Toward Improving Engagement in Neural Rehabilitation: Attention Enhancement Based on Brain–Computer Interface and Audiovisual Feedback

Jiaxing Wang, Weiqun Wang, and Zeng-Guang Hou, *Fellow, IEEE*

***Abstract*—Both motor and cognitive function rehabilitation benefits can be improved significantly by patients' active participation. To this goal, an attention enhancement system based on the brain–computer interface (BCI) and audiovisual feedback is proposed. First, an interactive position-tracking riding game is designed to increase the training challenge and neural engagement. Subjects were asked to drive one of the avatars to keep up with another by adjusting their riding speed and attention. Second, the subject's electroencephalogram (EEG)-based attention level is divided into three regions (low, moderate, and high) by using the theta-to-beta ratio (TBR). According to the subject's attention states, different speed adjustment strategies are adopted to adjust the tracking challenge and improve the subject's attention. Besides, if the subject's attention focused on the training is moderate or low, an auditory feedback will be given to remind the subject to pay more attention to the training. The contrast experimental results show that subjects' performance indicated by overall attention level and average muscle activation can be improved significantly by using the attention enhancement system, which validates the feasibility of the proposed system for improving the neural and motor engagement.**

***Index Terms*—Attention enhancement, brain–computer interface (BCI), electroencephalogram (EEG), neural rehabilitation, virtual reality.**

Manuscript received June 11, 2019; revised September 14, 2019 and November 5, 2019; accepted December 6, 2019. Date of publication December 12, 2019; date of current version December 9, 2020. This work was supported in part by the National Key Research and Development Program of China under Grant 2018YFC2001700, in part by the National Natural Science Foundation of China under Grant 61720106012 and Grant 91648208, and in part by the Strategic Priority Research Program of Chinese Academy of Science under Grant XDB32000000. *(Corresponding author: Zeng-Guang Hou.)*

J. Wang is with the State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China, and also with the University of Chinese Academy of Sciences, Beijing 100049, China (e-mail: wangjiaxing2016@ia.ac.cn).

W. Wang is with the State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China (e-mail: weiqun.wang@ia.ac.cn).

Z.-G. Hou is with the State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China, with the University of Chinese Academy of Sciences, Beijing 100049, China, and also with the CAS Center for Excellence in Brain Science and Intelligence Technology, Beijing 100190, China (e-mail: zengguang.hou@ia.ac.cn)

Color versions of one or more of the figures in this article are available online at https://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TCDS.2019.2959055

I. Introduction

STROKE, which is caused by cerebrovascular blockage or rupture, is one of the leading causes of death and paralysis [1]. Clinical studies have shown that about 50%–80% of stroke patients still have lower limb motor dysfunction at different degrees even six months after a stroke [2]. Therefore, long-term rehabilitation training is necessary for stroke patients to recovery the self-care ability.

The optimal recovery period is the first three months after a stroke, and the likelihood of recovery from impaired function decreases over time [3]. Therefore, enhancing a patient's neural engagement plays an important role in improving the neural plasticity and motor recovery. However, patients can easily become tired in the routine high-repetitive training, which leads to low neural engagement and attention, not to mention patients with attention deficit disorders. Therefore, investigating how to promote patients' active participation and attention level has become a hot topic in the neurorehabilitation research domain [4]–[6].

Electroencephalogram (EEG) contains abundant information of the cerebral cortex activity. Through the analysis of EEG, the thinking mechanism of human can be further understood, which can be used to guide the information exchange between patients with a nervous system injury and the surrounding environment [7]. Therefore, EEG signals have been an indispensable data source in the current brain–computer interface (BCI) technology and neurological rehabilitation domain [8]–[10].

EEG signals can be divided into five bands, namely delta (1–3 Hz), theta (3–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30 Hz) rhythms. Delta wave generally occurs when the body is in a state of deep sleep or unconsciousness, and theta wave is the waveform of drowsiness or unfocused state of the brain. When alpha wave is the main component of the EEG signals, the subjects are relaxed but alert, which is the best state for learning and thinking. With the increase of the beta wave energy, the subjects are concentrated and gradually turn into mental activity [11], [12]. From the description given above, we can see that the brain is gradually in a state of mental concentration with the increase of the EEG signals' main frequency. Besides, studies have indicated that the beta wave has a positive effect on the development of attention and cognitive behavior [13]. Good performance and cognitive state often related to a decreased slow-wave EEG activity (a decrease of the delta and theta energy) and an increased fast wave EEG activity (an increase of the alpha and beta energy) [14]–[17]. Therefore, EEG signals can be used to monitor patients' real-time attention state. By recording and analyzing the changes of the post-stroke patients' EEG signals during rehabilitation training, patients' attention level can be monitored in real time, which can be used to guide the adjustment of the training strategy or feedback, thus improving patients' attention, neural engagement, and speeding up the recovery.

Many methods have been used to analyze EEG-based attention states. In 2015, Wang *et al.* [18] developed an EEG-based attention tracking system during human distracted driving by using a radial basis function (RBF)-based support vector machine (SVM). First, two categories of EEG signals were recorded when the subject was doing a lane-driving task or a mathematical problem-solving task (e.g., $12 + 25 = 47$?). These two kinds of data were used to train the RBF-based SVM classifier. Finally, a focus of attention assessment system was built, which was used to track subjects' attention. 84.6±5.8% and 86.2±5.4% classification accuracies were achieved by applying this system to detect the subjects' focus of attentions on the math versus driving tasks, respectively. In 2018, correlation-based feature selection and *k*-nearest-neighbor data mining algorithm were used by Hu *et al.* to model the EEG-based attention recognition system [19]. In addition, other attention classification models, such as deep learning-based classification model, can be found in [20]–[23].

As mentioned above, these classification-model-based attention evaluation methods can only roughly manifest participants' current concentration state (attention or inattention) on a specific task, but cannot quantitatively give the participants' attention scores. Since good performance and cognitive state often relate to a decreased slow-wave EEG activity (delta and theta rhythms) and an increased fast wave EEG activity (alpha and beta rhythms), the difference of the signals between different bands can also be used to quantitatively analyze participants' attention scores.

In 2017, Lin *et al.* [24] used the TBR method to determine subjects' attention states throughout the experiment. If the subject's TBR score was higher than the threshold which was defined before the experiment, the subject will be deemed to have inadequate attention focused on the training. Meanwhile, visual and auditory feedback will be transmitted by the designed virtual reality (VR) system to remind the subject to pay attention to the training. Besides, studies have indicated that when the subject is highly concentrated, his brain neurons have to process a higher amount of information and the resulting EEG signals are reported to be more complex [25]. Therefore, entropy function can also be used to quantitatively analyze human attention level. Many entropy functions, such as sample entropy [26] and multiscale entropy [25], have been used to calculate subjects' attention.

Based on the previous work [27] and analysis given in this article, the TBR method is chosen to evaluate participants' real-time attention scores owing to the obvious difference between the energy of theta and beta bands in different attention states. With subjects' attention enhancement, the energy of theta and beta bands shows prominently decreased and increased, respectively. In order to enhance the participant's attention level, the subject has to suppress theta wave activity and enhance beta wave activity. Reference [27] also indicates that the frontal and temporal regions are two brain regions that can reflect subjects' different attention states significantly. Therefore, electrodes distributed in two regions are used to calculate the subjects' attention scores.

When subjects are recognized with inadequate attention, traditionally, visual or auditory feedback will be given to remind them to pay attention to the training. If the feedback signals are presented in the framework of a computerized game, users will feel more motivated and rewarded [26]. Since VR-based games have shown an advantage in improving rehabilitation effectiveness by changing their attitudes to the rehabilitation training and engaging them to the designed VR game, attention-based VR games have also been developed in many researches [28].

In 2017, Alchalabi *et al.* [29] designed an EEG-controlled VR game to increase the engagement and attention of the patients with attention deficit hyperactivity disorder or attention deficit disorders. The participants had to use mental commands to control the avatar shown in the VR game to move forward. The experimental results showed an average improvement of 10% in engagement and 8% in focus for healthy people who used the EEG-controlled VR game, which confirmed that the EEG-based VR system has the potential to augment individuals' attention.

In this article, an interactive position-tracking riding game is designed to enhance subjects' attention and neural engagement. The riding speeds of the two avatars are determined by the participant's actual riding speed and the calculated attention score. Subjects were asked to drive the avatar_subject to keep up with the avatar_companion as quickly as possible. If the subject's attention focused on the training is moderate or low, on the one hand, an auditory feedback will be given to remind the subject to pay attention to the training. On the other hand, the speed of the avatar_subject will be lower than the actual riding speed, or even be equal to zero. The subject has to improve his attention timely to drive the avatar_subject to keep up with the avatar_companion as soon as possible. Only when the subject is highly focused, the speed of the avatar_subject will be equal to the actual riding speed. Moreover, if it is still hard for subjects to keep up with the companion, the avatar_companion will adaptively adjust his riding speed according to the speed and position error between them to reduce the tracking error and adjust the tracking challenge properly. This condition is served as a reward for the better training state of the subject. The contrast experimental results show that subjects' performance indicated by overall attention level and average muscle activation can be improved significantly by using the attention-driven system, which validates the feasibility of the proposed system for neural and motor engagement improvement.

In Section II, the system architecture and the design of the interactive position-tracking game are presented. Then, the attention calculation and speed adjustment algorithms are introduced, which are used to design the speed of the two avatars in the game. The calibration of different attention

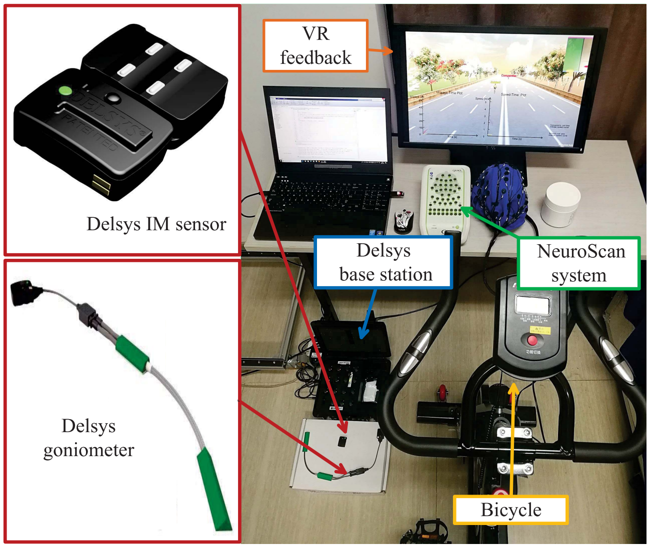

Fig. 1. Device used in the experiment.

regions, experiments, and results are, respectively, given in Section III. Finally, the conclusion and future work are presented in Section IV.

II. System Architecture and Design

This article presents an attention regulation system for post-stroke patients to enhance their attention engaged in the training and improve rehabilitation benefits. Delsys Trigno device [a portable base station, one goniometer, and surface electromyogram (sEMG) sensors], NeuroScan system (one 32-channel EEG cap, and one Grael EEG amplifier, one Curry 8 software), one bicycle, and one computer are used in this experiment, which can be seen in Fig. 1.

The sample rates of the Delsys Trigno device are 148.15 Hz for goniometer and 1111.11 Hz for IM (sEMG) sensor. The goniometer bound on the subjects' knee joint is used to acquire their knee joint angle variations. By using the zero-crossing detection method, the current riding speed of the subject can be calculated correspondingly (see our previous work [27] for the detailed realization of the speed calculation method). Besides, the sEMG sensor is used to calculate the degree of muscle activation during cycling training, which is taken as a parameter to measure subjects' motor engagement.

Subjects' real-time brain activities during cycling training is recorded by the 32-channel NeuroScan system with a 256-Hz sample rate. The recorded EEG signals can be used to measure the subjects' attention level by using the TBR method. Besides, the signal transmission between the NeuroScan system (Delsys Trigno device) and the computer is via a LAN cable (universal serial bus) [27]. The communication protocol between the Delsys Trigno device (NeuroScan system) and the computer is TCP/IP, whose latency acknowledgment time is typically several hundred milliseconds. Considering that the proposed system does not require as much synchronization as a robotic control system, we assume that the data received by the computer is collected at the same time by the two devices. Finally, the calculated attention score and riding speed are used to design the riding speed of the two humanoid avatars in the interactive position-tracking game.

A. Design of the Interactive Position-Tracking Game

In this article, an interactive position-tracking riding game is designed to enhance subjects' attention focused on the training. The game is designed by using Unity3d game engine [30] (Unity 2018.2.6f1, Unity Technologies, United States) and is based on C# programming language (Microsoft Visual Studio 2015).

In the game, there are two avatars, named "Subject" and "Companion," riding bicycles on a straight 500-m-long road. The virtual camera is behind the avatars and is a little higher than them. Besides, it follows the movement of the subject's avatar, by which the game is played in a third-person perspective. In this way, during the training, subjects can clearly see the leg movements of avatar they controlled in the game, which can be served as a visual feedback to the subjects. Besides, subjects can clearly know their position relative to the companion's avatar, thus better perform the position-tracking task. One screenshot of the game is given in Fig. 2.

Real-time mileage and speed curves are shown at the bottom of the screen. The initial speed of the avatar_companion is fixed at 2.5 m/s, and the real-time speeds of the two avatars are determined by subjects' actual riding speed and attention level. The detailed speed adjustment algorithm is given in the next section.

Participants' goal is to drive avatar_subject to keep up with avatar_companion as quickly as possible by adjusting their speed and attention. When the participant's attention is low, no matter how fast he rides, the speed of the avatar_subject will keep zero (visual feedback). Moreover, an auditory prompt, "Your current attention is low, please pay attention to the training," will be emitted to remind the subject to pay attention to the training. To keep up with the companion, the subject has to improve his attention to drive the avatar_subject to ride again. When the subject's attention focused on the training is moderate, the speed of the avatar_subject will be lower than the actual riding speed, and an auditory prompt, "Your current attention is moderate, please focus on the training," will be emitted to remind the subject to pay attention to the training. Due to that the speed of avatar_subject is lower than actual riding speed, the subject has to pay more effort to keep up with the avatar_companion, which will increase the tracking challenge and enhance the subject's attention focused on the training accordingly. If the subject is focused on the training, the speed of the avatar_subject will be equal to the actual riding speed. If it is still hard for subjects to keep up with the companion, the avatar_companion will adaptively adjust his riding speed according to the speed and position error between them to reduce the tracking error and adjust the tracking challenge properly.

From the description given above, we can see, in order to drive the avatar_subject to keep up with the avatar_companion as quickly as possible, subjects must focus on the training. Therefore, subjects' attention focused on the training and neural engagement can be enhanced.

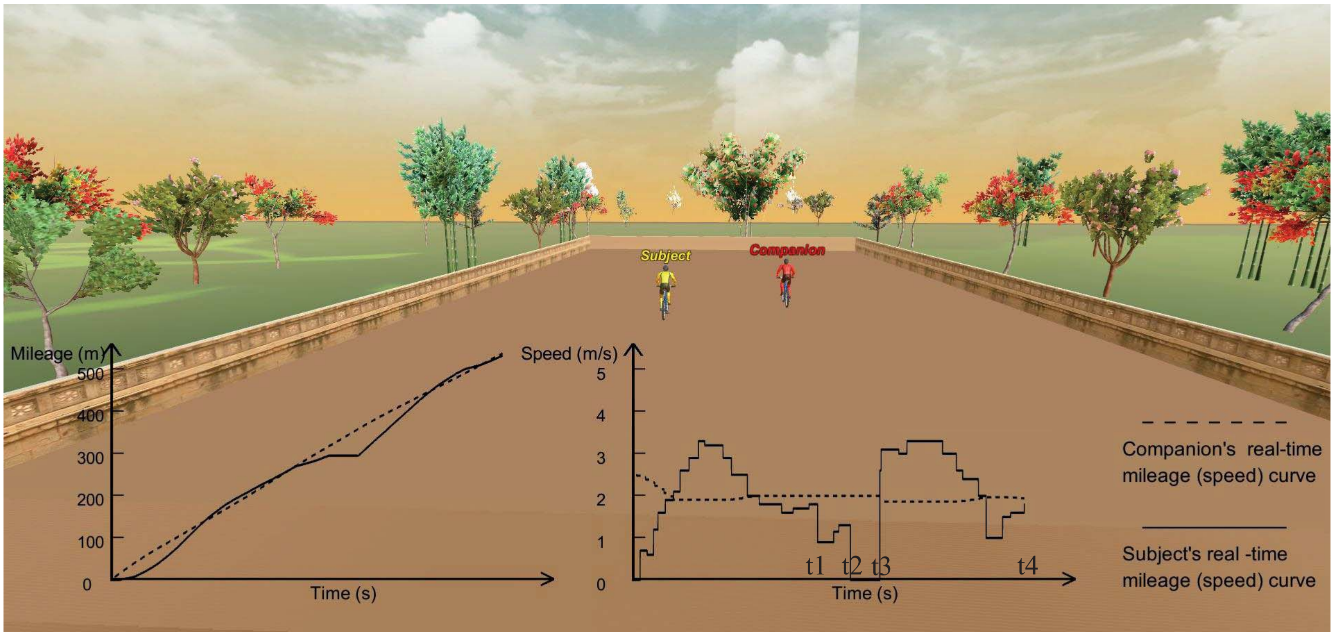

Fig. 2. One screenshot of the designed attention-driven position tracking game. The dashed (solid) lines represent the real-time mileage and speed curves of the companion (subject), respectively. The meaning of the time nodes (*t*1, *t*2, *t*3, *t*4) will be given in Section III.

B. Attention Calculation and Speed Adjustment Algorithms

The subjects' attention focused on the training is a crucial parameter for the adjustment of the riding speeds of the two avatars in the game. The TBR method is chosen to measure subjects' attention in the experiment.

Before the attention calculation, the raw EEG signals need to be filtered with a Butterworth bandpass filter (0.5–50 Hz) and a notch filter (50 Hz) to filter out noise and power line interference. Moreover, baseline drift is avoided through removing the mean method, and a fast Fourier transform is used to extract theta (3–8 Hz) and beta (12–30 Hz) bands. Finally, the following TBR calculation equation is applied to calculate the subjects' attention:

$$\mathrm{TBR} = \sum_{c=1}^{n} \frac{E(\mathrm{Theta})}{E(\mathrm{Beta})} \tag{1}$$

where c represents the channel index ranging from 1 to n; $E(\mathrm{Theta})$ or $E(\mathrm{Beta})$ represents the energy of theta or beta band of each channel, and the calculated attention score is expressed as TBR. The lower the TBR value is, the higher attention the subject is paid to the training.

Before the experiment, each subject needs to undergo three separate trials (Trial A, B, and C) to elicit different EEG signals with different attention states (low, moderate, and high), and the specific design of the trials is given in Section III. The EEG signals obtained from the three trials are used to calculate the average attention scores (LAS, MAS, and HAS) by using the TBR method. Specifically, LAS, MAS, and HAS represent the EEG-based average attention scores in low, moderate, and high attention states, respectively. The specific calculation method is given in

$$\mathrm{LAS} = \frac{1}{N_L} \sum_{i=1}^{N_L} \mathrm{TBR}_i \tag{2}$$

$$\mathrm{MAS} = \frac{1}{N_M} \sum_{i=1}^{N_M} \mathrm{TBR}_i \tag{3}$$

$$\mathrm{HAS} = \frac{1}{N_H} \sum_{i=1}^{N_H} \mathrm{TBR}_i. \tag{4}$$

N_L, N_M, and N_H represent the number of the calculated attention scores (TBR) in the trial A, B, and C, respectively. TBR_i represents the ith attention score calculated by using the EEG signals obtained from trial A, B, or C.

Due to that the subjects' psychological and physiological states are different at different times of day, the three predefined attention values (LAS, MAS, and HAS) need to be calibrated before the experiment. Finally, these three parameters are used to define the ranges of different attention regions.

The low, moderate, and high attention regions (Region 1, Region 2, and Region 3) are defined according to the predefined mean attention values. Let

$$\mathrm{Boundary}_{\mathrm{low}} = \frac{\mathrm{LAS} + \mathrm{MAS}}{2} \tag{5}$$

$$\mathrm{Boundary}_{\mathrm{mid}} = \frac{\mathrm{MAS} + \mathrm{HAS}}{2} \tag{6}$$

then

$$\text{Region 1} \in \left[\mathrm{Boundary}_{\mathrm{low}}, +\infty\right) \tag{7}$$

$$\text{Region 2} \in \left[\mathrm{Boundary}_{\mathrm{mid}}, \mathrm{Boundary}_{\mathrm{low}}\right) \tag{8}$$

$$\text{Region 3} \in \left[0, \mathrm{Boundary}_{\mathrm{mid}}\right). \tag{9}$$

The speed adjustment strategy in the designed VR game is switched according to the number of attention scores contained in each region in the last 5 s. Which attention region contains the most attention score points, which the region's speed adjustment strategy will be triggered. The detailed speed adjustment strategy in each region is given in the following formula:

$$\text{Speed}_{\text{subj}} = \begin{cases} 0, & \text{Region 1} \\ \frac{\text{TBR}}{\text{Boundry}_{\text{low}}} \times S_{\text{actual}}, & \text{Region 2} \\ S_{\text{actual}}, & \text{Region 3} \end{cases} \tag{10}$$

$$\text{Speed}_{\text{comp}} = \begin{cases} \text{keep}, & \text{Region 1} \\ \text{keep}, & \text{Region 2} \\ v_{t+1}, & \text{Region 3.} \end{cases} \tag{11}$$

$\text{Speed}_{\text{subj}}$ and $\text{Speed}_{\text{comp}}$ represent the speeds of the avatar_subject and avatar_companion, respectively. S_{actual} means the participant's actual riding speed, which is calculated by using a goniometer bound on the knee joint. TBR represents the participant's current attention score which is calculated by using the TBR method. The calculation and update strategy of v_{t+1} is as follows:

$$\begin{cases} \Delta v_t = \frac{v_{\text{comp}} - v_{\text{subj}}}{5}, & v \in [0, 5] \Rightarrow \Delta v \in [-1, 1] \\ \Delta x_t = \frac{x_{\text{comp}} - x_{\text{subj}}}{500}, & x \in [0, 500] \Rightarrow \Delta x \in [-1, 1] \end{cases} \tag{12}$$

$$\Delta v_{t+1} = \begin{cases} -\frac{1}{2}\ln\frac{1+\Delta v_t}{1-\Delta v_t}, & \text{if } \begin{cases} |\Delta x_t| \geq 0.1 \\ \text{sign}(\Delta v_t \times \Delta x_t) = 1 \end{cases} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

$$v_{t+1} = v_t(1 + \Delta v_{t+1}) \tag{14}$$

where v_{comp} and x_{comp} (v_{subj} and x_{subj}) represent the speed and mileage of the avatar_companion (avatar_subject), respectively.

It can be seen that when the subject's attention focused on the training is moderate or low (Region 2 or Region 1), we will reduce the cycling speed of avatar_subject from S_{actual} to $(\text{TBR}/\text{Boundary}_{\text{low}}) \times S_{\text{actual}}$ or 0, which can increase the tracking challenge and thus enhance the subject's attention focused on the training. If the subject is highly concentrated (Region 3), the speed of the avatar_subject will be equal to the actual riding speed, and the avatar_companion will adaptively adjust his riding speed according to the speed and position error between them to reduce the tracking error and adjust the tracking challenge properly.

The specific adaptive adjustment algorithm is given by (12)–(14). When the distance error between the two avatars is bigger than 100 m, and the avatar_companion is riding ahead (behind) of the avatar_subject and his riding speed is bigger (smaller) than the avatar_subject, the inverse hyperbolic tangent function will be used to adjust the speed of the avatar_companion. The purpose of this adjustment is to actively reduce the tracking error between this two avatars and adjust the tracking task difficulty properly. Therefore, the subject can keep up with avatar_companion as soon as possible.

During the experiment, we found that when the avatar_subject keeps up with the avatar_companion, he/she can easily get distracted if the speed of the avatar_companion still remains a constant. In order to maintain the subject's attention focused on the training, a speed disturbance module is added to the avatar_companion to increase the uncertainty of the game, thus increasing the tracking challenge. In this way, the overall attention level and neural engagement of the subjects can be further improved.

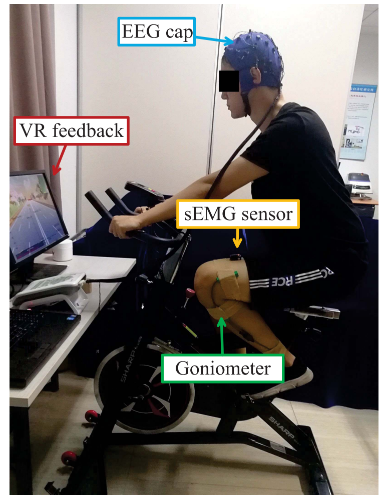

Fig. 3. One subject's experiment preparation scenario.

III. Experiment and Results

In order to validate the feasibility of the proposed system in attention enhancement, ten healthy subjects (8 males and 2 females, aged from 22 to 27) were recruited in the experiment. One subject's experiment preparation scenario is given in Fig. 3. Before the experiment, subjects were required to wear a 32-channel EEG cap and attach a goniometer on the knee joint. Besides, one sEMG sensor was attached to the rectus femoris muscle, which was used to analyze the subjects' muscle activation throughout the experiment. This parameter was used to qualitatively evaluate the motor engagement of the subjects.

Subjects' movement introduced some muscle artifacts to the EEG signals inevitably. In order to ensure the quality of the EEG signals, subjects were asked to keep their upper body motionless as much as possible, and the overall cycling speed during the experiment was relatively low (0–4 m/s), by which the muscle artifacts caused by cycling can be reduced as much as possible.

A. Calibration of Different Attention Regions

In the experiment, the subjects' attention level was divided into three stages: 1) low; 2) moderate; and 3) high. Different control strategies were adopted in different attention regions. Therefore, before the experiment, three parameters named LAS, MAS, and HAS needed to be calibrated first.

Three different experiments are designed to elicit subjects' different attention levels. First, a traditional experiment which lasts around 2 min is used to elicit subjects' low-attention EEG signals. All they had to do was staring at a black screen while they were riding, during which they were asked to think about something that were not related to this task (Trial A). The EEG signals recorded in this process were saved as low-attention data, and these data were used to calculate the LAS parameter.

Based on the proposed interactive position-tracking game, a simple game is designed to elicit subjects' moderate-attention EEG signals. In this game, there is only one humanoid avatar riding on the road and his speed is synchronized with subjects' actual riding speed. Subjects' were asked to focus on the game and control the avatar to ride to the destination. But there were

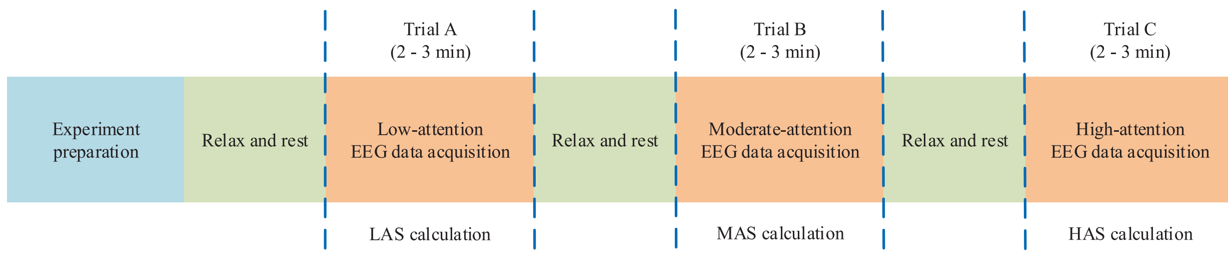

Fig. 4. Experiment paradigm of the calibration of the three parameters (LAS, MAS, and HAS).

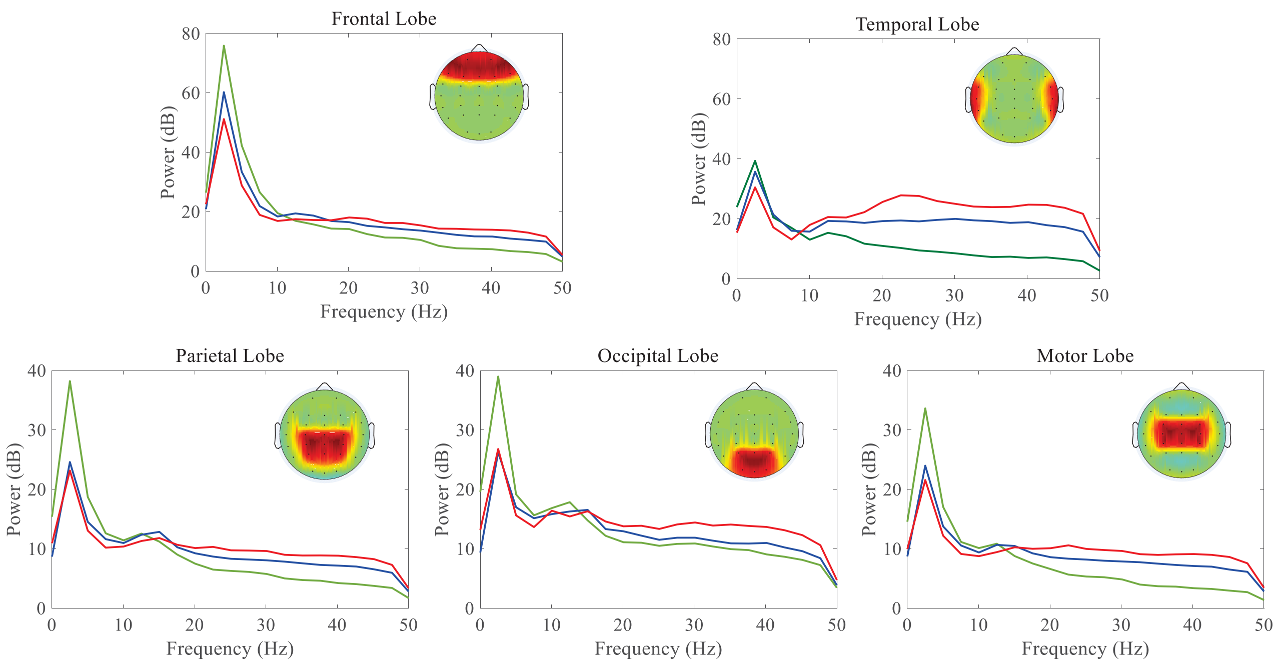

Fig. 5. One of the subjects' five brain regions' power spectra under three different trials. The green, blue, and red lines represent the average power spectrum information of the trial A, trial B, and trial C, respectively.

no limits on their riding speed or time they can cost to arrive to the destination (Trial B). The EEG signals recorded in this trial were labeled with moderate attention, and these data were used to calculate the MAS parameter.

Besides, the proposed position-tracking game is also used to elicit subjects' high-attention EEG signals. The difference is that subjects' attention states do not effect the speed of the two avatars. The speed of the avatar_subject is always synchronized with the actual riding speed. The avatar_companion's speed is determined by the speed adaptive adjustment module and the speed random disturbance module. Subjects were asked to try their best to focus on the training, and their purpose was to keep up with the companion as quickly as possible (Trial C). The EEG signals, recorded in this trial, were used to calculate the HAS parameter.

Experiment paradigm of the calibration of the three parameters (LAS, MAS, and HAS) is given in Fig. 4. The first step was the experiment preparation step. We should make sure that all the data can be recorded correctly and precisely, and the subjects were asked to be relaxed throughout the experiment. Then, the mean attention calculation step and short-time break would be implemented in turns.

In order to see whether the acquired EEG data can represent subjects' different attention states, five brain regions' power spectra under three different trials are given in Fig. 5. In each subgraph, the brain region only includes the channels distributed in the red area of the topographic map, and these channels' power spectra are averaged and plotted as the final power spectrum. The green, blue, and red lines represent the average power spectrum information of the trial A, trial B, and trial C, respectively.

In each subgraph, we can see that the theta band's power of the red line is the lowest, and the beta band's power is the highest, and vice versa in the green line. Previous study has also convinced that good performance and high attention level often relate to the phenomenon of a decrease in theta band oscillation and an increase in beta band. Therefore, the results obtained from Fig. 5 are consistent with the phenomena described above, which validates the feasibility of the proposed paradigm in eliciting EEG signals with different attention states.

Moreover, the difference of the power spectra in each subgraph is most prominent in the frontal and temporal lobes. Therefore, only the channels distributed in the frontal and temporal lobes are used to calculate the subjects' attention scores (frontal region: Fp1, Fp2, F7, F3, FZ, F4, F8; temporal region: FT7, FT8, T7, T8, TP7, TP8).

Based on the results obtained from [31]–[33], it has demonstrated that the subjects' attention levels are significantly correlated with the frontal and temporal lobe's activities. With the increase of subjects' attention, decreased theta is more prominent in frontal regions, and increased beta is more prominent in temporal regions, which is consisted with our results. Therefore, in this article, only theta rhythm (3–8 Hz) in the frontal lobe and beta rhythm (12–30 Hz) in the temporal lobe were used to measure the subjects' attention level. Relevant to EEG recordings, it has been reported that the frequencies of the frontal and temporal muscle artifacts are around 20–30 Hz and 40–80 Hz, respectively [34]. Because only theta rhythm (3–8 Hz) in the frontal lobe and beta rhythm (12–30 Hz) in the temporal lobe were used to measure subjects' attention level, and in order to ensure the real-time performance of online attention calculation, we did not apply any artifact reduction methods.

Once these three parameters were obtained, the three different attention regions (Region 1, Region 2, and Region 3) could be calculated out accordingly by using (5)–(9).

B. Experiment Design

After the calibration of the subjects' different attention regions, the ten volunteers were randomly assigned to one of the groups (one control group, and one experiment group) with equal size 5 to validate the feasibility of the proposed system in attention enhancement. The subjects' task was to control the avatar_subject to keep up with the avatar_companion as quickly as possible by adjusting their own riding speed and attention.

In the control group, regardless the subjects' attention state and tracking accuracy, the speed of the avatar_subject was always equal to the actual riding speed and the speed of the avatar_companon kept a constant. On the contrary, in the experiment group, the speeds of the two avatars were determined by subjects' actual riding speed and attention states. Once the subject's attention was unacceptable (moderate or low), audiovisual feedback would be given to remind him to pay attention to the training.

The subject's current attention score was updated every 3 s, and it was calculated by using the EEG signals acquired in the latest 3 s. The lower the TBR value was, the higher attention the subject was paid to the training. One of the subjects' attention scores variation in the experiment group is shown in Fig. 6.

If the attention score is distributed in the red, blue, or yellow region (Region 1, Region 2, or Region 3), the subject's attention will be deemed as low, moderate, or high, respectively. From the figure, we can see that the attention scores of the subject were mainly distributed in Region 3 throughout the experiment, which indicated that his overall attention level was relatively high in this experiment.

Besides, one of the subjects' tracking results in the experiment group is given in Fig. 2. Throughout the experiment, in the time intervals of (0, t1) and (t3, t4), the subject's attention focused on the training was high (Region 3), during which the speed of the avatar_subject was equal to the actual riding speed, and the avatar_companion adaptively adjusted his riding speed to reduce the tracking error. In the time interval of (t1, t2), the subject's attention was moderate (Region 2). Therefore, the speed of the avatar_subject was lower than the actual riding speed, and the speed of the avatar_companion stayed the same. In the time interval of (t2, t3), the subject's attention was low (Region 1) and the speed of the avatar_subject kept 0. Subjects had to improve their attention to drive the avatar_subject to ride again and keep up with the avatar_companion as soon as possible.

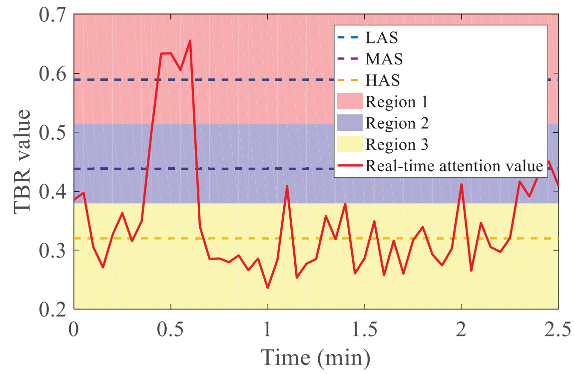

Fig. 6. One of the subjects' attention variation throughout the experiment in the experiment group.

C. Results

The ranges of the three attention regions were different among subjects. In order to expediently depict the subjects' attention states during the experiment, only the number of attention scores contained in different attention regions (low, moderate, and high attention regions) are given. In order to ensure the consistency of the length of EEG signals in each experiment, only the first 150 s of data were used to calculate attention scores. Since the attention score was calculated every 3 s, each person had a total of 50 attention scores. According to the ranges of each subject's attention regions calibrated before the experiment, the number of attention scores contained in different regions could be counted accordingly, which are given in Fig. 7.

From the figure, we can see that in the control group, subjects' attention scores were mainly distributed in the moderate attention region. However, in the experiment group, the attention scores were mainly distributed in the high attention region, which validated the feasibility of the proposed method in attention enhancement. In the experiment group, when the subjects' attention focused on the training was moderate or low, multimodal feedback would be given to remind the subjects to pay attention to the training. Moreover, in order to keep up with the avatar_companion, subjects had to adjust their attention in real time to drive the avatar_subject to keep up with the companion as quickly as possible. Therefore, the attention scores in the experiment group was higher than that of the control group.

Besides, the tracking task performance of each subject in each group, indicated by their tracking accuracy are summarized and given in Fig. 8.

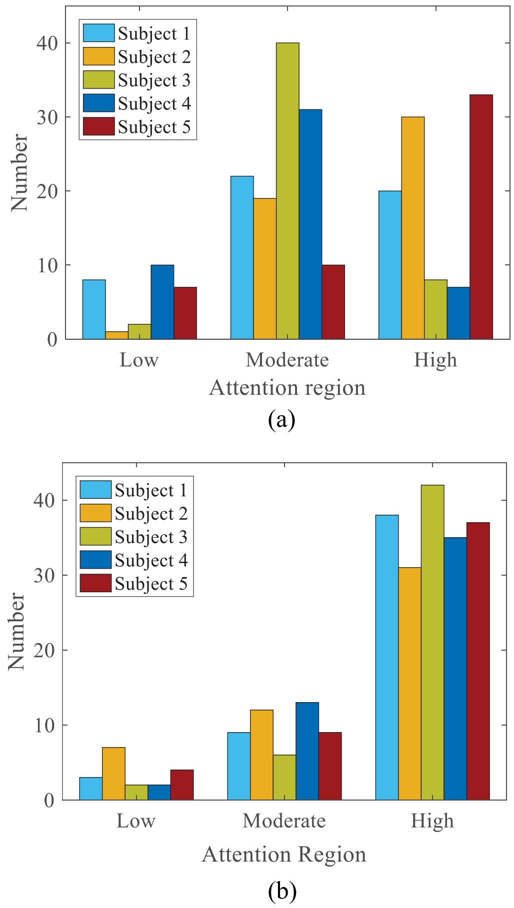

Fig. 7. Number of different subjects' attention scores contained in different attention regions. (a) Control group. (b) Experiment group.

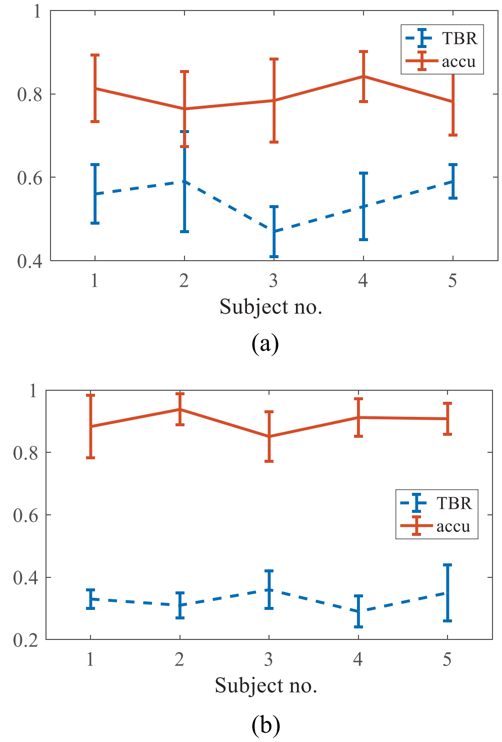

Fig. 8. Mean (± standard error of the mean) tracking accuracy of each subject in (a) control group and (b) experiment group.

The dashed lines represent the mean (± standard error of the mean) TBR of each subject in each group, and the solid lines represent the mean (± standard error of the mean) tracking accuracy of each subject in each group, which is calculated by using

$$\text{accu} = 1 - \left|\frac{x_{\text{subj}} - x_{\text{comp}}}{x_{\text{comp}}}\right|. \quad (15)$$

It can be seen that the position-tracking accuracy in the experiment group is higher than that of the control group with significant difference ($p = 0.001$), and the mean TBR in the experiment group is decreased significantly ($p = 0.00003$). This phenomenon illustrates that all subjects' attention states can be improved by using the proposed attention-driven system.

Fig. 9 shows the average muscle activation of each subject in control and experiment groups, respectively.

The average muscle activation is calculated by using the following equation:

$$\text{Activation}_{\text{muscle}} = \frac{\sum_{t=t_s}^{t_f} |\text{AMP}_{\text{semg}}(t)|}{t_f - t_s} \quad (16)$$

t_s and t_f represent the starting and finishing time of the training, respectively. The $\text{AMP}_{\text{semg}}(t)$ means the amplitude of the sEMG signal at time t.

From the figure, we can see that the muscle activation in the experiment group was significantly higher than that of the control group ($p = 0.0002$), which indicated that the subjects had to pay more effort to ensure the tracking accuracy. In the control group, the speed of the avatar_subject was equal to the subjects' actual riding speed. However, in the experiment group, the speed of the avatar_subject was determined by subjects' actual riding speed and attention state. If the attention focused on the training was unacceptable (low or moderate), the riding speed of the avatar_subject would be lower than their actual cycling speeds. The subjects needed to ride harder or enhance their attention to increase the tracking accuracy. Therefore, the muscle activation in the experiment group was significantly higher than that of the control group.

D. Discussion

In this article, three trials were designed to induce subjects' EEG signals with three different attention states. Before the rehabilitation training, three attention regions (Region 1, Region 2, and Region 3) needed to be calibrated first by using these three trials. Once the calibration step finished, the range of the three attention regions would be fixed in the following rehabilitation training. However, some subjects' attention scores only fluctuated in a small range in the experiment, which leaded that the speed adjustment strategy can only be triggered partly. It would be better that if the ranges of different attention regions can be adjusted in real time according to the actual performance of the subjects in the experiment.

Besides, in the calibration step, the sequence of three trials is fixed rather than random. If we shuffle the sequence of trials A, B, and C, the order of trials C, B, and A will be

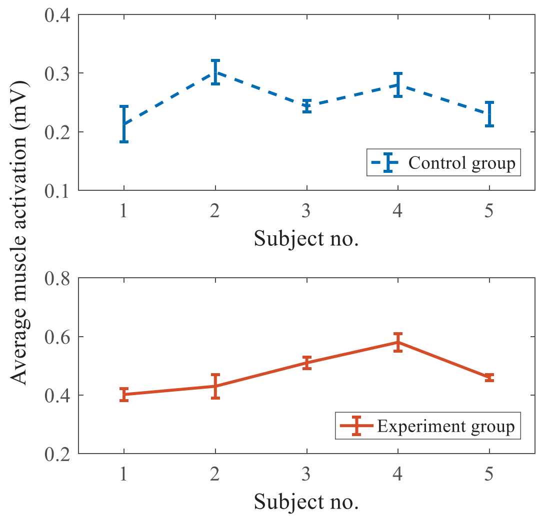

Fig. 9. Average muscle activation of each subject in control group and experiment group, respectively.

included inevitably. Empirically speaking, subjects can easily adjust their attention from low to high. However, if the subjects' current attention is high, it is difficult to adjust to a low attention level quickly. Moreover, the same sequence of trials A, B, and C can ensure the consistency of the experimental paradigm among different subjects. Therefore, the sequence of trials A, B, and C in the calibration stage is fixed. However, a fixed experiment sequence would reduce the randomness of the experiment and increase participants' familiarity to the system. The degree of familiarity would affect the calculated TBR values. For example, the more familiar the subject is to the system, the lower the TBR value it would be. Contrast experiment will be conducted in the future to evaluate the ordering effect on the experiment results.

In the experiment, only the EEG signals acquired from the frontal and temporal regions were used to calculate subjects' attention scores. Although subjects' three mean attention scores can be different over time due to the different psychological and physiological states of the subjects, in the experiment, it was found that one subject's attention scores varied significantly from time to time. More experiments need to be carried out to find out what causes this phenomenon. For example, the data acquired are not accurate, or the TBR attention calculation method is not universal and so on.

IV. Conclusion

In this article, an attention enhancement system based on the BCI and audiovisual feedback was proposed to enhance the subjects' neural engagement. The subjects' task was to control the avatar_subject in the proposed position-tracking game to keep up with the avatar_companion by using a goniometer bound on the knee joint and an EEG device. If the subject's attention focused on the training is unacceptable (moderate or low), audiovisual feedback will be given to remind the subject to pay attention to the training. Unlike our previous work [27] or other studies [24], where the subject's attention does not effect the performance of the task, the speed of the avatar_subject, in this experiment, is partly driven by the subject's attention, which would directly affect the tracking accuracy. In this way, subjects will feel more motivated and rewarded. If the subject is deemed with inattention, the speed of the avatar controlled will be lower than the actual riding speed or equal to 0. In order to ensure the performance of the task, they have to improve their attention timely to increase the tracking accuracy, thus realizing the purpose of attention enhancement.

Results obtained from Figs. 7–9 preliminarily validate the feasibility of the proposed system in attention enhancement, thereby increasing the participants' neural involvement. Since the active engagement of the human nervous system is of great importance to the neurorehabilitation in the rehabilitation training, the proposed system can easily be adapted to post-stroke rehabilitation [35]–[37]. In the future, more abundant and interesting games will be designed for patient experiments, which can further verify the feasibility of the proposed system in post-stroke attention enhancement and neural rehabilitation. Moreover, according to the patients' motor ability and the degree of muscle fatigue, the bicycle damping should be adjusted properly to reach a balance between training challenge and muscular capacity, thus prevent muscle damage from overtraining and ensure the safety of training.

References

[1] P. Langhorne, J. Bernhardt, and G. Kwakkel, "Stroke rehabilitation," *Lancet*, vol. 377, no. 9778, pp. 1693–1702, 2011.

[2] S. K. Ostwald, S. Davis, G. Hersch, C. Kelley, and K. M. Godwin, "Evidence-based educational guidelines for stroke survivors after discharge home," *J. Neurosci. Nursing*, vol. 40, no. 3, pp. 173–179, 2008.

[3] A. Heller, D. T. Wade, V. A. Wood, A. Sunderland, R. L. Hewer, and E. Ward, "Arm function after stroke: Measurement and recovery over the first three months," *J. Neurol. Neurosurg. Psychiatry*, vol. 50, no. 6, pp. 714–719, 1987.

[4] J. Wang, W. Wang, Z.-G. Hou, X. Liang, S. Ren, and L. Peng, "Towards enhancement of patients' engagement: Online modification of rehabilitation training modes using facial expression and muscle fatigue," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, 2018, pp. 2304–2307.

[5] F. A. Bright, N. M. Kayes, C. Cummins, L. M. Worrall, and K. M. McPherson, "Co-constructing engagement in stroke rehabilitation: A qualitative study exploring how practitioner engagement can influence patient engagement," *Clin. Rehabil.*, vol. 31, no. 10, pp. 1396–1405, 2017.

[6] E. A. Kringle, L. Terhorst, M. A. Butters, and E. R. Skidmore, "Clinical predictors of engagement in inpatient rehabilitation among stroke survivors with cognitive deficits: An exploratory study," *J. Int. Neuropsychol. Soc.*, vol. 24, no. 6, pp. 572–583, 2018.

[7] J. Wang, W. Wang, Z.-G. Hou, X. Liang, S. Ren, and L. Peng, "Brain functional connectivity analysis and crucial channel selection using channel-wise CNN," in *Proc. Int. Conf. Neural Inf. Process.*, 2018, pp. 40–49.

[8] T. Ebrahimi, J.-M. Vesin, and G. Garcia, "Brain–computer interface in multimedia communication," *IEEE Signal Process. Mag.*, vol. 20, no. 1, pp. 14–24, Jan. 2003.

[9] Y. R. Tabar and U. Halici, "A novel deep learning approach for classification of EEG motor imagery signals," *J. Neural Eng.*, vol. 14, no. 1, 2017, Art. no. 016003.

[10] L. Yao *et al.*, "A stimulus-independent hybrid BCI based on motor imagery and somatosensory attentional orientation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 9, pp. 1674–1682, Sep. 2017.

[11] S. K. Loo and R. A. Barkley, "Clinical utility of EEG in attention deficit hyperactivity disorder," *Appl. Neuropsychol.*, vol. 12, no. 2, pp. 64–76, 2005.

[12] E. Başar and B. Güntekin, "Review of delta, theta, alpha, beta, and gamma response oscillations in neuropsychiatric disorders," in *Supplements to Clinical Neurophysiology*, vol. 62. Amsterdam, The Netherlands: Elsevier, 2013, pp. 303–341.

[13] W. Klimesch, "EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis," *Brain Res. Rev.*, vol. 29, nos. 2–3, pp. 169–195, 1999.
[14] M. Arns, C. K. Conners, and H. C. Kraemer, "A decade of EEG theta/beta ratio research in ADHD: A meta-analysis," *J. Attention Disorder*, vol. 17, no. 5, pp. 374–383, 2013.
[15] J. D. Kropotov, "Theta beta ratio as inattention index," in *Quantitative EEG, Event-Related Potentials and Neurotherapy*, 1st ed. San Diego, CA, USA: Academic, 2009, pp. 399–400.
[16] A. R. Bakhshayesh, S. Hänsch, A. Wyschkon, M. J. Rezai, and G. Esser, "Neurofeedback in ADHD: A single-blind randomized controlled trial," *Eur. Child Adolescent Psychiatry*, vol. 20, no. 9, pp. 481–491, 2011.
[17] G. Ogrim and K. A. Hestad, "Effects of neurofeedback versus stimulant medication in attention-deficit/hyperactivity disorder: A randomized pilot study," *J. Child Adolescent Psychopharmacol.*, vol. 23, no. 7, pp. 448–457, 2013.
[18] Y.-K. Wang, T.-P. Jung, and C.-T. Lin, "EEG-based attention tracking during distracted driving," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 6, pp. 1085–1094, Nov. 2015.
[19] B. Hu, X. Li, S. Sun, and M. Ratcliffe, "Attention recognition in EEG-based affective learning research using CFS+KNN algorithm," *IEEE/ACM Trans. Comput. Biol. Bioinformat.*, vol. 15, no. 1, pp. 38–45, Jan./Feb. 2018.
[20] M. M. Hasib, T. Nayak, and Y. Huang, "A hierarchical LSTM model with attention for modeling EEG non-stationarity for human decision prediction," in *Proc. IEEE EMBS Int. Conf. Biomed. Health Informat. (BHI)*, 2018, pp. 104–107.
[21] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces," *J. Neural Eng.*, vol. 15, no. 5, 2018, Art. no. 056013.
[22] L. Ma, J. W. Minett, T. Blu, and W. S. Wang, "Resting state EEG-based biometrics for individual identification using convolutional neural networks," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*. 2015, pp. 2848–2851.
[23] W. Biesmans, N. Das, T. Francart, and A. Bertrand, "Auditory-inspired speech envelope extraction methods for improved EEG-based auditory attention detection in a cocktail party scenario," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 5, pp. 402–412, May 2017.
[24] B.-S. Lin, J.-L. Chen, and H.-C. Hsu, "Novel upper-limb rehabilitation system based on attention technology for post-stroke patients: A preliminary study," *IEEE Access*, vol. 6, pp. 2720–2731, 2018.
[25] D. Ming, M. Zhang, Y. Xi, H. Qi, Y. Hu, and K. D. K. Luk, "Multiscale entropy analysis of attention related EEG based on motor imaginary potential," in *Proc. IEEE Int. Conf. Comput. Intell. Meas. Syst. Appl.*, 2009, pp. 24–27.
[26] K. P. Thomas and A. P. Vinod, "A study on the impact of neurofeedback in EEG based attention-driven game," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, 2016, pp. 320–325.
[27] J. Wang *et al.*, "BCI and multimodal feedback based attention regulation for lower limb rehabilitation," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, 2019, pp. 1–7.
[28] N. Schenkman, (Charlottesville, Chahin, Jonathan, Krupski, and Tracey), "Measuring surgical attention on robotic virtual reality (VR) simulator using a novel electroencephalographic (EEG) device," *J. Urol.*, vol. 189, no. 4, pp. 639–640, 2013.
[29] A. E. Alchalcabi, A. N. Eddin, and S. Shirmohammadi, "More attention, less deficit: Wearable EEG-based serious game for focus improvement," in *Proc. IEEE 5th Int. Conf. Serious Games Appl. Health (SeGAH)*, 2017, pp. 1–8.
[30] Unity3d game engine. [Online]. Available: http://unity3d.com/
[31] C. A. Mann, J. F. Lubar, A. W. Zimmerman, C. A. Miller, and R. A. Muenchen, "Quantitative analysis of EEG in boys with attention-deficit-hyperactivity disorder: Controlled study with clinical implications," *Pediatric Neurol.*, vol. 8, no. 1, pp. 30–36, 1992.
[32] J. F. Lubar, "Discourse on the development of EEG diagnostics and biofeedback for attention-deficit/hyperactivity disorders," *Biofeedback Self Regulation*, vol. 16, no. 3, pp. 201–225, 1991.
[33] K. Dujardin, J. L. Bourriez, and J. D. Guieu, "Event-related desynchronization (ERD) patterns during memory processes: Effects of aging and task difficulty," *Electroencephalography Clin. Neurophysiol. Evoked Potentials Sec.*, vol. 96, no. 2, pp. 169–182, 1995.
[34] I. I. Goncharova, D. J. Mcfarland, T. M. Vaughan, and J. R. Wolpaw, "EMG contamination of EEG: Spectral and topographical characteristics," *Clin. Neurophysiol.*, vol. 114, no. 9, pp. 1580–1593, 2003.
[35] Z. Warraich and J. A. Kleim, "Neural plasticity: The biological substrate for neurorehabilitation," *PM R*, vol. 2, no. 12, pp. 208–219, 2010.
[36] N. Hogan *et al.*, "Motions or muscles? Some behavioral factors underlying robotic assistance of motor recovery," *J. Rehabil. Res. Develop.*, vol. 43, no. 5, pp. 605–618, 2006.
[37] A. Gaggioli *et al.*, "Training with computer-supported motor imagery in post-stroke rehabilitation," *Cyberpsychol. Behav.*, vol. 7, no. 3, pp. 327–332, 2004.

Jiaxing Wang received the B.E. degree in automation from Central South University, Changsha, China, in 2016. She is currently pursuing the Ph.D. degree in control science and engineering with the State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing.

Her current research interests include braincomputer interface, rehabilitation robot control, and signal processing.

Weiqun Wang received the B.S. degree in mechanical engineering from Yanshan University, Qinhuangdao, China, in 2002, the M.S. degree in control theory and control engineering from the Beijing Research Institute of Automation for Machinery Industry (BRIAMI), Beijing, China, in 2006, and the Ph.D. degree in control theory and control engineering from the Institute of Automation, Chinese Academy of Sciences (IACAS), Beijing, in 2014.

From 2006 to 2011, he was an Electrical Engineer with BRIAMI. He is currently an Associate Professor with the State Key Laboratory of Management and Control for Complex Systems, IACAS. His current research interests include rehabilitation robotics, dynamic identification, interaction control, and optimization algorithms.

Zeng-Guang Hou (F'18) received the B.E. and M.E. degrees in electrical engineering from Yanshan University, Qinhuangdao, China, in 1991 and 1993, respectively, and the Ph.D. degree in electrical engineering from the Beijing Institute of Technology, Beijing, China, in 1997.

From 1997 to 1999, he was a Post-Doctoral Research Fellow with the Key Laboratory of Systems and Control, Institute of Systems Science, Chinese Academy of Sciences (CAS), Beijing. He was a Research Assistant with the Hong Kong Polytechnic University, Hong Kong, from 2000 to 2001. From 2003 to 2004, he was a Visiting Professor with the Intelligent Systems Research Laboratory, College of Engineering, University of Saskatchewan, Saskatoon, SK, Canada. He is currently a Professor and the Deputy Director of the State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, CAS. His current research interests include computational intelligence, robotics, and intelligent systems.

Prof. Hou was a recipient of the National Outstanding Youth Fund in 2012, the IEEE Transactions on Neural Networks Outstanding Paper Award in 2013, the National Natural Science Award of China (Second-Prize), and the Outstanding Achievement Award of Asia Pacific Neural Network Society in 2017. He was an Associate Editor of the *IEEE Computational Intelligence Magazine* and the IEEE TRANSACTIONS ON NEURAL NETWORKS, and the Chair of the Neural Network Technical Committee of Computational Intelligence Society (CIS) and the Adaptive Dynamic Programing and Reinforcement Learning Technical Committee of CIS. He is an Associate Editor of the IEEE TRANSACTIONS ON CYBERNETICS and an Editorial Board member of *Neural Networks*. He is on the Board of Governors of the International Neural Network Society.