A VR-Based Motor Imagery Training System With EMG-Based Real-Time Feedback for Post-Stroke Rehabilitation

Meiai Lin, Jianli Huang, Jianming Fu, Ya Sun, and Qiang Fang

***Abstract*— Rehabilitation is essential for post-stroke body function recovery. Supported by the mirror neuron theory, motor imagery (MI) has been proposed as a potential stroke therapy capable of facilitating the rehabilitation. However, it is often quite difficult to estimate the degree of the participation of patients during traditional MI training as well as difficult to evaluate the efficacy of MI based rehabilitation methods. The goal of this paper is to develop a virtual reality (VR) based MI training system combining electromyography (EMG) based real-time feedback for poststroke rehabilitation, with the immersive scenario of the VR system providing a shooting basketball training for bilateral upper limbs. Through acquiring electroencephalography (EEG) signal, the brain activity in alpha and beta frequency bands was mapped and the correlation analysis could be achieved. Furthermore, EMG data of each patient was collected and calculated as threshold with root-mean-square algorithm for feedback of the performance score of the shooting basketball training in virtual environment. To investigate the feasibility of this newly-built rehabilitation training system, four experiments namely initial assessment experiment, motor imagery (MI), action observation (AO), and combined motor imagery and action observation (MI+AO) were carried out on stroke patients at different recovery stages. The result shows that MI+AO can generate more pronounced event-related desynchronization (ERD) in alpha band compared to other cases and induce relatively obvious ERD in beta band compared to AO, which demonstrates that VR-based observation has ability to facilitate MI training. Furthermore, it has been found that the muscle strength from MI+AO is the highest through the EMG analysis. This proves that the feedback of EMG can be used to quantify patient's training engagement and promote MI training at a certain extent. Hence, by incorporating such an EMG feedback, a VR-based MI training system has the potential to achieve higher efficacy for post-stroke rehabilitation.**

***Index Terms*— Motor imagery, virtual reality, rehabilitation, EEG, EMG, real-time feedback.**

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of the Second Hospital of Jiaxing, and performed in line with the Declaration of Helsinki.

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I. Introduction

STROKE has become one of the leading cause of adult long-term disability in the world [1]. The most common symptom of stroke is hemiplegia or hemiparesis. Hemiplegic patients suffer from severe limb impairment and decreased quality of daily living because of impaired mobility on one side of the body [2]. It has been reported that a time-limited window of neuroplasticity can provide the great benefits in recovery following a stroke [3]. Therefore, the challenge in improving stroke recovery is to understand how to optimally engage and modify the network of surviving neuronal to provide new response strategies to compensate for tissue damage.

Conventional rehabilitation methods, including physical therapy and occupational therapy, are the relearning of functions in different ways, such as increasing the number of repetitions, providing an uninterrupted environment, and grading task difficulty and authorization [4]. However, conventional therapies commonly with repetitive and simple movements are boredom and monotony, which may reduce participants' motivation to engage in rehabilitation therapy [5]. Moreover, patients with impaired limbs, especially in flaccid paralysis period after stroke, are unable to move to perform training accordingly.

Motor imagery (MI), which is a cognitive operation, can increase the activity of neural networks to some extent in the cerebral cortex through neuroplasticity [6], [7]. The basic mechanism behind MI is thought to be involved in the activation of the mirror neuron system, an extended motor network in the cerebral cortex that is activated during the execution of MI [8]. As has been pointed out, practicing a skill mentally enables increasing the amount of treatments during recovery in a safe and low-cost way [9], [10]. Since MI training might contribute to the motor recovery and motor cortical excitability [11], [12] through the network reorganization, such as promoting the efficiency of regional neuronal communication [13], MI has been suggested as a promising therapy method that can be applied for post-stroke patients [14], [15], [16]. For example, Crosbie *et al.* [14] concluded that MI can be useful as an adjunct in the rehabilitation of the upper limb after stroke. And Hwang *et al.* [15] investigated that MI training can be considered as an available option for individuals with hemiparetic stroke in physical gait training. It has been reported that MI can induce event-related desynchronization

(ERD) [17], which refers to a reduction in oscillating brain activity in alpha (8-12 Hz) and beta (12-30 Hz) frequency bands [18], [19]. Although MI has been suggested to be an useful method for rehabilitation, the traditional MI training usually instructed by therapists requires patients to perform repetitive and simple movements, which may reduce patients' motivation to achieve successful rehabilitation goals [5].

As an emerging visualization technology, virtual reality (VR) has exerted the positive impact on fundamentals of neuroscience [20]. The VR headset, as a kind of medium, can provide an immersive virtual environment for users who can perceive the illusion and spatial embodiment. Besides vision, VR technology also can provide touch and hearing functions to strengthen the sense of reality and immersion in the virtual world [21]. Furthermore, virtual embodiment has a great potential in the fields of physical and neural rehabilitation. Through the first person perspective, the real body can perceive the understanding that the virtual body perceives in the virtual environment [22]. A real-time visual feedback that is consistent with the participant' s MI, not only can assist in making BCI a more natural interface for MI based BCI rehabilitation [23], [24], but also can be applied in the research related to electromyogram (EMG) to measure changes in muscle activity correlated with movements of the virtual arm followed MI [22]. For instance, Athanasios *et al.* [25] examined the efficacy of an EEG-based BCI-VR system using a MI paradigm and applied this method for chronic stroke patients.

Action observation (AO), which refers to observing another individual performing a motor task, can enhance the effects of motor training after stroke in association with physical training [26]. Researches about the mirror neuron system have shown that AO and MI share the same basic motor circuit as action execution, thus providing an additional source of motor training that maybe useful to promote recovery from stroke [27], [28]. Besides, AO by visual guidance can enhance brain activity when used along with MI, because both are related to the activation of targeted brain regions [29], [30]. For instance, Kynan and colleagues [31] presented a 2D VR-based motor neurorehabilitation system combing AO with goal-directed MI for stroke patients, which could facilitate motor re-learning and improve functional recovery. And Choi *et al.* [32] suggested that AO with the use of immersive VR headsets can more effectively improve MI training with better discriminating spatial features from the brain compared to with the monitor display.

Another important issue in MI-based rehabilitation concerns the participant's engagement degree in the rehabilitation training. It is as yet still not easy to determine whether participants concentrate on MI training as instructed due to the lack of effective assessment methods to quantify the engagement degree [6]. As physiological signal, EMG has been applied in biomedical field for monitoring or feedback [33], [34]. The neurofeedback rehabilitation system combining VR and EMG has been verified to increase volitional muscle activity and cause changes in corticospinal communication [35]. And it also can provide real-time feedback in robotic prosthesis to improve training [36]. Recent researches suggested that MI can induce measurable change in muscle activity levels, indirectly confirmed through the increased corticospinal cord and motor neuron pool excitability [37], [38]. Based on the discussion above, EMG signal detected during VR-based MI training may act as real-time feedback for quantitative method to assess participants' engagement.

TABLE I

DEMOGRAPHIC DATA OF THE PARTICIPATED STROKE PATIENTS

Characteristics	Stroke (N=8)
Gender (male: female)	7:1
Age (SD)	64.75 (10.34)
Infarct side (left: right)	3:5
Time after stroke in month (SD)	11.12 (23.85)
Brunnstrom stage (I: II: III)	2:4:2

In this study, we have developed a VR-based MI training system with EMG-based real-time feedback for post-stroke rehabilitation. A VR headset can offer immersive virtual training scenarios for participants to perform MI and observation training. The system enables real-timely measuring EEG in alpha and beta frequency bands to evaluate brain activation map and EMG signal based on each individual participant's performance as feedback to control each training result. To test our developed system and demonstrate its potential applications in observation-based MI training for clinical post-stroke rehabilitation, experimental scheme of four experiments, including assessment, MI training, AO training and MI+AO training, has been specially designed and carried out for 8 post-stroke patients via clinical recruitment. The EEG and EMG data were acquired and analyzed for each experiment. All comparative results demonstrate that VR-based MI training system with EMG real-time feedback has ability to actively engage post-stroke patients in personalized rehabilitation training and facilitate the effectiveness of MI training.

II. PROCEDURES

A. Participants

A total of 8 post-stroke patients with the age ranging from 40 to 75 participated in the research. None of the participants had any neurological diseases or other issues that would affect their performance of MI training. Before engaging in the experiment, each participant was informed and signed informed consent prior to participation. The study was approved by the Ethics Committee of the 2nd Hospital of Jiaxing and carried out according to the declaration of Helsinki. Table I shows the basic information of post-stroke participants.

The inclusion criteria were as follows: (i) unilateral brain lesion due to first-ever ischemic or hemorrhagic stroke; (ii) being aged between 18 and 75 years; (iii) assessment of Brunnstrom stages between I and III; (iv) having normal or corrected-to-normal vision and normal hearing; (v) being able to adapt to three-dimensional virtual environment and no dizziness; (vi) following instructions correctly.

B. Experimental Setup

The helmet-mounted display (HMD) of HTC VIVE PRO EYE (High Tech Computer Corporation, Taoyuan, Taiwan)

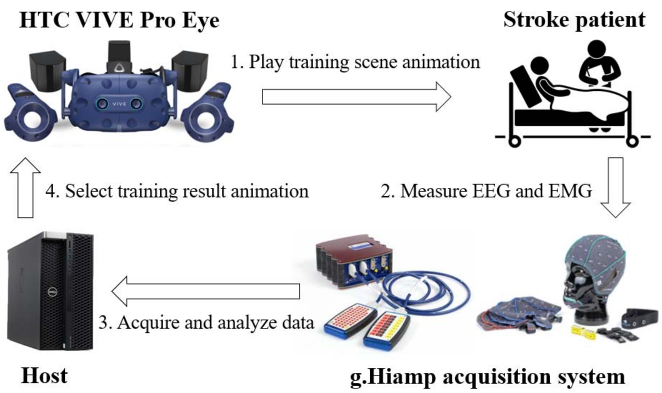

Fig. 1. The schematic diagram of the whole experimental device.

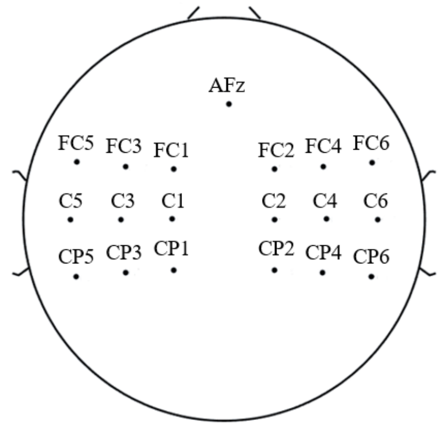

Fig. 2. The distribution positions of the EEG electrodes.

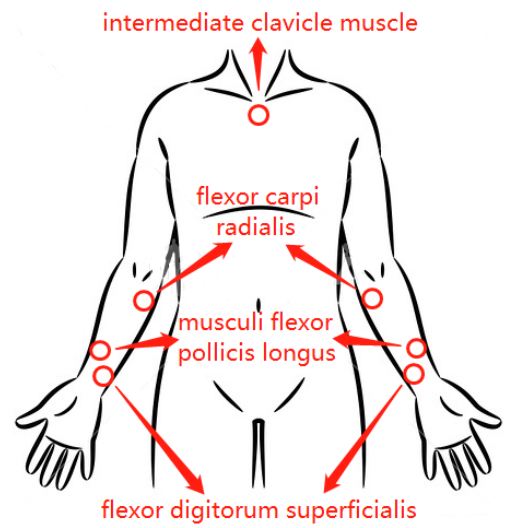

Fig. 3. The distribution positions of the EMG electrodes.

with supporting 1440 × 1600 resolution per eye and 110° Field of View was used to display VR scenario. This VR device can provide immersive virtual environment and vivid embodiment for participant. In the work, in order to mobilize the upper limbs, a shooting basketball training scene, which contains decompositions of joint movements involving fingers, wrists, and elbows, was created by using the Unity3D Game Engine (Unity Technologies, San Francisco, CA, USA). The training procedure includes the following steps: reaching forward for the basketball, bending the arms, raising the arms, and throwing the basketball. When the participants wear the HMD, they can see the virtual hands and arms from the first-person perspective, with instruction by voice command during the whole training.

As a physiological signal acquisition device, the g.HIamp (g.tec medical engineering GmbH, Schiedlberg, Austria) with 80 channels was used to collect EEG and surface EMG signal data. The acquisition system consists of signal amplifier, active electrode box, passive electrode box and EEG cap. The signal amplifier can detect and filter the signal. The active electrode box works with the cap to collect EEG signal and the passive electrode box is able to capture EMG signal. To accommodate different participant's head circumference, the system offers three sizes of EEG caps. Additionally, the software of g.Recorder is utilized to record data and map signals in real time. All experimental setups and their connection is displayed in Fig. 1.

C. Data Acquisition

Since it has been well proved that the MI training can contribute to activate the sensorimotor cortex [39], [40] and sensorimotor activation occurs mostly in the C3 and C4 channels [41], here we selected a total of 18 channels (FC5, FC3, FC1, FC2, FC4, FC6, C5, C3, C1, C2, C4, C6, CP5, CP3, CP1, CP2, CP4, CP6) centered on C3 and C4 respectively locating in the sensorimotor cortex, with ground and reference electrodes placed at positions AFz and left earlobe respectively (as shown in Fig. 2). The active electrodes were placed according to the international 10-20 system to collect EEG signal [42]. Alpha and beta are the main acquisition frequency bands in the study because the rhythms are functionally related to major sensorimotor system [18].

Seven channels of the passive electrode box were used to collect EMG signal from the upper limb muscles and the intermediate clavicle muscle (as shown in Fig. 3). The muscles of the upper limbs included the flexor digitorum superficialis, musculi flexor pollicis longus and flexor carpi radialis of the two arms, and the flexor digitorum superficialis of each arm was used as its own reference electrode. The intermediate clavicle muscle served as the ground electrode. Both EEG and EMG signals were recorded with the sampling rate of 1200 Hz, bandpass filtering between 0.5 and 100 Hz, notch filtering between 48 and 52 Hz.

D. Experimental Protocol

In this study, participants were asked to perform four experiments in sequence, including assessment experiment, MI experiment, AO experiment, MI+AO experiment. Fig. 4 shows a schematic representation of the four experiments. Each experiment lasts for 30 minutes and participant performs one experiment a day. And all participants were required to complete all experiments in four days. In order to maintain the uniformity of different experiments and reduce instability, participants were asked to lie in bed before each experiment.

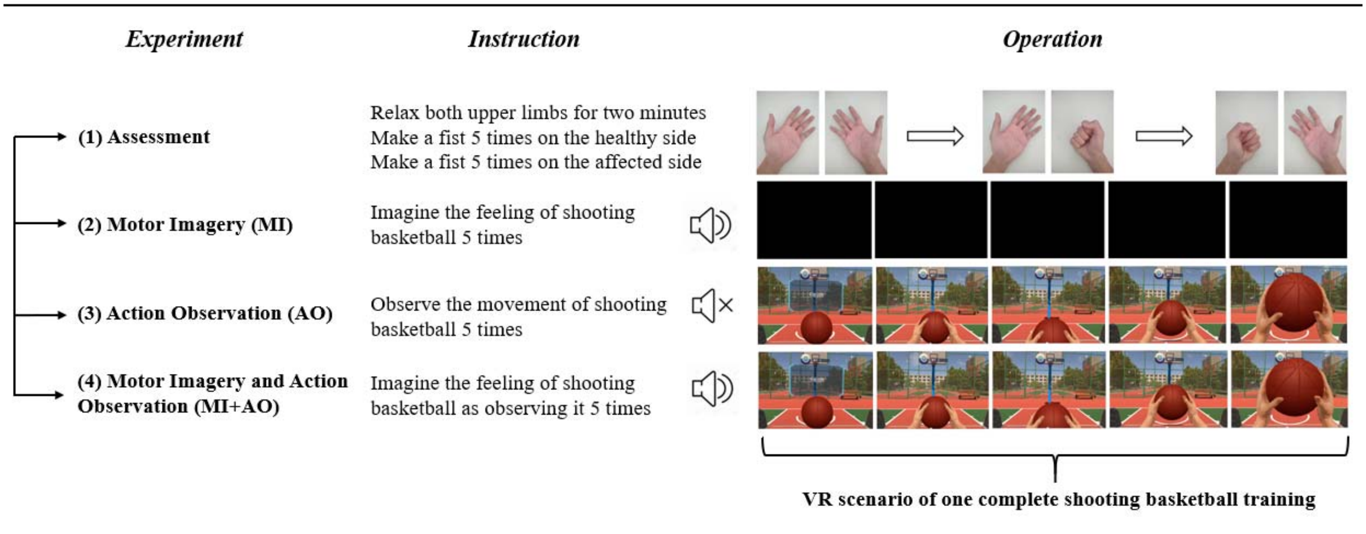

Fig. 4. Illustration of experimental design.

First, the assessment experiment is designed to acquire the physiological parameters of EEG and EMG signals. The muscle strength of each participant in a relaxed state or fisting state can be obtained by extracting EMG data, which was used as real-time feedback in subsequent VR-based experiments. Besides that, the result can also be utilized as reference to monitor and evaluate the engage degree of participant when performing MI training. To be specific, participants need to close eyes and relax firstly 2 times, one minute each time, and subsequently, make a fist 5 times with the healthy side of upper limbs and then 5 times with the affected side, according to instructions. Each fist lasts for 2 to 3 seconds decided by instructions of instructor. In the meantime, EEG and EMG signal datas were recorded for further real-time feedback and offline analysis.

Next, each participant was guided to complete MI experiment with procedure quite similar to conventional training. The difference lies in that, in our design participants need to put on the headphones which can play voice commands of specific shooting steps. During the experiment, participants were told to imagine they were shooting basketball with their hands but without actually moving their bodies. Each participant should perform the shooting basketball training 5 times with EEG and EMG acquired.

To investigate the effect of only observation-based activation for rehabilitation excluding MI effect, the subsequent AO experiment that includes VR-based observation and real-time EMG-based feedback was performed. Specifically, participants were placed in the center of virtual environment built by using two laser locators and then were required to wear the HMD that displays the animation of vivid shooting basketball movement with two virtual hands and arms in the first-person perspective. Here, participants were instructed to open eyes and carefully observe the virtual movement of shooting 5 times without performing imagination training. Note that the HMD didn't provide voice instruction for participant and the experiment adopted the same collection strategy of EEG and EMG data.

Finally, the experiment based on both MI and AO was carried out to investigate the synchronous activation for the rehabilitation. Similar to the procedure described above, each participant was asked to engage in MI training as well as observe the action of shooting in the virtual scenario of HMD. Compared to AO experiment, the experiment provided voice instructions from HMD headphone for participant. The training need to carry out simultaneously 5 times and EEG and EMG of each participant were collected as well.

III. Methods

A. EEG Analysis

Growing attention has been dedicated to analyzing EEG of MI because the brain's activity in a specific area could be changed [43]. Rhythm in alpha and beta bands, which can be activated through MI [44], [45], correlates with major sensorimotor system functions [46]. ERD from the motor cortex, defined as a percentage of relative power loss in a particular frequency band [47], is associated with motor execution, action observation and motor imagery [48], [49]. Therefore, ERD can be used to measure brain activity [32], [50] and discriminate difference under different experiments.

In the preprocessing stage, inappropriate data is first eliminated from every experimental data on every participant, only reserving the period from 5 seconds to 50 seconds in order to keep uniformity. This is because it is the preparation phase and the formal training has not begun yet before the fifth second, the signal collected at this stage is invalid. And after fifty seconds, the last time training ends with only the score of showing in the video or playing in the audio. Thus, the subsequent signal is ineffective. And then for each participant, the data under each experiment needs to re-reference to participant's own average for filtering out noise and unstable values via the EEGLAB toolbox by MATLAB (MathWorks Inc., Natick, USA). Consequently, data in alpha and beta bands can be acquired respectively. In order to map and compare the brain activity in four experiments, we further computed the data to obtain the power spectrum. The brain activation can be mapped via the power of 18 electrode positions.

B. EMG Analysis

The surface EMG has been suggested to be useful to estimate the muscle strength and assess the recovery phase from stroke [51]. So we adopted the method of root-mean-square (RMS) to extract feature value of EMG signal as muscle strength for each status or condition in different time periods for different experiments. The corresponding equation is given by

$$M = \sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}} \tag{1}$$

where x_i represents the EMG signal value at each sampling moment and n means the number of sampling points in a period of time calculated according to the sampling rate.

In the assessment experiment, we first calculated the RMS valus of the EMG signals of the musculi flexor pollicis longus and flexor carpi radialis of the healthy upper limb and the affected upper limb for each participant of relaxed state and fisting state respectively, and then averaged the two RMS values corresponding to the two muscles of each upper limb, so as to obtain the relaxed muscle strength and the maximum muscle strength of the participant's healthy and affected side. Finally, the relaxed comprehensive muscle strength M_{relax} was calculated by averaging the relaxed muscle strength of the healthy side and the affected side, as in equation (2). And the maximum comprehensive muscle strength M_{max_muscle} was obtained by averaging the maximum muscle strength of both sides, as in equation (3).

$$M_{relax} = \left(M_{healthy\_relax} + M_{affected\_relax}\right) / 2 \tag{2}$$

$$M_{max\_muscle} = \left(M_{healthy\_max} + M_{affected\_max}\right) / 2 \tag{3}$$

Since a complete shooting basketball consists of four parts and lasts for 50 seconds, we took the sampling time of 3 seconds for each part (as shown in Fig. 5) and obtained the RMS value, which represents the comprehensive muscle strength, using the same strategy of assessment experiment to calculate, in the current training. In the Fig. 5, symbols I, II, III and IV are respectively four phases of shooting basketball. Because of each MI training session being long and providing timely real-time feedback, we just sampled the last three seconds of each phase and got a twelve seconds of sample signal data, which can reflect the performance at maximum extent.

In order to study the effect of EMG as real-time feedback on personalized training for participants, two parameters of M_{th1} and M_{th2} based on M_{max_muscle} for each participant were defined and calculated by equation (4) and (5) respectively. The values of M_{th1} and M_{th2} were used to set two thresholds in both AO and MI+AO experiments with EMG-based real-time feedback. For MI experiment which didn't involve real-time feedback, we also took the same method to acquire muscle strength for comparison. In the equation, the symbols A and B, which can be set according to patient's status and recovery process, both have value range between 0 and 1, and the value

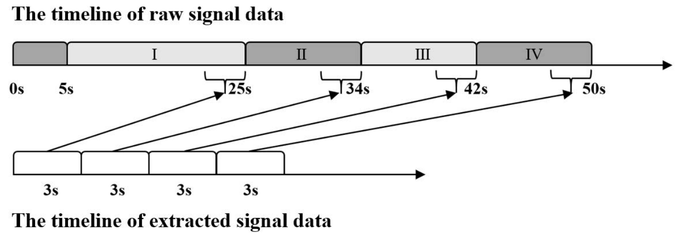

Fig. 5. The periods of raw and extracted signal data.

of A has to be less than the value of B. In the study, we valued A and B at 0.2 and 0.6 respectively.

$$M_{th1} = M_{max\_muscle} \times A \tag{4}$$

$$M_{th2} = M_{max\_muscle} \times B \tag{5}$$

Specifically, in AO and MI+AO experiments, because the Unity3D program integrates the VR scene training part and the bioelectrical signal acquisition part, the EMG data can be measured and compared to the thresholds based on M_{th1} and M_{th2} in real time and then the training result can be visually fed back to the participant via HMD. As a result, the different comparison results lead to different scores of shooting basketball. Participants can get three kinds of scores according to their performance. When their real-time muscle strength in the current training is less than M_{th1}, they will get one point. While their muscle strength is not less than M_{th1} and less than M_{th2}, they will get two points. And if their muscle strength is greater or equal to M_{th2}, they finally will get three points.

IV. Results

The system combined VR and EMG-based real-time feedback was designed to test the differences in changes in brain activity under four experiments: assessment, MI, AO, and MI+AO. Then the effect of VR-based observation on motor imagery training to promote brain activity was investigated. Since MI can induce a specific change in alpha and beta frequency bands, such as ERD [18], [19], we can analyze the change of the spectrum power in corresponding bands. Moreover, a total of 18 electrodes to measure EEG was placed on brain and then the detected whole brain activity was mapped to compare the discrepancy.

As displayed in Fig. 6, the brain activity of alpha and beta bands extracted from EEG data of four designed experiments was mapped. It can be seen from the figure that assessment and MI have similar results with power of alpha higher than that of beta in the sensorimotor cortex. In addition, the difference of power between electrodes is more obvious in alpha band than in beta band. Furthermore, the activity in beta has greater discrepancy and higher power by comparing the data of MI with AO and MI+AO which both involve additional observing training in virtual environment. This may be due to the fact that the observing behavior can increase power in beta band [8], [52]. Moreover, the mapping result shows that the power of alpha band in MI+AO obviously becomes weaker and is lower than that in beta band. But the trend in alpha band of AO is consistent with assessment as well as MI.

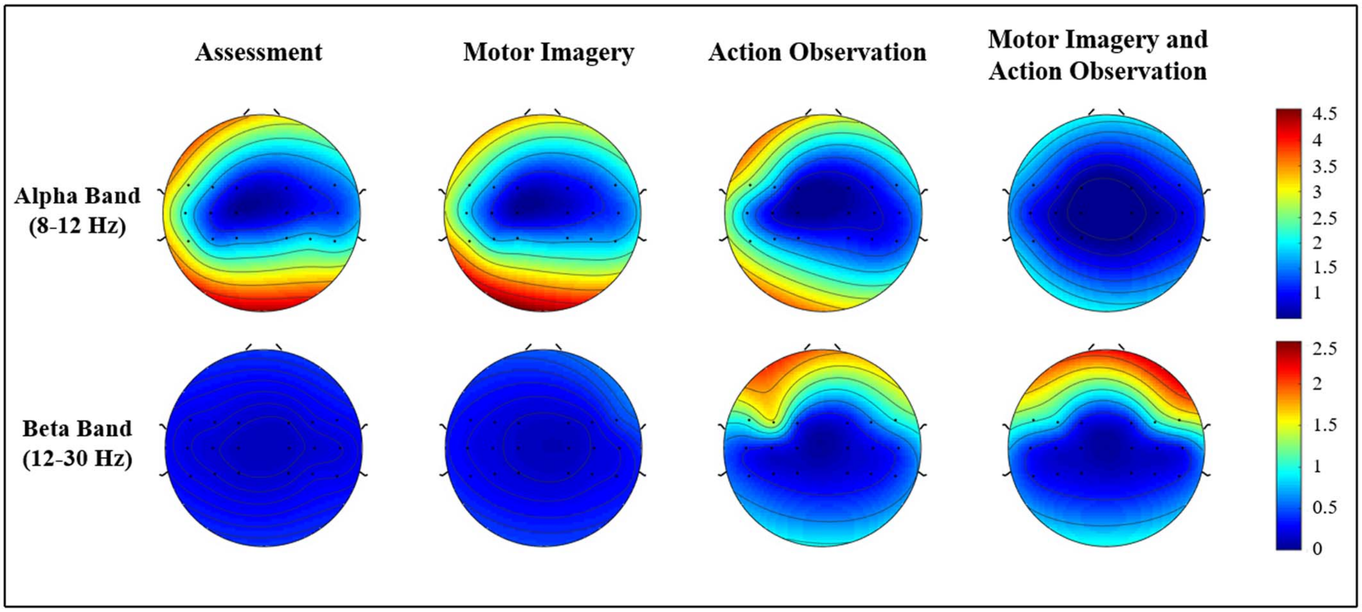

Fig. 6. Analysis of brain activity for the different experimental conditions.

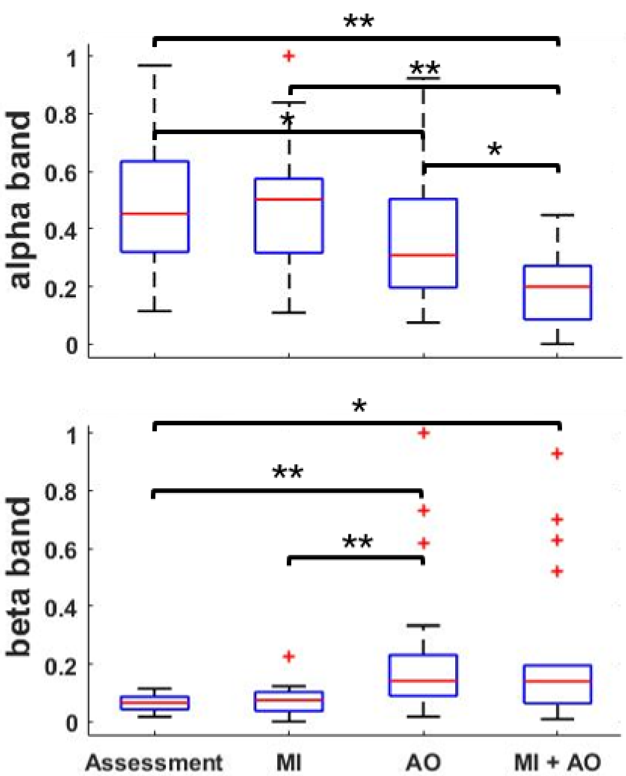

Fig. 7. Normalized power for alpha and bate frequency bands in four experiments. On each box, the center mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentile, respectively. The whisker extends to the farthest data point that is not the outlier. * and ** indicates $p < 0.05$ and $p < 0.01$ respectively.

The further comparative analysis of four experiments was performed and showed in Fig. 7. To be specific, the non-parametric Friedman's test was used to conduct correlation analysis to assess the change of spectrum power in alpha and beta frequency bands respectively based on the software SPSS v26 (IBM Corporation, New York, USA). For each experiment, all electrodes power in brain of all participants were averaged and normalized. Both assessment and MI have similar range in both alpha and beta bands, which is consistent with the result of spectrum power map. Upper subfigure of Fig. 7 reveals the comparison result of alpha frequency bands in four experiments. We can see that the result of MI+AO shows relatively apparent difference compared to other experiments. And the normalized power response of two experiments involving the AO training decreases. The reason may be that the observing action which is based on virtual environment probably can decrease the trend and amplitude of power in alpha frequency [52]. However, the decrease is more obvious in MI+AO, which may be attributed to the predominant function of MI training as well as the enhancing effect by AO training on ERD of alpha frequency. The comparison of difference of beta frequency bands in four experiments is also depicted in Fig. 7. It is obvious that beta frequency of AO shows significant difference compared to both results of assessment and MI. Opposed to the case in alpha band, the powers of beta bands in AO and MI+AO increase observably when compared to results of other experiments. This is reasonable since observing movement in virtual environment is believed to enable enhancement of the power in beta band. Moreover, MI+AO has lower power than in AO probably because of the effect of MI.

The comparisons of brain activity map and correlation analysis indicate that the MI training has minimal effect on significant difference, which is very similar to the result of assessment experiment. This can be attributed to the low engagement and inaccurate execution of participation in short-term MI training. Besides, observing action is able to affect the change of spectrum power in alpha and beta bands. In addition, performing MI training in virtual environment has significant difference in alpha band compared to other three experiments. In order to investigate the performance of shooting feedback as a kind of personalized training, the EMG-based real-time feedback was incorporated in the rehabilitation system.

TABLE II
THE MUSCLE STRENGTH IN RELAXED AND CLENCHED STATE ON BOTH SIDES FOR THE PARTICIPATED STROKE PATIENTS. THE SYMBOL H AND A INDICATE HEALTHY SIDE AND AFFECTED SIDE OF UPPER LIMB RESPECTIVELY

Muscle Strength	H - Relax	A - Relax	H - Fist	A - Fist
Participant 1	2.57045	2.44095	487.0497	71.9314
Participant 2	36.53575	3.9912	133.1249	46.0437
Participant 3	2.6258	18.8543	68.1234	17.4232
Participant 4	19.10965	3.63545	109.2364	65.3202
Participant 5	3.6183	3.45115	70.3016	11.4072
Participant 6	6.2528	11.6316	132.9792	10.38
Participant 7	6.8584	9.54495	63.5097	14.0948
Participant 8	12.2878	8.21005	63.5121	17.1509

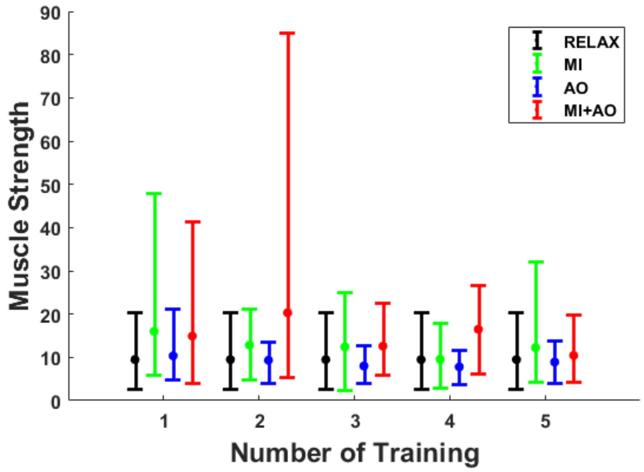

Fig. 8. Mean muscle strength for all participants in five trainings for four experiments. On each error bar, the center point indicates the mean value, and the bottom and top edges of the error bar indicate the minimum and maximum value, respectively.

Consequently, the EMG signal in assessment experiment was acquired and then the feature of muscle strength was extracted. Table II shows the detailed information of muscle strength for all participants when they were asked to relax or clench their fists on both sides of upper limb. From the table, it shows no obvious difference between H-Relax and A-Relax in the whole. However, all patients manifest more muscle strength with their healthy limb compared with affected limb when making a fist, which is in line with our expectations.

In order to reasonably evaluate the muscle strength of participant's upper limbs, we averaged the muscle strength of the healthy side and the affected side to represent current level of upper limb rehabilitation. Therefore, we can take the comprehensive muscle strength to assess the performance of training and degree of participation. Figure 8 shows the comparison of the mean muscle strength for all participants in five times training for four different experiments. As expected, the trend of muscle strength is relatively steady in AO compared to MI and MI+AO that both are required to perform movement mentally. And the trend of AO is close to the result of the relaxed state that was measured in the assessment experiment. This is because participants were asked to observe movement without motor imagery, which results in no or little muscular movement. As expected, the muscle strength values of MI and MI+AO are both higher than that of AO in all five times training, though both trends of muscle strength

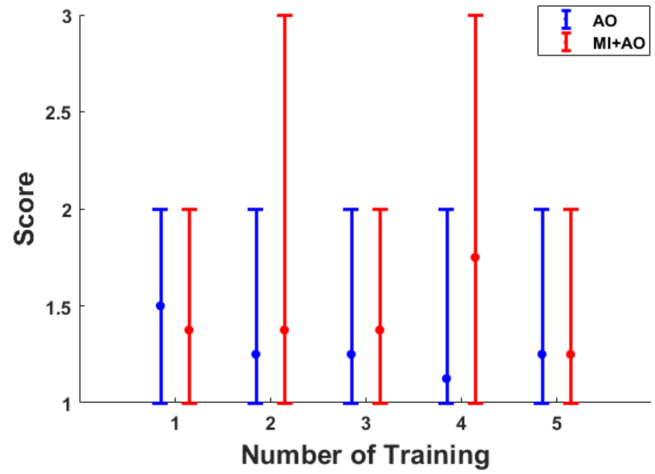

Fig. 9. Mean scores for all participants in five trainings for AO and MI+AO experiments. On each error bar, the center point indicates the mean value, and the bottom and top edges of the error bar indicate the minimum and maximum value, respectively.

present some obvious range variation. In comparison to MI, the muscle strength of MI+AO is higher, which means that the additional AO behavior does improve the conventional MI training. Moreover, the overall trend of the curve of MI+AO fluctuates more pronouncedly. To sum up, the EMG-based real-time feedback can induce the change of EMG signal in MI-based training, both MI and MI+AO. Therefore, it can be used to quantify the participation of participants in MI-based training and assess the level of rehabilitation.

Figure 9 shows the mean scores for all participants in five times training in AO and MI+AO that both are performed in virtual environment combing EMG-based real-time feedback. Participants can observe the action of shooting basketball with HMD with corresponding scores of every training performance shown on the HMD. Compared to AO, the score of MI+AO is almost higher. As both experiments having obvious trend of score change, it demonstrates that EMG-based feedback can enhance the performance of MI-based training. Besides, the VR-based AO training can also promote engagement of participant. Therefore, we propose that the EMG-based real-time feedback has the potential and the ability to customize the personalized training for post-stroke patients.

Correlation analysis of muscle strength value and training score was performed and showed in Fig. 10. Upper subfigure of Fig. 10 reveals the comparison result of muscle strength in four experiments. Compared with AO, both MI and MI+AO have significant difference. Moreover, the distribution range of muscle strength of MI+AO is higher than that of MI. Lower subfigure of Fig. 10 shows the normalized training score in AO and MI+AO experiments. Although the results of the two experiments are not significantly different, the training score range of MI+AO is obviously higher than that of AO.

According to the effect of EMG-based real-time feedback on four experiments, the result shows that the feedback has positive influence on MI-based training which generates recordable EMG signal so as to train the damaged or immobile limb. Furthermore, the score variation in five times training manifests the degree of participation and attention of participant during training. On the whole the performance

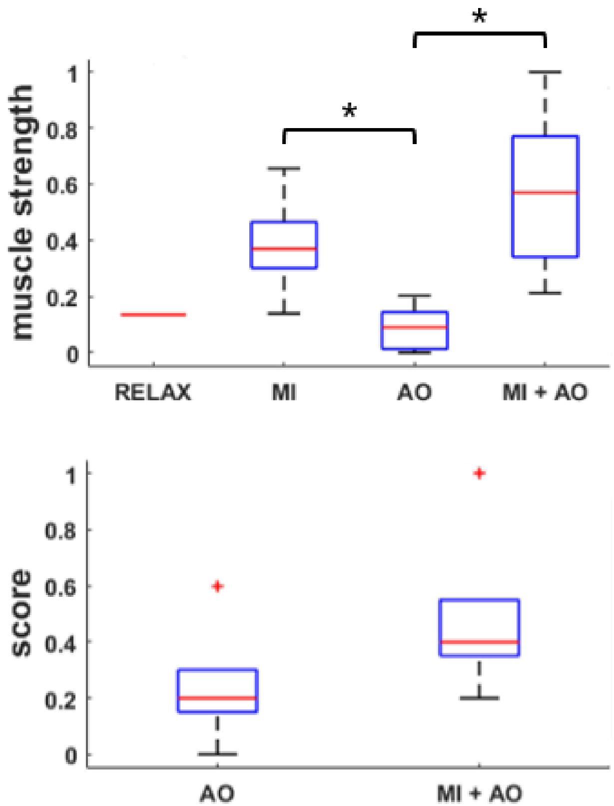

Fig. 10. Normalized muscle strength in four experiments and normalized training score in AO and MI+AO experiments. On each box, the center mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentile, respectively. The whisker extends to the farthest data point that is not the outlier. * indicates $p < 0.05$.

in MI+AO is better than MI, since the result of former shows higher values of muscle strength and scores of shooting basketball. The difference between two experiments is whether to train in a virtual environment and observe the movement of the virtual upper limbs from the first-person perspective. Therefore, we can conclude that VR-based AO can promote the MI-based rehabilitation therapy. All results demonstrate that the MI system combining EMG-based real-time feedback and VR has the potential to promote the rehabilitation training of affected limbs.

V. Discussion

To investigate the effect of the combination of VR-based action observation and EMG-based real-time feedback on motor imagery training, we carried out four different experiments: assessment, MI, AO and MI+AO for clinical post-stroke patients to analyze and compare the results. Conventional motor imagery training without action observation in real or virtual environment has been verified that it has a rehabilitative effect on post-stroke patients to dynamically reorganize through neuroplasticity [53], [54], [55]. Furthermore, MI can elicit the decrease in oscillatory brain activity in the alpha and beta bands [56], [57]. It can be found that the brain activity maps in alpha and beta in MI are very similar to that in the assessment experiment. This may be attributed to the fact that the involved MI and AO training are short term trials in this work as our investigation is mainly focus on the real-time changes of EEG and EMG signals generated during MI and AO training. As described above, each participant was instructed to perform each experiment, except the assessment experiment, 30 minutes one day to complete 5 trainings of shooting basketball. Besides that, the low participation of MI training also may affect the measurement result.

Badia *et al.* [58] verified the VR system can promote cortical reorganization during MI training because their results indicate desynchronization of neural responses. From the result of MI+AO, we can observe the pronounced ERD in the sensorimotor area of brain especially in alpha band. Takemi *et al.* [59] investigated the relation between ERD during MI and the change of motor evoked potentials and provided evidence that MI involving ERD can induce changes in corticospinal excitability that is similar to actual movements. To further confirm the origination of ERD, we designed AO experiment excluding the effect of MI. The result shows that the brain activity in alpha band in AO has significant difference compared to the result in MI+AO. By comparing the differences between viewing the video and the static image, Kondo *et al.* [48] draw a conclusion that observing the target movement during MI can improve the associated training effect with more higher ERD. This is consistent with our results though immersive VR is used in our study instead of 2D video. Therefore, it is believed that observing action in virtual environment can promote the more obvious ERD in alpha band and MI therapy [60].

In the beta band, in comparison to assessment and MI, both the spectrum power of AO and MI+AO increase without the pronounced ERD. However, from the subfigure at the bottom of Fig. 7, we can observe that AO has more significant difference compared to assessment and MI (both $p < 0.01$), and MI+AO has significant difference ($p < 0.05$) compared to the assessment. Moreover, the power values and reasonable range of MI+AO is relatively smaller and lower than AO. Berends *et al.* [61] shows that MI+AO can induce more significant ERD compared to AO-only in all electrodes and frequency bands, including alpha and beta bands, which well confirms and supports our results.

Based on above discussion, it can be argued that in the beta band, observation of virtual movement can obviously increase the power. While on the other hand, MI training is able to lower the power to facilitate desynchronization of rhythm. But the former has a stronger effect on brain activity, without generating significant ERD. Previous studies [62], [63] investigated that action observation can facilitate motor cortical activity in stroke patients because the ERD power of alpha activity in AO was significantly higher than that in MI. On the contrary, AO had greater beta synchronization over bilateral region than MI [63].

Another important point lies in the incorporation of EMG-based real-time feedback that is employed to monitor MI training by obtaining the comprehensive muscle strength for each participant through averaging the muscle strength of healthy and affected side as reference thresholds. From the Fig. 8 and Fig. 9, both the values of muscle strength in MI-based experiments (MI and MI+AO) are higher than others which is in line with expectations. Besides, in comparison to MI, the value of MI+AO is higher. Moreover, the score of shooting basketball in MI+AO has better performance compared to the

AO. We demonstrate that the feedback of EMG provides an effective method to facilitate MI training.

There are several limitations need to improve in the future. In this study, we designed VR scenario of shooting basketball for bilateral upper limb training. However, as previously reported, different visual scenarios for limb movements may lead to different MI performances [32], [64]. Thus, more VR training scenarios could be included to make experimental scheme more comprehensive and comparable for future improvement. In addition, although the real-time EMG signal was proved to be useful to monitor patient's engagement during training to some extent, more physiological parameters that enable synchronously characterizing MI behavior need to further explore and test to achieved personalized training with high accuracy. Also, only 18 channels in the sensorimotor cortex were used to collect EEG data, which can be extended to 64 channels to better depict brain patterns and connections in the future investigation. And the method of computing muscle strength from EMG can also be improved and optimized. Furthermore, the sample size of this study is not large enough to perform more comprehensive analysis, so the results need to treat conditionally. The age distribution of clinical participants is relatively large, which may also affect the effectiveness and restrict the generalization of our training system. Lastly, although training of each experiment is repetitive, the overall time of MI training is too short to exert lasting positive effects on patient's rehabilitation. Therefore, our system and scheme can be further improved and investigated for long-term post-stroke rehabilitation.

VI. Conclusion

Many evidences indicate that the efficacy of post-stroke rehabilitation depends on whether it starts at the right time and how well the patient has been engaged in the training process. In this investigation, a VR-based MI training system with EMG real-time feedback for post-stroke rehabilitation has been developed with the aim to study whether VR, which provides an immersive visual environment, could boost the brain engagement during a motor imagery training session. Four different experiments were designed to acquire and analyze EEG and EMG signals. In the comparative analysis of EEG, through mapping brain activity in alpha and beta bands and performing correlation analysis of electrode power, the result shows that observing action in virtual environment by first-person perspective can facilitate the MI training because of MI+AO experiment generating pronounced ERD compared to other three experiments in alpha band and inducing relatively obvious ERD compared to AO experiment in beta band.

Moreover, in order to study the effect of EMG-based real-time feedback, EMG signal of each patient is collected and calculated to indicate comprehensive muscle strength as the threshold feedback in virtual environment. The real-time EMG during each training session is compared with this threshold. Then the performance score of shooting basketball can be acquired. From the results, it can be concluded that the feedback of EMG has the potential to promote MI training and further enhance the degree of participation for patients.

The MI rehabilitative training system supported by a VR-based action observation and EMG-based real-time feedback mechanism could provide an effective way for post-stroke limb rehabilitation specially when the patients are at their initial flaccidity stage in which they cannot voluntarily move their limbs.

References

[1] D. Mozaffarian *et al.*, "Heart disease and stroke statistics—2015 update a report from the American heart association," *Circulation*, vol. 131, no. 4, pp. E29–E322, Jan. 2015.

[2] F. J. Carod-Artal and J. A. Egido, "Quality of life after stroke: The importance of a good recovery," *Cerebrovascular Diseases*, vol. 27, no. 1, pp. 204–214, 2009.

[3] T. H. Murphy and D. Corbett, "Plasticity during stroke recovery: From synapse to behaviour," *Nature Rev. Neurosci.*, vol. 10, no. 12, pp. 861–872, Dec. 2009.

[4] K. P. Liu, C. C. Chan, T. M. Lee, and C. W. Hui-Chan, "Mental imagery for promoting relearning for people after stroke: A randomized controlled trial," *Arch. Phys. Med. Rehabil.*, vol. 85, no. 9, pp. 1403–1408, Sep. 2004.

[5] P. Langhorne, F. Coupar, and A. Pollock, "Motor recovery after stroke: A systematic review," *Lancet Neurol.*, vol. 8, no. 8, pp. 741–754, Aug. 2009.

[6] S. de Vries and T. Mulder, "Motor imagery and stroke rehabilitation: A critical discussion," *J. Rehabil. Med.*, vol. 39, no. 1, pp. 5–13, Jan. 2007.

[7] P. Cicinelli, B. Marconi, M. Zaccagnini, P. Pasqualetti, M. M. Filippi, and P. M. Rossini, "Imagery-induced cortical excitability changes in stroke: A transcranial magnetic stimulation study," *Cerebral Cortex*, vol. 16, no. 2, pp. 247–253, Feb. 2006.

[8] G. Buccino, A. Solodkin, and S. L. Small, "Functions of the mirror neuron system: Implications for neurorehabilitation," *Cognit. Behav. Neurol.*, vol. 19, no. 1, pp. 55–63, Mar. 2006.

[9] S. M. Braun, J. C. van Haastregt, A. J. Beurskens, A. I. Gielen, D. T. Wade, and J. M. Schols, "Feasibility of a mental practice intervention in stroke patients in nursing homes; a process evaluation," *BMC Neurol.*, vol. 10, no. 1, pp. 1–9, Aug. 2010.

[10] G. Lee, C. Song, Y. Lee, H. Cho, and S. Lee, "Effects of motor imagery training on gait ability of patients with chronic stroke," *J. Phys. Therapy Sci.*, vol. 23, no. 2, pp. 197–200, 2011.

[11] N. A. Grigorev *et al.*, "A BCI-based vibrotactile neurofeedback training improves motor cortical excitability during motor imagery," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 1583–1592, 2021.

[12] J. Pan *et al.*, "Prognosis for patients with cognitive motor dissociation identified by brain-computer interface," *Brain*, vol. 143, no. 4, pp. 1177–1189, Apr. 2020.

[13] H. Wang *et al.*, "The reorganization of resting-state brain networks associated with motor imagery training in chronic stroke patients," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 10, pp. 2237–2245, Oct. 2019.

[14] J. H. Crosbie, S. M. McDonough, D. H. Gilmore, and M. I. Wiggam, "The adjunctive role of mental practice in the rehabilitation of the upper limb after hemiplegic stroke: A pilot studya," *Clin. Rehabil.*, vol. 18, no. 1, pp. 60–68, Feb. 2004.

[15] S. Hwang, H.-S. Jeon, C.-H. Yi, O.-Y. Kwon, S.-H. Cho, and S.-H. You, "Locomotor imagery training improves gait performance in people with chronic hemiparetic stroke: A controlled clinical trial," *Clin. Rehabil.*, vol. 24, no. 6, pp. 514–522, Jun. 2010.

[16] S. A. Hosseini, M. Fallahpour, M. Sayadi, M. Gharib, and H. Haghgoo, "The impact of mental practice on stroke patients' postural balance," *J. Neurol. Sci.*, vol. 322, nos. 1–2, pp. 263–267, Nov. 2012.

[17] J. Feng *et al.*, "Towards correlation-based time window selection method for motor imagery BCIs," *Neural Netw.*, vol. 102, pp. 87–95, Jun. 2018.

[18] G. Pfurtscheller and C. Neuper, "Motor imagery activates primary sensorimotor area in humans," *Neurosci. Lett.*, vol. 239, pp. 65–68, Dec. 1997.

[19] Y. Jeon, C. S. Nam, Y.-J. Kim, and M. C. Whang, "Event-related (de)synchronization (ERD/ERS) during motor imagery tasks: Implications for brain–computer interfaces," *Int. J. Ind. Ergonom.*, vol. 41, no. 5, pp. 428–436, Sep. 2011.

[20] A. Vourvopoulos and S. B. I. Badia, "Motor priming in virtual reality can augment motor-imagery training efficacy in restorative brain-computer interaction: A within-subject analysis," *J. Neuroeng. Rehabil.*, vol. 13, no. 1, Dec. 2016.

[21] H. Q. Dinh, N. Walker, L. F. Hodges, C. Song, and A. Kobayashi, "Evaluating the importance of multi-sensory input on memory and the sense of presence in virtual environments," in *Proc. IEEE Virtual Reality*, Mar. 1999, pp. 222–228.

[22] D. Perez-Marcos, M. Slater, and M. V. Sanchez-Vives, "Inducing a virtual hand ownership illusion through a brain–computer interface," *Neuroreport*, vol. 20, no. 6, pp. 589–594, Apr. 2009.

[23] T. Sollfrank, D. Hart, R. Goodsell, J. Foster, and T. Tan, "3D visualization of movements can amplify motor cortex activation during subsequent motor imagery," *Frontiers Hum. Neurosci.*, vol. 9, p. 463, Aug. 2015.

[24] J. Jin, Z. Wang, R. Xu, C. Liu, X. Wang, and A. Cichocki, "Robust similarity measurement based on a novel time filter for SSVEPs detection," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Oct. 14, 2021, doi: 10.1109/TNNLS.2021.3118468.

[25] A. Vourvopoulos, C. Jorge, R. Abreu, P. Figueiredo, J.-C. Fernandes, and S. B. I. Badia, "Efficacy and brain imaging correlates of an immersive motor imagery BCI-driven VR system for upper limb motor rehabilitation: A clinical case report," *Frontiers Hum. Neurosci.*, vol. 13, p. 244, Jul. 2019.

[26] P. Celnik, B. Webster, D. M. Glasser, and L. G. Cohen, "Effects of action observation on physical training after stroke," *Stroke*, vol. 39, no. 6, pp. 1814–1820, Jun. 2008.

[27] K. A. Garrison, C. J. Winstein, and L. Aziz-Zadeh, "The mirror neuron system: A neural substrate for methods in stroke rehabilitation," *Neurorehabilitation Neural Repair*, vol. 24, no. 5, pp. 404–412, Jun. 2010.

[28] M. Song and J. Kim, "A paradigm to enhance motor imagery using rubber hand illusion induced by visuo-tactile stimulus," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 3, pp. 477–486, Mar. 2019.

[29] M. Conson, M. Sarà, F. Pistoia, and L. Trojano, "Action observation improves motor imagery: Specific interactions between simulative processes," *Exp. Brain Res.*, vol. 199, no. 1, pp. 71–81, Oct. 2009.

[30] M. Sakamoto, T. Muraoka, N. Mizuguchi, and K. Kanosue, "Combining observation and imagery of an action enhances human corticospinal excitability," *Neurosci. Res.*, vol. 65, no. 1, pp. 23–27, Sep. 2009.

[31] K. Eng *et al.*, "Interactive visuo-motor therapy system for stroke rehabilitation," *Med. Biol. Eng. Comput.*, vol. 45, no. 9, pp. 901–907, Sep. 2007.

[32] J. W. Choi, B. H. Kim, S. Huh, and S. Jo, "Observing actions through immersive virtual reality enhances motor imagery training," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 7, pp. 1614–1622, Jul. 2020.

[33] D.-W. Oh, J.-S. Kim, S.-Y. Kim, E.-Y. Yoo, and H.-S. Jeon, "Effect of motor imagery training on symmetrical use of knee extensors during sit-to-stand and stand-to-sit tasks in post-stroke hemiparesis," *NeuroRehabilitation*, vol. 26, no. 4, pp. 307–315, Jun. 2010.

[34] R. Dickstein, M. Gazit-Grunwald, M. Plax, A. Dunsky, and E. Marcovitz, "EMG activity in selected target muscles during imagery rising on tiptoes in healthy adults and poststroke hemiparetic patients," *J. Mot. Behav.*, vol. 37, no. 6, pp. 475–483, Nov. 2005.

[35] O. Marin-Pardo, C. M. Laine, M. Rennie, K. L. Ito, J. Finley, and S.-L. Liew, "A virtual reality muscle–computer interface for neurorehabilitation in chronic stroke: A pilot study," *Sensors*, vol. 20, no. 13, p. 3754, Jul. 2020.

[36] P. Shenoy, K. J. Miller, B. Crawford, and R. P. N. Rao, "Online electromyographic control of a robotic prosthesis," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 3, pp. 1128–1135, Mar. 2008.

[37] L. Fadiga, G. Buccino, L. Craighero, L. Fogassi, V. Gallese, and G. Pavesi, "Corticospinal excitability is specifically modulated by motor imagery: A magnetic stimulation study," *Neuropsychologia*, vol. 37, no. 2, pp. 147–158, Nov. 1998.

[38] R. Hashimoto and J. C. Rothwell, "Dynamic changes in corticospinal excitability during motor imagery," *Exp. Brain Res.*, vol. 125, no. 1, pp. 75–81, Feb. 1999.

[39] A. J. Szameitat, S. Shen, A. Conforto, and A. Sterr, "Cortical activation during executed, imagined, observed, and passive wrist movements in healthy volunteers and stroke patients," *NeuroImage*, vol. 62, no. 1, pp. 266–280, Aug. 2012.

[40] H. Yuan, A. Doud, A. Gururajan, and B. He, "Cortical imaging of event-related (de)synchronization during online control of brain-computer interface using minimum-norm estimates in frequency domain," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 5, pp. 425–431, Oct. 2008.

[41] C. Neuper, M. Wörtz, and G. Pfurtscheller, "ERD/ERS patterns reflecting sensorimotor activation and deactivation," *Progr. Brain Res.*, vol. 159, pp. 211–222, Jan. 2006.

[42] G. H. Klem, H. O. Lüeders, H. H. Jasper, and C. Elger, "The ten-twenty electrode system of the international federation," *Electroencephalogr. Clin. Neurophysiol.*, vol. 52, no. 3, pp. 3–6, 1999.

[43] Y. Pei *et al.*, "A tensor-based frequency features combination method for brain-computer interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 30, pp. 465–475, 2022.

[44] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 8, no. 4, pp. 441–446, Dec. 2000.

[45] J. Jin, R. Xiao, I. Daly, Y. Miao, X. Wang, and A. Cichocki, "Internal feature selection method of CSP based on L1-norm and Dempster–Shafer theory," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 11, pp. 4814–4825, Nov. 2021.

[46] N. E. Crone *et al.*, "Functional mapping of human sensorimotor cortex with electrocorticographic spectral analysis. I. Alpha and beta event-related desynchronization," *Brain*, vol. 121, no. 12, pp. 2271–2299, Dec. 1998.

[47] G. Pfurtscheller, "Functional brain imaging based on ERD/ERS," *Vis. Res.*, vol. 41, nos. 10–11, pp. 1257–1260, May 2001.

[48] T. Kondo, M. Saeki, Y. Hayashi, K. Nakayashiki, and Y. Takata, "Effect of instructive visual stimuli on neurofeedback training for motor imagery-based brain-computer interface," *Hum. Movement Sci.*, vol. 43, pp. 239–249, Oct. 2015.

[49] J. Long, Y. Li, H. Wang, T. Yu, J. Pan, and F. Li, "A hybrid brain computer interface to control the direction and speed of a simulated or real wheelchair," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 5, pp. 720–729, Sep. 2012.

[50] D. Huang, K. Qian, D. Fei, W. Jia, X. Chen, and O. Bai, "Electroencephalography (EEG)-based brain-computer interface (BCI): A 2-D virtual wheelchair control based on event-related desynchronization/synchronization and state control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 3, pp. 379–388, May 2012.

[51] L. Liparulo, Z. Zhang, M. Panella, X. Gu, and Q. Fang, "A novel fuzzy approach for automatic Brunnstrom stage classification using surface electromyography," *Med. Biol. Eng. Comput.*, vol. 55, no. 8, pp. 1367–1378, Aug. 2017.

[52] K. E. Laver, S. George, S. Thomas, J. E. Deutsch, and M. Crotty, "Virtual reality for stroke rehabilitation," *Cochrane Database Syst. Rev.*, no. 2, 2015, Art. no. CD008349. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/25927099/

[53] P.-M. Lledo, M. Alonso, and M. S. Grubb, "Adult neurogenesis and functional plasticity in neuronal circuits," *Nature Rev. Neurosci.*, vol. 7, no. 3, pp. 179–193, Mar. 2006.

[54] P. M. Rossini, C. Calautti, F. Pauri, and J.-C. Baron, "Post-stroke plastic reorganisation in the adult brain," *Lancet Neurol.*, vol. 2, no. 8, pp. 493–502, Aug. 2003.

[55] N. Sharma, J.-C. Baron, and J. B. Rowe, "Motor imagery after stroke: Relating outcome to motor network connectivity," *Ann. Neurol.*, vol. 66, no. 5, pp. 604–616, Nov. 2009.

[56] S.-J. You and J. H. Lee, "Effects of mental activity training linked With electromyogram-triggered electrical stimulation on paretic upper extremity motor function in chronic stroke patients: A pilot trial," *Turkiye Fiz. Tip ve Rehabil. Dergisi-Turkish J. Phys. Med. Rehabil.*, vol. 59, no. 2, pp. 133–139, Jun. 2013.

[57] D. J. McFarland, L. A. Miner, T. M. Vaughan, and J. R. Wolpaw, "Mu and beta rhythm topographies during motor imagery and actual movements," *Brain Topogr.*, vol. 12, no. 3, pp. 177–186, Feb. 2000.

[58] S. B. I. Badia, A. G. Morgade, H. Samaha, and P. F. M. J. Verschure, "Using a hybrid brain computer interface and virtual reality system to monitor and promote cortical reorganization through motor activity and motor imagery training," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 2, pp. 174–181, Mar. 2013.

[59] M. Takemi, Y. Masakado, M. Liu, and J. Ushiba, "Event-related desynchronization reflects downregulation of intracortical inhibition in human primary motor cortex," *J. Neurophysiol.*, vol. 110, no. 5, pp. 1158–1166, Sep. 2013.

[60] H. Nagai and T. Tanaka, "Action observation of own hand movement enhances event-related desynchronization," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 7, pp. 1407–1415, Jul. 2019.

[61] H. I. Berends, R. Wolkorte, M. J. Ijzerman, and M. J. A. M. van Putten, "Differential cortical activation during observation and observation-and-imagination," *Exp. Brain Res.*, vol. 229, no. 3, pp. 337–345, Sep. 2013.

[62] M. Tani *et al.*, "Action observation facilitates motor cortical activity in patients with stroke and hemiplegia," *Neurosci. Res.*, vol. 133, pp. 7–14, Aug. 2017.

[63] J. J. Gonzalez-Rosa *et al.*, "Action observation and motor imagery in performance of complex movements: Evidence from EEG and kinematics analysis," *Behav. Brain Res.*, vol. 281, pp. 290–300, Mar. 2015.

[64] S. Liang, K. S. Choi, J. Qin, W. M. Pang, and Q. Wang, "Improving the discrimination of hand motor imagery via virtual reality based visual guidance," *Comput. Methods Programs Biomed.*, vol. 132, pp. 63–74, Aug. 2016.