At the end of the experiment, participants were asked to answer questions regarding their feelings of the identification results' influence on their attentiveness and emotions in AO_BCI on a Likert scale (strongly agree = 5, not at all = 1).

D. EEG Data Recording

EEG data were recorded with the Cerebus™ Data Acquisition System [24]. In brief, 32 Ag/AgCl passive electrodes located at Fp1, Fpz, Fp2, AF3, AF4, F3, Fz, F4, FC3, FCz, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P3, Pz, P4, PO7, PO3, POz, PO4, PO8, O1, Oz, and O2 were used for data recording, following the international 10-20 system. The left ear lobe was used as the reference and AFz was used as ground. The sampling rate was 1000Hz and the signals were low-pass filtered at 50Hz. All EEG data and event timestamps (the beginning and the end of each trial, and the classification results) were recorded for subsequent processing.

E. Online Identification Method

In AO_BCI and AO + MI, EEG data from electrodes PO3, POz, PO4, O1, Oz, and O2 were selected for online identification. Firstly, EEG data (0 to 2.5s) were band-pass filtered from 3Hz to 40Hz with the Butterworth filter. Subsequently, the CCA-based target identification method was utilized to analyze the six channels' data in the first block. Meanwhile the EEG data from this stage were used as individual training data for the TRCA method. In other blocks, the TRCA-based target identification method was utilized. The details of the identification methods are described below.

1) CCA-Based Target Identification: CCA is a statistical way to measure the underlying correlation between two multidimensional variables, which has been widely used to detect the frequency of SSVEPs [25]. In the current study, multichannel EEG data in the occipital region (PO3, POz, PO4, O1, Oz, and O2) and template signals were calculated by the following formula.

$$\rho(x, y) = \frac{E[w_x^T X Y^T w_y]}{\sqrt{E[w_x^T X X^T w_y E[w_x^T Y Y^T w_y]]}} \tag{1}$$

where ρ is the CCA correlation coefficient, X is the EEG data and Y is the template signal.

Template signals are sinusoidal signals as follows:

$$Y = \begin{Bmatrix} \sin(2 \times \pi \times f \times t) \\ \cos(2 \times \pi \times f \times t) \\ \sin(4 \times \pi \times f \times t) \\ \cos(4 \times \pi \times f \times t) \end{Bmatrix}, \tag{2}$$

where f is the frame rate of the action observation stimuli.

The target on which the participant focused on could be identified by taking the maximum CCA coefficient.

2) TRCA-Based Target Identification: Task related component analysis is an approach to extract task-related components from a linear weighted sum of multiple time series. TRCA was firstly proposed to maximize the reproducibility during task periods from near-infrared spectroscopy data [26]. As it had the ability to maximize inter-block covariance and to remove task-unrelated artifacts, TRCA was successfully used as a spatial filter to remove background EEG activities in SSVEP-based BCIs [27]. The spatial filter can be achieved as follow:

$$\omega = \arg\max_{\omega} \frac{\omega^T S \omega}{\omega^T Q \omega} \tag{3}$$

The normalization matrix Q is defined as:

$$Q = \sum_{j_1, j_2 = 1}^{N_c} Cov(x_{j_1}(t), x_{j_2}(t)) \tag{4}$$

where $x_{j_1}(t)$ is the EEG data in the j_1-th channel and $x_{j_2}(t)$ is the EEG data in the j_2-th channel. N_c is the number of total channels. The $Cov(.,.)$ represents the cross covariance.

The symmetric matrix $S = (S_{j_1 j_2})_{1 \le j_1, j_2 \le N_c}$ is defined as:

$$S_{j_1 j_2} = \sum_{\substack{h_1, h_2 = 1 \\ h_1 \ne h_2}}^{N_t} Cov(x_{j_1}^{(h_1)}(t), x_{j_2}^{(h_2)}(t)) \tag{5}$$

where $x_{j_1}^{(h_1)}(t)$ is the EEG signal in h_1-th trial in the j_1-th channel. $x_{j_2}^{(h_2)}(t)$ is the EEG signal in h_2-th trial in the j_2-th channel

With the help of the Rayleigh-Ritz theorem, the eigenvector of the matrix $Q^{-1}S$ provides the optimal coefficient vector of the objective function in (3).

As there were four individual training data corresponding to four AO stimuli, four different spatial filters could be obtained. Thus an ensemble spatial filter W was obtained as follows:

$$W = [\omega_1 \quad \omega_2 \quad \omega_3 \quad \omega_4] \tag{6}$$

Through spatial filtering $X_{test}^T W$, the test data X_{test} were expected to be optimized to achieve maximum performance.

The correlation coefficient was selected as the feature. The Pearson's correlation analysis between the single-trial test signal X_{test} and average training data $\bar{X}_i$ across trials for i-th stimulus was calculated as:

$$r_i = \rho\left(X_{test}^T W, \left(\bar{X}_i\right)^T W\right) \tag{7}$$

where ρ is Pearson's correlation.

The target on which the participant focused on could be also identified by taking the maximum coefficient as follows.

$$Target = \max(r_i), \quad i = 1, 2, 3, 4 \tag{8}$$

F. Analysis of EEG Data From the Sensorimotor Region

To compare the effects of different motor tasks on the sensorimotor region, the analysis of EEG data from the sensorimotor region were performed using EEGLAB [28]. First, the EEG data were filtered from 2 Hz to 40 Hz. The EEG data were then visually inspected for artifacts (e.g., electrode cable movements, swallowing, etc.) and affected trials were removed from further analysis. On average, 86.68 ± 2.56% of the trials of each participant's EEG data was used in subsequent analysis.

Next, the preprocessed datasets of EEG and electrooculogram (EOG) were decomposed by independent component analysis (ICA) [29]. ICA was performed on individual subjects over all trials within one condition. Based on the individual component scalp maps and component activations (scroll), the component mainly containing EOG was rejected. As we were interested in left hand motor functions, we focused on the channel C4. As such, Laplacian spatial filtering was applied to C4, and four channels surrounding it, namely, FC4, C2, C6 and CP4. Laplacian filtering has been shown to improve quality of sensory-motor rhythm estimation [30].

Finally, the event-related spectral perturbation (ERSP) [31] was computed. Relative changes in spectral power were obtained by averaging the difference between each single-trial log spectrogram and baseline (−1.4 to 0s). The ERD index was calculated as the log ratio of the power in a certain frequency band during each condition and the power during the baseline, which ranged from −1.4s to 0s. The ERD index was calculated [32]:

$$ERD\ Index = 10 \times log_{10}\frac{P}{R} \tag{9}$$

where R is the power in the reference period (baseline) and P is the power during the task period.

This index quantified the degree of EEG power reduction across the spectrum resulting from the desynchronization of the cortical neuron when executing a motor task [33]. Considering that most reactive frequency band can vary for each individual [34], [35], the frequency band of each participant was determined by selecting the frequency band of bandwidth 4 Hz from frequency band mu-beta [8 26] Hz that resulted in the maximum averaged ERD ratio of all the tasks.

G. Analysis of EEG Data From the Frontal Region

EEG activity from the frontal region in the alpha rhythm (8 to 13 Hz) was modulated by sustained voluntary attention [36]. Thus, the power spectral density (PSD) estimation was performed through the periodogram technique to detect the attention-level of the participant [37]. The average power of alpha rhythms (8 to 13 Hz) was extracted below.

$$Att\_P = \frac{1}{N_\alpha} \times \sum_{f=8}^{13} Att\_S(f) \tag{10}$$

where $Att\_S(f)$ is the value of the periodogram at frequency f. N_α is the number of frequencies used to calculate the Att_P in alpha rhythms.

H. Statistical Analysis

A mixed-effect analysis of variance (ANOVA) was used to analyze the ERD index and the power of alpha rhythms, where task (1: AO-alone, 2: AO_BCI, 3: AO + MI) was the fixed factor and subject was a random factor. Bonferroni post hoc analysis was used to test the significance. The statistical significance level was 0.05 for all tests.

III. Results

A. Amplitude Spectra of SSMVEP Induced by the Stimuli

Stimulus frequency is a key parameter for SSVEP/SSMVEP-based stimuli. As for the AO stimuli, the analysis of the amplitude of the SSMVEP component for different stimulation frequencies is still missing. The low frequency region (4 Hz to 15 Hz), which could induce the larger amplitude response [38] in the traditional SSVEP stimulus, was selected as the stimulus frequency range in the current study. Limited by the screen refresh rate, only twelve frequencies could be generated in the designed AO stimulus in the low frequency region. Figure 3(a) illustrated the spectra of the EEG data averaged from all the trials in the AO-alone session in S9. Figure 3 (b) illustrates the amplitude images for all stimulation frequencies (4∼15 Hz) as functions of stimulation frequency and response frequency averaged from all the participants in the AO-alone session. It showed that the designed AO stimulus could induce a corresponding frequency and its harmonics frequency in the low frequency region. Figure 3 (c) showed the amplitudes of the peak in the spectra at the stimulus frequency in each participant. The correlation analysis yielded significant relationships between amplitudes and stimulus frequencies ($r = -0.452$, $p < 0.001$). As the stimulus frequency increased, the amplitude of the peak in the spectra of the induced SSMVEP was decreased. Furthermore, the amplitude of the SSMVEP induced by the stimulus with 15Hz was significantly lower than the other amplitudes induced by the stimulus with other frame rates. It was different from the traditional SSVEP response, which had the optimal response at 15Hz in low frequency region [38].

B. Target Identification Accuracy

AO_BCI and AO + MI were two online cued-tasks. Figure 4 shows the target identification accuracy in each participant in these two sessions. The average accuracy was 72.81 ± 13.55% in the AO_BCI session, which was slightly higher than the average accuracy in the AO + MI session (71.15 ± 11.39%). Paired t tests indicated that there was no significant difference in accuracy between AO_BCI and AO + MI ($p = 0.184$). It suggested that multiple types of movement using the proposed FRR method to generate the stimulus could induce the SSMVEP in the occipital region and these features could be identified by the TRCA method. Across individuals, the minimal and maximal accuracy were 46.43% (S1) and

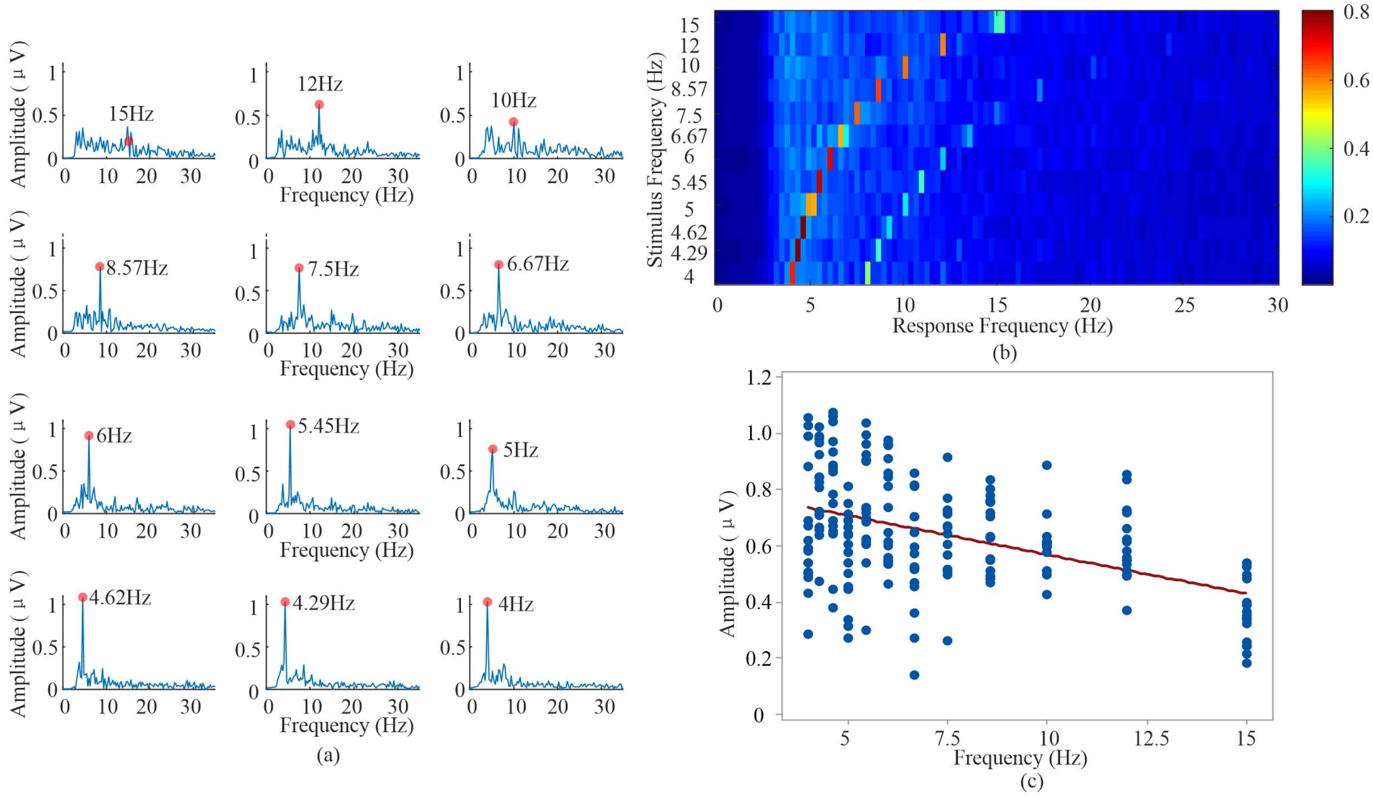

Fig. 3. Amplitude spectra of SSMVEP induced by the designed stimuli. (a) The spectra of the EEG data averaged from all the trials in AO-alone session in S9. (b) The amplitude images for all stimulation frequencies (4∼15 Hz) as functions of stimulation frequency and response frequency averaged from all the participants in AO-alone session. (c) The amplitudes of the peak in the spectra at the stimulus frequency in each participant.

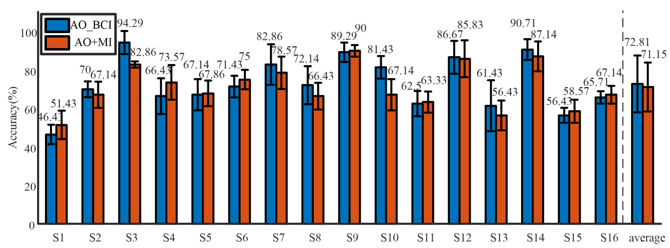

Fig. 4. The target identification accuracy in each participant (the values at the top of each bar chart are the accuracies (%) of each participant).

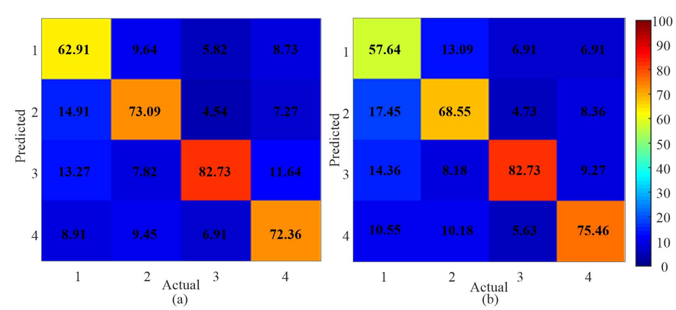

Fig. 5. The confusion matrices of the identification accuracy (%). (a) AO_BCI session (b) AO + MI session (1: observing the movement of index finger, 2: observing the movement of thumb, 3: observing the movement of grasping, and 4: observing the movement of grasping a ball).

94.29% (S3) in AO_BCI session, respectively. The minimal and maximal accuracy were 51.43% (S1) and 90% (S9) in AO + MI session, respectively. The results indicated that a certain individual difference existed in the ability to induce SSMVEP by the designed stimuli.

To further compare the relative identification performance of the designed stimulus targets with different hand movements, the confusion matrices of the identification accuracy (%) for all participants were calculated as shown in Figure 5. The color scale revealed the average classification accuracies and the diagonals labeled the correct classification accuracies among all the participants. We observed that the target of index finger movement resulted in the lowest identification accuracy in all cases, whereas the target of grasping resulted in the highest identification accuracy, indicating that the type of movement might have a certain influence on the identification accuracy.

C. Analysis of ERD Performance

Figure 6(a) presents the grand average ERSP from channel C4 across the data from all participants. During the task period (from 0 to 2.5s), all these three tasks evoked clear and sustained ERD in the mu-beta band (8 to 26 Hz). Furthermore, the desynchronization in the mu-beta band in AO_BCI was visibly stronger than that in AO-alone. The desynchronization in the mu band in AO + MI was slightly stronger than that in AO_BCI.

To further investigate the effects of the tasks on the sensorimotor area of the EEG, the ERD indexes in the mu-beta band during the task period were calculated. Across individuals

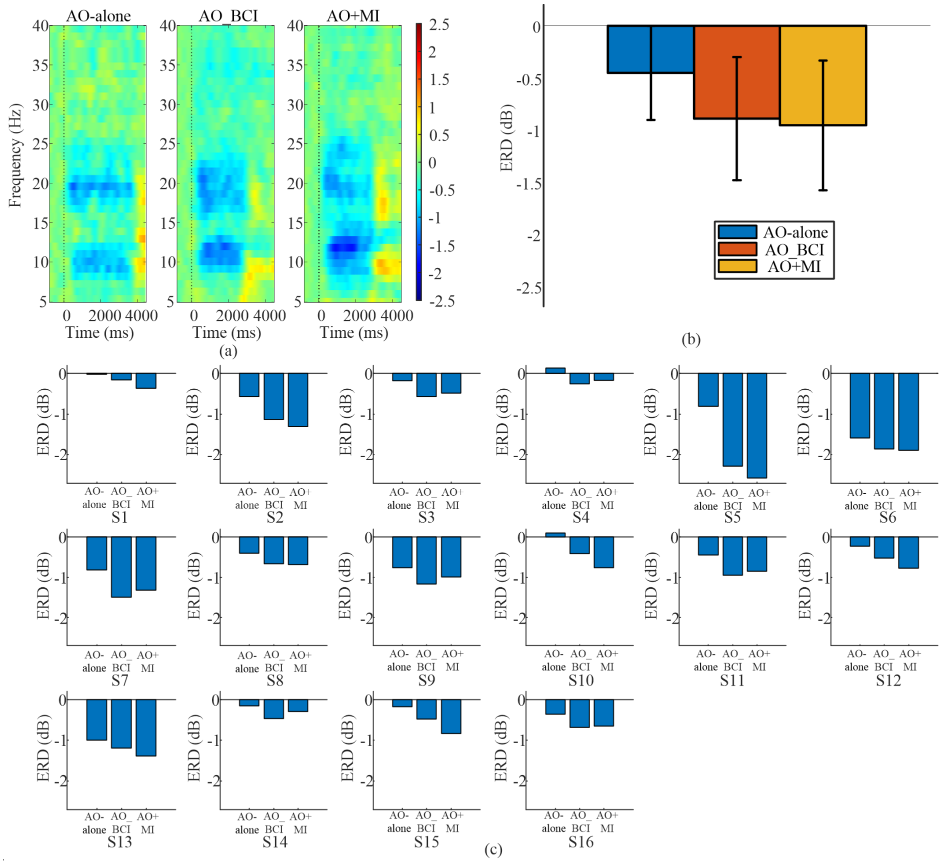

Fig. 6. The ERD over the sensorimotor region in the three motor tasks. (a) The grand average ERSP from channel C4 across the data from all participants. (b) The ERD index in the mu-beta band. (c) The grand average ERSP from channel C4 in each participant.

as shown in Figure 6(b), the ERD was enhanced among all the participants by the designed AO_BCI compared with AO-alone. The results also showed that AO-alone could evoke the ERD in most participants, except S4 and S10. Comparing the ERD in AO_BCI, the ERD in AO + MI was not always enhanced in all participants. Furthermore, a mixed-effect model of ANOVA was used to quantify the differences. The task had a significant effect on the ERD index values ($F = 22.73$, $p < 0.001$). The ERD index values in AO_BCI were significantly lower than that in AO-alone ($p < 0.001$). The ERD index values in AO + MI were also significantly lower than the ERD values in AO-alone ($p < 0.001$), whereas there was no significant difference in the ERD index values between AO_BCI and AO + MI ($p > 0.1$).

TABLE I

THE POWER IN ALPHA RHYTHMS DURING TASK PERIOD

Subject	AO-alone	AO_BCI	AO+MI
S1	4.433503	0.969391	1.152608
S2	16.55358	3.035679	4.060792
S3	2.907397	1.290662	1.228152
S4	2.621166	2.996605	2.910811
S5	3.238956	2.527802	2.160333
S6	7.993248	6.086976	5.193295
S7	3.547551	2.154858	2.31626
S8	3.204339	4.05329	4.147989
S9	3.430002	1.93639	2.440112
S10	8.387392	6.282726	4.455816
S11	5.591394	2.586237	2.875189
S12	2.88336	2.97195	2.906575
S13	6.9183645	3.0919402	1.4687746
S14	3.4793591	3.0455019	2.0453706
S15	10.204808	3.1976097	1.4820096
S16	4.4099202	3.1790841	4.556828

D. Analysis of Attention Level

Table I shows the power (Att_P in Eqn. (10)) of the averaged EEG data from the frontal channels (Fp1, Fpz, Fp2, AF3, AF4, F3, Fz, F4) in the alpha rhythms in each participant during the task period (0 to 2.5s). A mixed-effect model of ANOVA was used to quantify the differences. The task (1: AO-alone, 2: AO_BCI, 3: AO + MI) was the fixed factor and subject was a random factor. Bonferroni post hoc analysis was used to test the significance. The statistical significance level was 0.05 for the test. The task had a significant effect on the powers ($F = 8.79$, $p = 0.001$). In post hoc analysis, the powers in AO_BCI were significantly lower than in AO-alone ($p = 0.005$). The powers in AO + MI were also significantly lower than in AO-alone ($p = 0.002$). While there was no significant difference in powers between AO_BCI and AO + MI ($p > 0.1$). Furthermore, Figure 7 showed that the enhancement of the mu-beta suppression $((ERD\ Index_{AO\_BCI} - ERD\ Index_{AO})/ERD\ Index_{AO})$ tended to show a positive correlation with the change of

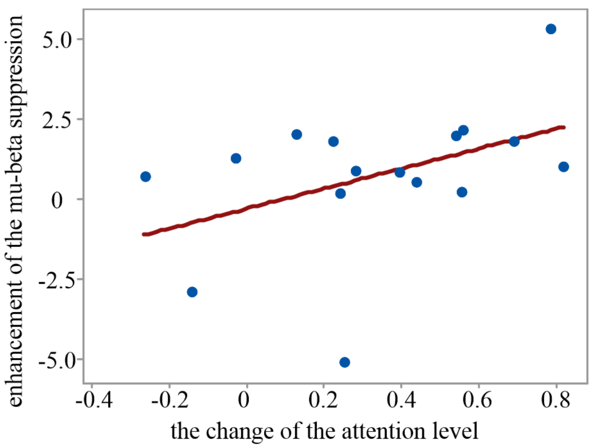

Fig. 7. The relationship between the change of attention level and the enhancement of mu-beat suppression.

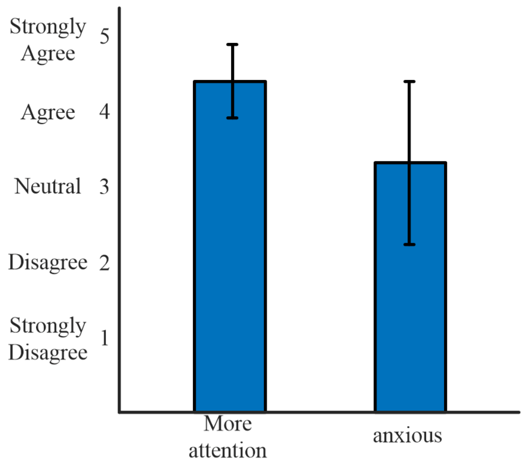

Fig. 8. Results of the attentiveness questionnaire.

the attention level under AO_BCI relative to AO-alone ($(Att\_P_{AO} - Att_{P_{AO\_BCI}})/Att\_P_{AO}$) ($r = 0.620$, $p = 0.042$).

Figure 8 shows the subjective responses to the attentiveness questionnaire. Most participants strongly agreed that the feedback prompted the participants to pay more attention in the next trial when a misidentification occurred. The average score was 4.31 ± 0.48. By contrast, the participants were neutral to that the misidentification made participants felt anxious. The average score was 3.25 ± 1.06, indicating that the identification results played a positive role on the participants.

IV. Discussion

In this study, we proposed a novel online AO-based BCI that could maintain the participants' engagement through effective interactions to enhance the ERD over the sensorimotor region. Four visual stimuli of different hand movements (index finger movement, thumb movement, grasping, and grasping a ball), which contained no flicker, were designed by utilizing the FRR method. The visual feedback was provided according to the induced SSMVEP.

Although AO has been widely used in post stroke rehabilitation, there have been few studies focusing on the EEG response to the AO stimulation, which is the key factor to build closed-loop training. The current study focused on building the AO-based BCI and analyzing the role of BCI in AO-based BCI. Thus, EEG responses from multiple brain regions (occipital region, sensorimotor region and frontal region) were analyzed in the three motor tasks (AO-alone, AO_BCI, and AO + MI) in the current study. The results showed that the designed AO stimuli could induce the SSMVEP in the occipital area and the induced SSMVEP frequency was mainly at the frame rate. The amplitudes at the response frequencies were decreased as the stimulus frequencies in low frequency region (4 Hz to 15 Hz) increased. Furthermore, these frequencies could be used to perform classification. The classification accuracy of the four targets reached 72.81 ± 13.55% within 2.5s duration. However, the amplitudes at the response frequencies induced by the designed AO stimulus in one trial were still lower than that induced by traditional SSVEP/SSMVEP-based stimuli (such as flicker and checkerboard stimulus). Thus the classification accuracy in current study was lower than that of traditional SSVEP/SSMVEP-based stimuli. Besides, the proposed AO_BCI induced a clear ERD in the mu-beta band in the sensorimotor area (Figure 6) and the ERD index in sensorimotor region and the powers in alpha rhythms in the frontal region were both significant lower than those in the AO-alone session, whereas there were no significant differences in the ERD index and the power in alpha rhythms between AO_BCI and AO + MI. Therefore, the present study describes the implementation of an online AO-based BCI and demonstrates that the proposed AO-based closed-loop BCI could attract more attention to enhance the ERD in the sensorimotor region.

Traditional stimulation adopts the frame-based 'on/off' pattern to present a flicker on the monitor [39]. The periodic changes in brightness induced the SSVEP in the occipital area [38]. The images with different brightness levels generated the flicker. Different from the existing stimuli, the designed AO stimulus in the current study contained no flicker. The periodic changes in the position of the fingers induced the SSMVEP. To guarantee the normal speed of movement, the FRR method was utilized. Results elaborated the effects of the stimulus frequency on the intensity of the SSMVEP, which provided guidelines for the design of the AO-based stimulus. Notably, the intensity of the SSMVEP showed a certain difference from the traditional SSVEP response, especially at 15Hz. The reason remains to be determined.

To our best knowledge, this is the first study to classify the participants' intention of observing different fine movements of the hand. The TRCA method was utilized to deal with the EEG data from the occipital region. The four targets classification accuracy reached 72.81 ± 13.55% when the duration of the stimulus was 2.5s. It is difficult to classify fine movement utilizing the ERD over the sensorimotor region. Thus, the current study provided an alternative to BCI-based fine motor rehabilitation of the hand. Furthermore, thirteen of the participants were naïve to BCI, and no training was given to the participants before the experiment. Therefore, the designed AO-based BCI maintained the advantages of no training.

Mu and beta suppression have been widely used to explore the MNS, while some researchers are still concerned that changes in the mu power may be driven largely by attention processes rather than mirror neuron activity [40], [41]. The attention process was also found in our recent study when participants gazed at the stimulus [42]. Thus, we combined the mu band and the beta band to calculate the ERD index and to compare different motor tasks' effects on the sensorimotor region. Furthermore, the mu-beta suppression was weak during the feedback period (2.5s to 3.5s) in AO_BCI and AO + MI. One reason might be that the ability of the static images to activate MNS was weaker than that of the dynamic images. Another reason might be that the identification accuracy was not 100% and the text could not activate MNS.

Enhancing engagement could increase attentiveness and facilitate brain function [43]. The real time online feedback in the designed AO_BCI maintained the participants' engagement. Thus the attention level in AO_BCI was higher than that in AO-alone. A prominent ERD was observed in the designed AO_BCI compared with AO-alone in the current study. Furthermore, attention and motor rehabilitation showed a certain relationship in the post-stoke rehabilitation outcome [44]. One recent study reported that selective attention skills were positively related to the Fugl-Meyer upper extremity recovery index after stroke [45]. Robertson et al observed that preserved attention skills could positively impact the motor rehabilitation outcome [46]. The current study showed that the enhancement of the mu-beta suppression tended to show a positive correlation with the change of the attention level under AO_BCI relative to AO-alone. Thus, the increased attentiveness might be the one key factor for the enhancement of the ERD in the designed AO_BCI.

In addition, AO and MI are two covert forms of action processing that both engage in the sensorimotor region [47]. The neurocognitive mechanisms of AO + MI processes are still unknown. The current study showed that there was no significant difference in the ERD index values between AO_BCI and AO + MI. The reason might have been that participants spontaneously engaged in MI when they performed AO, consistent with an earlier report [48].

In conclusion, the designed hand movement stimuli were successfully applied to the online BCI which provided feedback to the participants to enhance engagement. The SSMVEP can be induced by different types of hand movement stimuli, and the amplitudes at the response frequencies in the spectra were decreased as the stimulus frequencies increased. Furthermore, the designed AO_BCI could enhance the ERD, which indicated an enhancement of the activating MNS. The increasing attentiveness might be one key factor for the enhancement of the ERD in the AO-based BCI. This paradigm might be an option for patients who cannot perform MI. Moreover, functional electrical stimulation or exoskeleton robots could also be utilized as feedback together with the visual feedback, which could enhance the stimulation of peripheral nervous. It is possible to optimize rehabilitation training by completing certain tasks through multi-object selection in the designed AO-based BCI. Nevertheless, further research on the new algorithms needed to improving the classification accuracy in AO-based BCI is key, and the physiological mechanisms of the designed AO-based BCI in rehabilitation applications also requires further study.

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