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RESEARCH ARTICLE

Applying Action Observation During a Brain-Computer Interface on Upper Limb Recovery in Chronic Stroke Patients

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ABSTRACT The study aimed to compare the effects of combined action observation and motor imagery (AOMI) and motor imagery (MI)-based brain-computer interface (BCI) training on upper limb recovery, cortical excitation, and cognitive task performance in chronic stroke patients. 17 chronic stroke patients were recruited and randomly assigned to AOMI-based BCI ($n = 9$) and MI-based BCI groups ($n = 8$). The AOMI-based BCI group received AOMI-based BCI training via functional electrical stimulation (FES) feedback, whereas the MI-based BCI group obtained MI-based BCI training via FES feedback. Both groups participated in training for 12 sessions (3 days/week, consecutive four weeks). To evaluate upper limb function recovery, the Fugl–Meyer Assessment for upper extremity (FMA-UE) was employed. Event-related desynchronization (ERD) and online classification accuracy were utilized to measure cortical excitation of the affected sensorimotor hand region and cognitive task performance, respectively. Both AOMI and MI-based BCI training improved upper limb function in chronic stroke patients. However, the AOMI-based BCI group showed significantly greater motor gain than the MI-based BCI group. In addition, the AOMI-based BCI group demonstrated significantly greater cortical excitation of the affected sensorimotor hand region and cognitive task performance. The correlation analysis revealed that higher cognitive task performance during AOMI-based BCI training may promote greater cortical excitation of the affected sensorimotor hand region, which contributes to greater upper limb function improvement compared to MI-based BCI training.

INDEX TERMS Brain-computer interface, motor imagery, action observation, stroke, rehabilitation.

I. INTRODUCTION

Stroke is a leading cause of death worldwide; moreover, the majority of stroke survivors experience hemiparesis or muscle weakness on one side of the body [1]. In particular, weakness of the upper limb muscles is a common issue among stroke patients that has a significant impact on their daily activities [2]. At present, constraint-induced movement therapy [3] and task-specific training [4] are effective therapeutic methods for enhancing the function of the upper limb in stroke patients. Nevertheless, some stroke patients with moderate to severe upper limb impairment may not be able to take benefits of these techniques effectively due to limited voluntary movement. Consequently, approximately 65% of patients are unable to use the affected upper limb for daily activities six months after the stroke. [5]. Therefore,

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there should be alternative therapeutic methods to assist these patients in regaining function in their upper limbs [6], [7].

Motor imagery (MI) training is a type of mental practice applied in stroke rehabilitation. MI is the mental rehearsal of an action that engages brain regions involved in movement planning and execution without actually performing the action [8], [9]. Consequently, MI can be employed in conjunction with conventional physical therapy to promote motor recovery in stroke patients with severe motor impairment [10], [11], [12]. However, the primary issue with MI training in stroke patients is a lack of feedback during the training. Therefore, stroke patients do not know whether they perform MI effectively.

To overcome this issue, an electroencephalography (EEG)-based brain-computer interface (BCI) system is used to improve the efficacy of MI training in stroke rehabilitation. BCI is a system that can acquire and interpret ongoing EEG signals while a stroke patient is performing MI. The system will subsequently provide stroke patients with useful feedback (e.g., neuromuscular electrical stimulation, robotic hand exoskeleton, and visual feedback) if they perform MI successfully [6]. Event-related desynchronization or synchronization (ERD/ERS) is a well-known EEG feature that emerges during MI and is commonly implemented in BCI systems based on MI. ERD is a decrease in EEG power in a specific frequency band (i.e., alpha (8–13 Hz) and beta bands (14–30 Hz)), whereas ERS is an increase in this power relative to the baseline reference or a moment before performing MI. ERD appears in the contralateral sensorimotor hand region during a hand MI. However, ERS occurs in the ipsilateral sensorimotor hand region and after MI termination. ERD refers to activated cortical neurons involved in sensory, motor, and cognitive processing, whereas ERS denotes neural activity inhibition [13], [14]. Thus, a BCI system based on MI can assist stroke patients in performing MI effectively through trial-and-error learning to generate ERD in the affected sensorimotor hand region. Moreover, ERD occurring in response to MI coincident with neurofeedback is a key strategy for promoting neural plasticity [6], [15], [16]. Thus, multiple studies have reported that MI-based BCI with neurofeedback training could restore upper limb function in stroke patients [17], [18], [19], [20], [21].

In addition to MI, action observation (AO) is another method for accessing motor-related brain regions without executing physical movement. AO is the careful observation of an action performed by another person. Through the mirror neuron system, it is possible to activate the same neural structures as if the individual actually performed the observed action [22], [23]. Moreover, previous EEG studies have reported that AO could also generate ERD in addition to MI [24], [25]. Therefore, combining AO with the BCI system is an alternative strategy to promote motor recovery in stroke patients with severe motor impairment [26], [27].

In addition, there is a proposal to combine MI and AO. Multimodal brain imaging studies have revealed that combined action observation and motor imagery (AOMI) activates motor execution-related brain regions more effectively than either technique alone [28], [29], [30], [31], [32], [33], [34]. AOMI involves imagining a movement while watching the imagined action shown on a computer display. [35], [36]. Previous studies with healthy participants have shown that AOMI is superior to MI for improving balance, muscle force, and aiming performance [37], [38], [39]. Nevertheless, few studies have examined the effect of AOMI training on motor recovery in stroke patients. Sun et al. [40] were the first to investigate the effect of AOMI training on upper limb function in subacute stroke patients. In Sun's study, the participants were randomly assigned to the experimental and control groups. In the experimental group, the participants received AOMI training together with conventional therapy, whereas the participants in the control group received asynchronous AOMI and conventional therapy. After completing four weeks of training, the participants in the experimental group demonstrated significantly greater improvements in upper limb function than the control group. Moreover, the participants in the experimental group also exhibited a significantly greater ERD in the affected sensorimotor hand region. In addition to Sun's study, Wang et al. [41] evaluated the effect of AOMI-based BCI training in chronic stroke patients. In Wang's study, participants were randomly assigned to intervention and sham groups. The intervention group received an AOMI-based BCI with robotic hand feedback, while the sham groups received an MI-based BCI with random robotic hand feedback. After completing 20 sessions of training, only the participants in the intervention group showed significant improvement in upper limb function.

Even though AOMI is not a novel technique, there is currently insufficient evidence of its application in BCI systems for motor recovery in stroke patients. Moreover, there is no research comparing the effects of AOMI and MI-based BCI training on motor recovery in chronic stroke patients. In Sun's study [40], the effects of AOMI and MI training on upper limb recovery in subacute stroke patients were compared; however, the BCI system was not incorporated into the training. In Wang's study [41], the BCI system was integrated into AOMI training for chronic stroke patients, but the researchers did not directly compare the effects of AOMI and MI-based BCI training.

To address the gaps in the literature, this study aimed to investigate the effects of AOMI and MI-based BCI training on upper limb recovery, cortical excitation, and cognitive task performance in chronic stroke patients.

II. MATERIALS AND METHODS

A. PARTICIPANTS

The current study enrolled seventeen chronic stroke patients who were outpatients from the Physical Therapy Center of Mahidol University (3 females; 4 right hemiparesis). The participants were randomly assigned to AOMI-based BCI (experiment group, n = 9) and MI-based BCI groups (control

TABLE 1. Participant details.

Participant	Gender	Stroke type	Paretic side	Age (years)	Time since stroke (months)	MMSE score	FMA-UE score
AOMI1	M	I	L	53	144	30	34
AOMI2	F	I	R	68	14	29	34
AOMI3	M	I	L	69	20	28	11
AOMI4	M	H	L	68	30	30	22
AOMI5	M	I	L	60	180	29	44
AOMI6	M	H	L	55	30	30	41
AOMI7	M	I	L	55	8	30	11
AOMI8	M	H	R	52	16	30	43
AOMI9	F	I	L	70	20	30	10
Mean ± SD				61.11 ± 7.16	51.33 ± 60.13	29.55 ± 0.68	27.78 ± 13.58
MI1	M	I	R	61	48	25	29
MI2	M	H	L	54	24	30	30
MI3	M	I	L	60	168	27	40
MI4	F	I	R	69	27	30	45
MI5	M	H	L	56	96	30	22
MI6	M	I	L	50	17	30	20
MI7	M	I	L	74	36	30	28
MI8	M	H	L	69	48	30	21
Mean ± SD				61.63 ± 7.83	58 ± 47.47	29 ± 1.8	29.38 ± 8.45

Abbreviations: M = Male; F = Female; I = Ischemic; H = Hemorrhagic; L = Left; R = Right

group, n = 8). The Fugl–Meyer Assessment for upper extremity (FMA-UE) was used to evaluate the severity of upper limb impairment in each participant before receiving the BCI training from blinded physical therapists. The FMA-UE scores of the participants ranged from 10–45 (mean = 28.53, standard deviation (SD) = 11.48), indicating severe to moderate-mild upper limb impairment [42]. The other inclusion criteria were as follows: 1) first-ever stroke caused by ischemia or hemorrhage; 2) more than six months since stroke; 3) age between 40–80 years; 4) no eyesight problems; 5) Mini-Mental State Exam (MMSE) score $\geq$ 25, indicating that the participant has normal cognitive status; and 6) no prior experience with AOMI and MI-based BCI training. All participants were right-handed before a stroke. Exclusion criteria included the presence of aphasia, apraxia, neglect syndrome or epilepsy history, and contraindication for neuromuscular electrical stimulation. All participants provided written informed consent to participate in this study, which was approved by the Mahidol University Central Institutional Review Board (COA No. MU-CIRB 2020/097.3107), and the Thai Clinical Trial Registry identification number was TCTR20200821002. The participant details are presented in Table 1.

B. BCI SYSTEM CALIBRATION

In this study, both groups received BCI training three times per week for four consecutive weeks (total of 12 training days). Additionally, each participant continued to receive one to two days of conventional physical therapy per week. Participants were required to engage in two phases per training day: BCI system calibration and BCI training with the neurofeedback. During the BCI system calibration phase, EEG data were collected while participants performed AOMI or MI task without neurofeedback in order to develop a classification model. The classification model was then implemented in the BCI training with neurofeedback phase. To calibrate the BCI system, the participants were seated in a comfortable chair and placed their paretic hands in the prone position on a table. Sixteen-channel EEG (FP1, FP2, FC3, FC4, C5, C6, C3, C4, C1, C2, CP3, CP4, P3, P4, O1, and O2 following the international 10–20 system) and a g. tec biosignal amplifier (g. USBamp, Graz, Austria) were employed to record the EEG data at a sampling rate of 512 Hz. The ground and reference electrodes were electrodes on the AFz and the left earlobe, respectively. A 14-inch laptop computer was used to provide a graphical user interface for participants engaged in the AOMI or MI task. It was placed in front of them, and the appropriate viewing distance was maintained. The graphical user interface was created using the tkinter, OpenCV, and Pillow python packages.

The participants in the AOMI-based BCI group were asked to perform the AOMI task, whereas the participants in the MI-based BCI group were requested to execute the MI task. The AOMI and MI paradigms were derived from our previous work [34]. Before participants performed the AOMI or MI task; the researcher instructed them on how to perform kinesthetic MI. The researcher would passively extend the participant's paretic wrist and hand, and ask them to feel and memorize the sensation of movement (such as skin contraction and proprioception) that they had to imagine while performing the AOMI or MI task.

The participants began the AOMI or MI task by observing a blank screen for 5 seconds. Next, a black cross appeared in the center of the screen for 3 seconds to alert the participant to begin preparing for the upcoming AOMI or MI task. During this period, participants were instructed to avoid

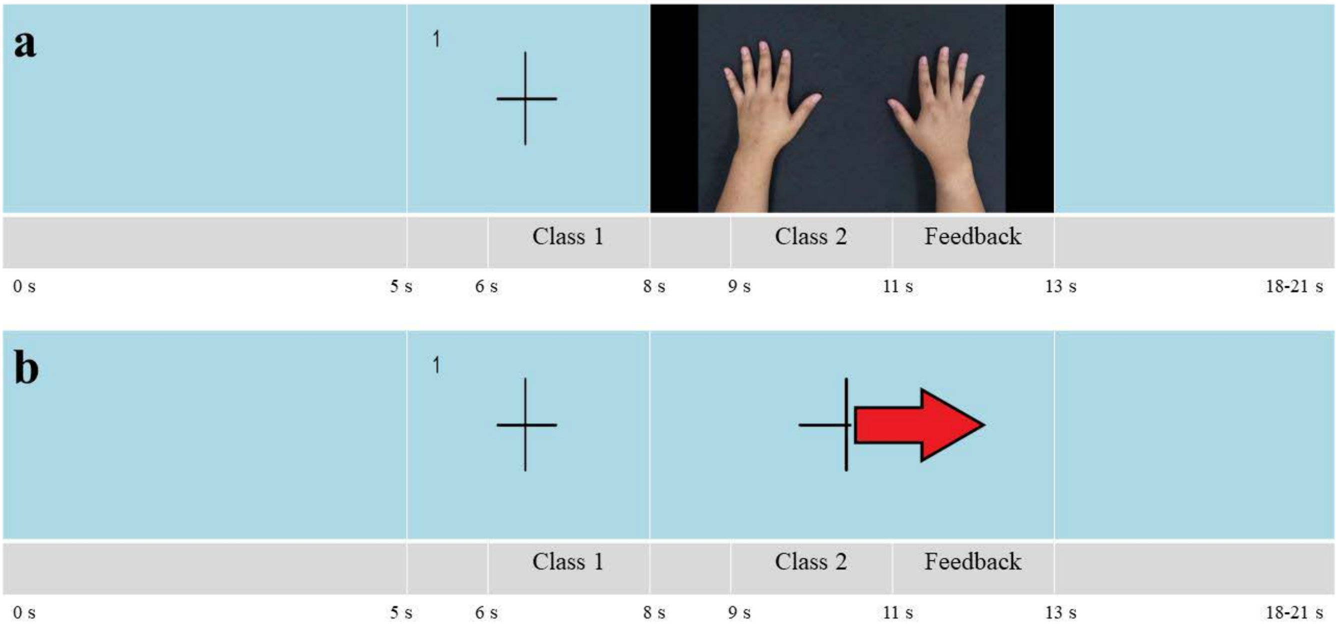

FIGURE 1. **Paradigm of a trial in the AOMI and MI tasks. (a) AOMI task. (b) MI task.**

any physical movements, including eye blinking and saliva swallowing. Then, for the AOMI task, the participants were instructed to simultaneously perform kinesthetic MI of wrist and hand extensions for 5 seconds while watching video-guided movement on the screen. The video-guided movement demonstrated how to perform wrist and hand extensions and appeared on the same side as the paretic hand from the first-person perspective. For the MI task, the participants were instructed to simultaneously perform kinesthetic MI of wrist and hand extensions while they were gazing at the red arrow pointing in the direction of the paretic hand for 5 seconds. During executing kinesthetic MI of wrist and hand extensions, the participants in both groups were not permitted to generate any movement with either the paretic or nonparetic hands, including eye blinking and saliva swallowing. Afterward, the blank screen then reappeared to inform the participants to relax. The relaxation time was randomly set between 5 and 8 seconds before the next trial started to prevent adaptation. The paradigm of a trial in the AOMI and MI tasks is depicted in (Fig 1a, b). During the BCI system calibration phase, participants were required to perform the AOMI or MI task for two sets, of 20 trials each, with 4-minute breaks between each set. Consequently, the EEG data resulting from the AOMI or MI task for a total of 40 trials were used to construct the classification model.

After receiving the EEG data from the 40-trial AOMI or MI task, the EEG data were bandpass filtered from 8–30 Hz by a 4th-order Butterworth filter. Then, we selected the EEG data from five channels placed over the affected sensorimotor region (FC3, C5, C3, C1, CP3 for right-sided hemiparesis and FC4, C6, C4, C2, CP4 for left-sided hemiparesis). Next, the EEG data were chunked into 2-second epochs to establish the data for a 2-class condition. The 6–8 and 9–11 second periods (Fig 1a, b) were represented as 2-second epochs for class 1 (baseline class) and class 2 (imagery class), respectively. Then, a common spatial pattern (CSP) filter was utilized to expand the difference between the two classes. The CSP filter matrix was projected into the original datasets to simultaneously maximize the variance for one class and minimize the variance for another class [43]. Afterward, the CSP-filtered data were squared and averaged to extract band power features. The vectors of band power features for the 2-class condition were subsequently inserted into the linear discriminant analysis (LDA) to generate the classification model [44]. If the model accuracy was less than 60%, the participants were requested to repeatedly calibrate the BCI system until the model accuracy was greater than 60%. The entire processes of building the classification model were carried out with OpenVibe software (v2.2.0) [45].

C. BCI TRAINING WITH NEUROFEEDBACK

In this phase, the participants performed the AOMI or MI task using functional electrical stimulation (FES) as neurofeedback. We selected FES as neurofeedback because it can improve muscle mass and endurance in the paretic arm. Moreover, it can provide somatosensory information and is commonly applied in BCI systems for stroke rehabilitation [46], [47]. The FES device was custom-made, and the parameters for muscle stimulation were as follows: 1) biphasic square waveform; 2) pulse width at 250 μs; 3) stimulation frequency at 50 Hz; 4) the FES electrodes were placed on the extensor digitorum muscle of the paretic arm; and

5) voltage intensities of approximately 60–80 volts, which were sufficient to produce painless wrist and hand extensions.

On each training day, participants were required to complete four sets of the AOMI or MI task with FES feedback, with 20 trials per set and 4-minute breaks between each set. Therefore, the participants performed 80 trials of the AOMI or MI task with FES feedback. The procedure of the AOMI or MI task in each trial was identical to the BCI system calibration phase, with the addition of FES feedback. The FES would be activated at seconds 11 to 13 (Fig 1a, b) if the participants could execute the AOMI or MI task effectively.

To evaluate the AOMI or MI task performance, the 2-second EEG data from five channels placed over the affected sensorimotor region during the AOMI or MI task (i.e., seconds 9 to 11 (Fig 1a, b)) were selected. Next, the EEG data were transformed into feature vectors using the procedures described in the section on BCI system calibration (i.e., 4th order Butterworth filter at 8–30 Hz, CSP filter, and band power features). Then, the feature vectors were classified by the LDA model. The FES was activated if the feature vectors were classified as class 2 (imagery class). In contrast, the FES was not activated if the feature vectors were classified as class 1 (baseline class). The whole process of BCI training with neurofeedback was conducted by OpenVibe software (v2.2.0) [45] and a Python script. (Fig 2a, b) depicts participants receiving AOMI and MI-based BCI training with FES feedback.

D. OUTCOME MEASURES

The purpose of the present study was to examine the effects of AOMI and MI-based BCI training on upper limb recovery, cortical excitation, and cognitive task performance in chronic stroke patients. The change in FMA-UE scores (Δ FMA-UE scores) was decided as the primary outcome. The blinded physical therapists measured the FMA-UE score in each participant before receiving and after completing the intervention within seven days. Cortical excitation and cognitive task performance constituted the secondary outcomes.

To compare the cortical excitation between AOMI and MI-based BCI training, ERD/ERS analysis of C3 (for right-sided hemiparesis participants) or C4 (for left-sided hemiparesis participants) channels was applied. We focused on analyzing % ERD/ERS values of C3 or C4 because they were located over the affected sensorimotor hand region, and the equation (1) for obtaining % ERD/ERS values was as follows [14].

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

$\boldsymbol{A}$ is the power spectrum value during the AOMI or MI task. $\boldsymbol{R}$ is the power spectrum value before executing the AOMI or MI task. The EEG data during AOMI or MI-based BCI training with FES feedback (80 trials) were used to calculate % ERD/ERS values. To obtain $\boldsymbol{A}$ and $\boldsymbol{R}$ values, the EEG data were first bandpass filtered between 8 and 30 Hz. Next, an independent component analysis (ICA) [48] was applied to eliminate muscle and electrical artifacts resulting from FES. Then, the EEG data from seconds 9 to 13 and from seconds 7 to 8 (Fig 1a, b) were employed to compute $\boldsymbol{A}$ and $\boldsymbol{R}$, respectively. The power spectrum values of the alpha (8–13 Hz) and beta (14–30 Hz) bands of $\boldsymbol{A}$ and $\boldsymbol{R}$ in each trial were estimated using Welch's method with a Hamming window (with 50% overlap). After averaging $\boldsymbol{A}$ and $\boldsymbol{R}$ across 80 trials, these values were plugged into the above equation to obtain the % ERD/ERS values of the alpha (8–13 Hz) and beta (14–30 Hz) frequency bands. We calculated % ERD/ERS values on each training day and averaged them across 12 training days to obtain the mean % ERD/ERS values. If the value of % ERD/ERS was a negative number, it referred to activated neural activity. However, if the value of % ERD/ERS was a positive number, it indicated inhibited neural activity [13], [14]. The whole process of calculating % ERD/ERS was facilitated by MATLAB (R2020a) and the EEGLAB (v2020.0) toolbox.

To compare the cognitive task performance between the AOMI and MI-based BCI groups, online classification accuracy was utilized. On each training day, we counted the number of times participants were able to activate FES in response to the AOMI or MI task and converted that number to a percentage using the following equation (2) [49], [50].

$$\% \textbf{\textit{online classification accuracy}} = \frac{\boldsymbol{i} \times \mathbf{100}}{\boldsymbol{N}} \tag{2}$$

$\boldsymbol{N}$ is the total number of AOMI or MI tasks in total (80 times). $\boldsymbol{i}$ represents the number of times that the FES was activated due to the AOMI or MI task. They were then averaged over 12 training days to determine the mean % online classification accuracy. A greater mean % of online classification accuracy indicated superior cognitive task performance.

E. STATISTICAL ANALYSIS

Due to the small sample size ($n = 17$), nonparametric tests were used for statistical analysis. The Mann Whitney U test was employed to compare age, time since stroke, MMSE scores, baseline FMA-UE scores, Δ FMA-UE scores, mean % ERD/ERS values of C3/C4 (alpha and beta bands), and mean % online classification accuracy between groups. The Wilcoxon signed-rank test was applied to compare FMA-UE scores between pre- and post-intervention within groups. Statistical significance was determined when p values were less than 0.05 (two-sided test). The statistical analysis was conducted by PASW Statistics software version 18.0 (formerly SPSS Statistics, Chicago).

III. RESULTS

At the beginning of the intervention, there were no significant differences between the AOMI and MI-based BCI groups in terms of age ($p = 0.735$), time since stroke ($p = 0.210$), MMSE scores ($p = 1$), or baseline FMA-UE scores ($p = 0.962$). Thus, the severity of upper limb impairment at baseline was comparable between the AOMI and MI-based BCI groups. When comparing FMA-UE scores between pre- and

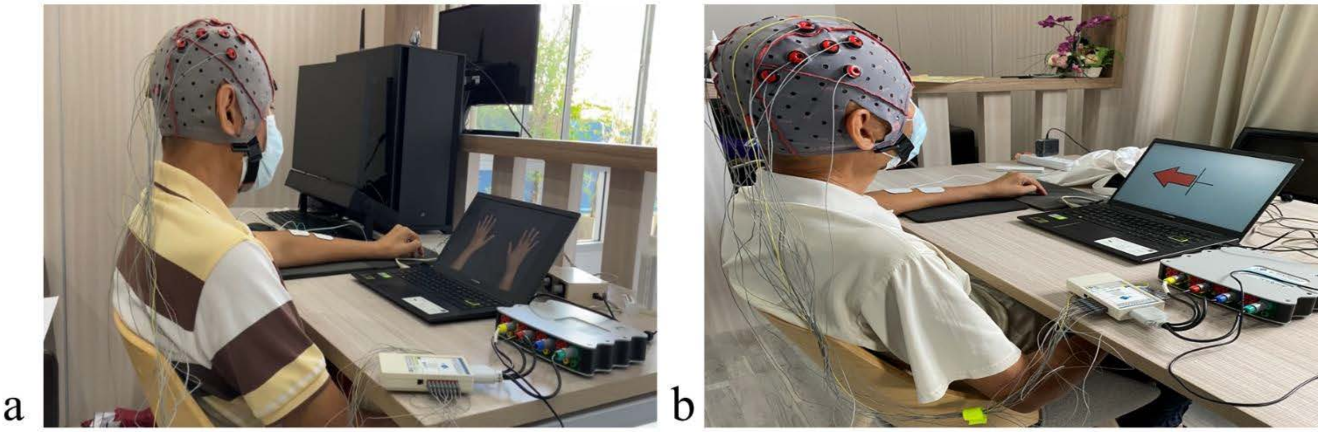

FIGURE 2. AOMI AND MI-based BCI training with FES feedback. (a) AOMI-based BCI group. (b) MI-based BCI group.

TABLE 2. FMA-UE scores between pre- and post-intervention of all participants.

Participant	FMA-UE scores	
	Pre-intervention	Post-intervention
AOMI1	34	46
AOMI2	34	42
AOMI3	11	15
AOMI4	22	29
AOMI5	44	50
AOMI6	41	46
AOMI7	11	15
AOMI8	43	48
AOMI9	10	10
Mean ± SD	27.78 ± 13.58	33.44 ± 15.36
p values	0.012*	
MI1	29	32
MI2	30	30
MI3	40	44
MI4	45	49
MI5	22	23
MI6	20	22
MI7	28	31
MI8	21	26
Mean ± SD	29.38 ± 8.45	32.125 ± 9.04
p values	0.018*	

* represents significance in Wilcoxon signed-rank test (p values < 0.05)

post-intervention, significant differences in FMA-UE scores in both AOMI and MI-based BCI groups ($p = 0.012$ and 0.018, respectively) were found. The results of FMA-UE scores between pre-and post-intervention of all participants are presented in Table 2.

For comparison of Δ FMA-UE scores between groups, we found that the AOMI-based BCI group had significantly higher Δ FMA-UE scores than the MI-based BCI group ($p = 0.022$). Furthermore, the mean % ERD/ERS values of C3/C4 in the alpha and beta bands and the mean % online classification accuracy were also found to be significantly higher in the AOMI-based BCI than in the MI-based BCI group ($p = 0.034$, 0.021, and 0.038, respectively). The results of Δ FMA-UE scores, mean % ERD/ERS values of C3/C4, and the mean % online classification accuracy of all participants are presented in Table 3. The results of % ERD/ERS values of C3/C4 and % online classification accuracy of each participant are depicted in (Fig 3).

In addition, we investigated the time-course of changes in % ERD/ERS values of C3/C4 and % online classification accuracy between the AOMI and MI-based BCI groups. Spearman's correlation was performed between the grand average of % ERD/ERS values of C3/C4 and % online classification accuracy and training session. The AOMI-based BCI group demonstrated a greater increase in % ERD/ERS values of C3/C4 in the alpha and beta bands over time compared to the MI-based BCI group. However, the time-course of changes in % online classification accuracy between AOMI and MI-based BCI groups were not different. Both AOMI and MI-based BCI groups presented increasing % online

TABLE 3. Δ FMA-UE scores, mean % ERD/ERS values, and mean % online classification accuracy of all participants.

Participant	Δ FMA-UE scores	Mean % ERD/ERS values of C3/C4		Mean % online classification accuracy
		Alpha band (8-13 Hz)	Beta band (14-30 Hz)	
AOMI1	12	−53.10	−29.52	83.85
AOMI2	8	−48.67	−35.60	90.31
AOMI3	4	−27.85	−14.22	69.69
AOMI4	7	−12.83	−20.24	74.16
AOMI5	6	−16.17	−32.55	63.75
AOMI6	5	−39.59	−21.92	82.5
AOMI7	4	−26.91	−36.83	74.58
AOMI8	5	−23.74	−26.01	67.5
AOMI9	0	−28.32	−19.79	65.73
Mean ± SD	5.67 ± 3.09	−30.8 ± 12.96	−26.3 ± 7.39	74.67 ± 8.60
MI1	3	-7.71	-7.35	49.18
MI2	0	-15.90	-4.64	73.38
MI3	4	-23.17	-10.04	69.98
MI4	4	-48.42	-31.68	90.23
MI5	1	-16.87	-21.80	63.75
MI6	2	-13.98	-7.15	49.79
MI7	3	-14.26	-21.38	67.08
MI8	5	0.55	-13.57	60.1
Mean ± SD	2.75 ± 1.56	−17.47 ± 13.4	−14.7 ± 8.79	64.31 ± 12.40
p values	0.022*	0.034*	0.021*	0.038*

* represents significance in the Mann–Whitney U test (p values < 0.05)

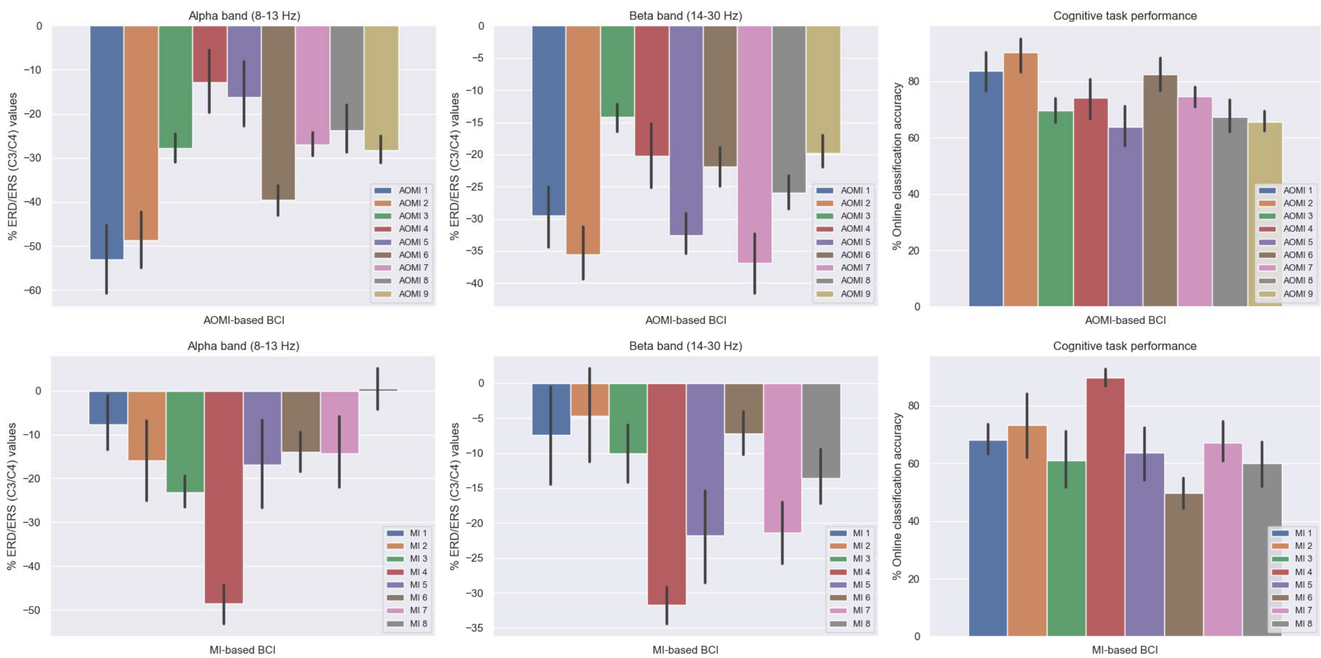

FIGURE 3. % ERD/ERS values of C3/C4 and % online classification accuracy of each participant.

classification accuracy as time passed. The results of the time-course of changes in % ERD/ERS values of C3/C4 and % online classification accuracy are shown in (Fig 4).

To explore whether greater mean % ERD/ERS values of C3/C4 and mean % online classification accuracy contributed to higher Δ FMA-UE scores, the correlation analysis was performed by using Spearman's correlation. Only a significant negative correlation between Δ FMA-UE scores and mean % ERD/ERS values of C3/C4 in the beta band ($r = -0.571$, $p = 0.017$) was observed. There was no significant correlation between Δ FMA-UE scores and mean % ERD/ERS values of C3/C4 in the alpha band ($r = -0.291$, $p = 0.257$) or between Δ FMA-UE scores and mean % online classification accuracy ($r = 0.459$, $p = 0.064$). The results of the correlation analysis between Δ FMA-UE scores and the other variables are shown in (Fig 5a, b, and c).

In addition, a significant negative correlation between the mean % online classification and mean % ERD/ERS values

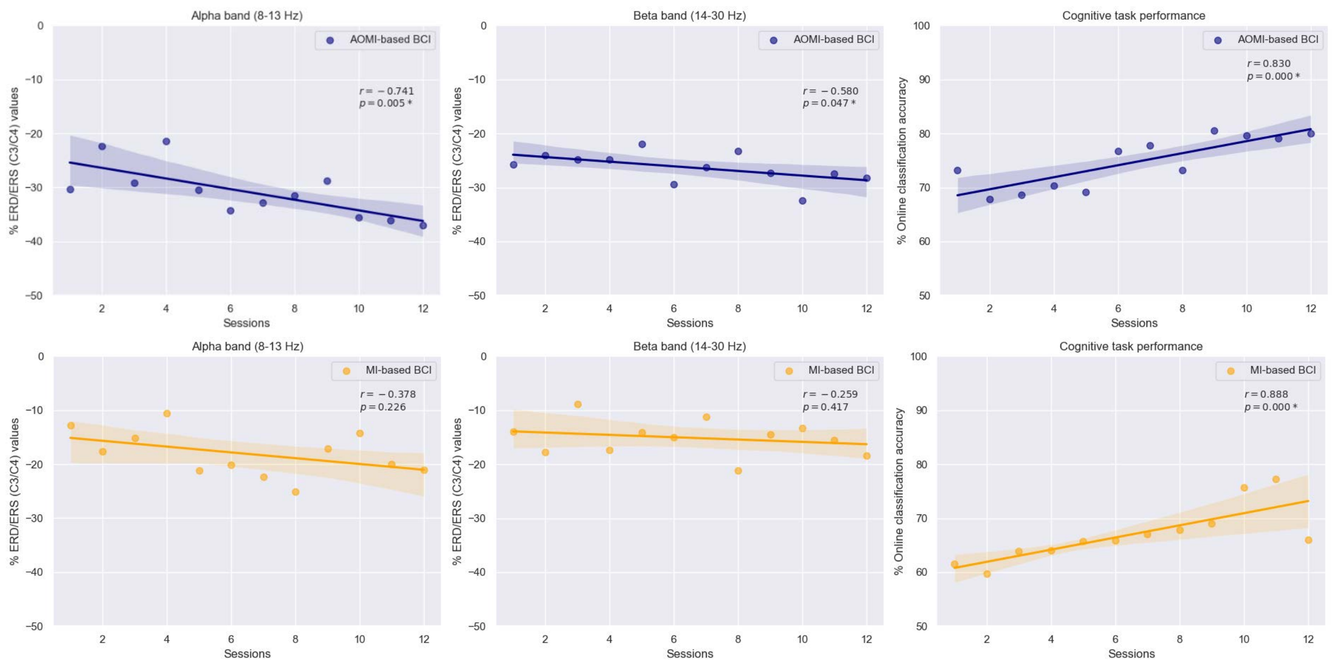

FIGURE 4. **Time-course of changes in the grand average of % ERD/ERS values of C3/C4 and % online classification accuracy between AOMI and MI-based BCI training. * represents significance in Spearman's correlation (p values < 0.05).**

of C3/C4 in both the alpha and beta bands ($r = -0.742$, $p = 0.001$ and $r = -0.553$, $p = 0.021$, respectively) were observed. These results indicated a correlation between higher online classical accuracy and greater cortical excitation of the affected sensorimotor hand region. The results of the correlation analysis between the mean % online classification accuracy and mean % ERD/ERS values of C3/C4 in both the alpha and beta bands are depicted in (Fig 6a, b).

IV. DISCUSSION

The purpose of this study was to compare the effects of AOMI and MI-based BCI training on upper limb recovery, cortical excitation, and cognitive task performance in chronic stroke patients. Both AOMI and MI-based BCI training with FES feedback was found to be effective in restoring upper limb function in chronic stroke patients. Nevertheless, AOMI-based BCI training resulted in significantly higher motor improvement than MI-based BCI training. Additionally, AOMI-based BCI training demonstrated significantly greater cortical excitation of the affected sensorimotor hand region. (% ERD/ERS values of C3/C4 in the alpha and beta bands) and cognitive task performance (% online classification accuracy). Moreover, the AOMI-based BCI training was found to be better than MI-based BCI in terms of facilitating greater cortical excitation of the affected sensorimotor hand region over the course of time. To discover whether the greater cortical excitation of the affected sensorimotor hand region and the higher cognitive task performance induced the increased upper limb recovery, a correlation analysis was conducted. We discovered a significant correlation between higher upper limb function improvement and greater ERD values of C3/C4 in the beta band. In addition, we discovered a significant correlation between cognitive task performance and cortical excitation in the affected sensorimotor hand region. These results indicated that the higher cognitive task performance during AOMI-based BCI training may have promoted the greater cortical excitation of the affected sensorimotor hand region, which contributed to the greater improvement in upper limb function compared to MI-based BCI training.

MI-based BCI training with neurofeedback has been shown to improve upper limb function in stroke patients, and our results are consistent with previous research [17], [18], [19], [20], [21], [51], [52], [53], [54], [55]. The therapeutic effect of BCI training may be involved in promoting Hebbian plasticity, the mechanism that strengthens the synaptic connections between neurons [56], [57]. Although, both AOMI and MI-based BCI training with FES feedback improved upper limb recovery, the AOMI-based BCI group demonstrated a significantly greater motor improvement. Even though there were differences in the stroke phase (subacute or chronic phase) and training method (pure AOMI or AOMI-based BCI training with FES feedback), these results were congruent with Sun's study [40]. In addition, we found that the mean improvement in the FMA-UE score in the AOMI-based BCI group was 5.67, which reached the threshold of the minimum clinically important difference (4.24 to 7.25 points) [58]. However, the mean improvement in the FMA-UE score for the MI-based BCI group was only 2.75. The greater improvement in upper limb function in the

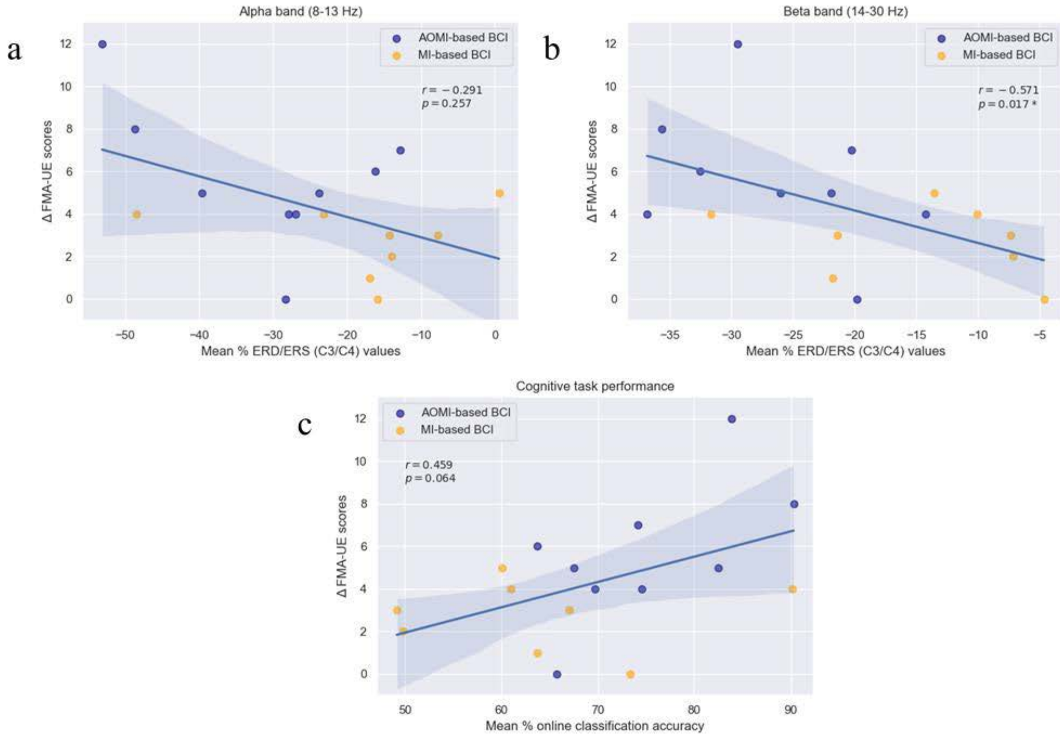

FIGURE 5. **Results of the correlation analysis between Δ FMA-UE scores and the other outcomes. (a) Δ FMA-UE scores and mean % ERD/ERS values of C3/C4 in the alpha band. (b) Δ FMA-UE scores and mean % ERD/ERS values of C3/C4 in the beta band. (c) Δ FMA-UE scores and mean % online classification accuracy. * represents significance in Spearman's correlation (p values < 0.05).**

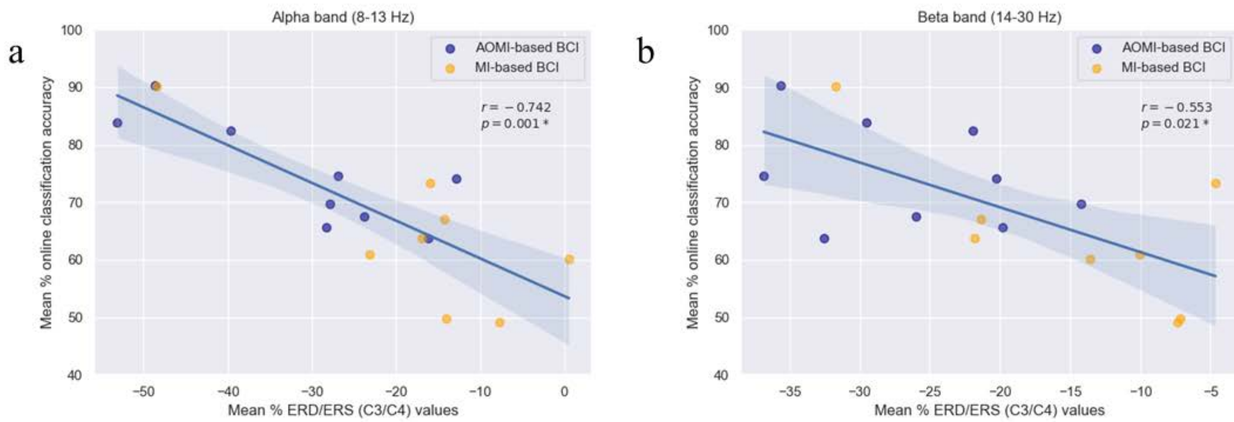

FIGURE 6. **Results of the correlation analysis between mean % online classification accuracy and mean % ERD/ERS values of C3/C4 in both the alpha and beta bands. (a) Mean % online classification accuracy and mean % ERD/ERS values of C3/C4 in the alpha band. (b) Mean % online classification accuracy and mean % ERD/ERS values of C3/C4 in the beta band. * represents significance in Spearman's correlation (p values < 0.05).**

AOMI-based BCI group may be attributed to the greater cortical excitation of the affected sensorimotor hand region during the AOMI task with FES feedback. Increasing neural excitation in the affected sensorimotor hand region is essential for enhancing motor recovery in stroke patients [52], [59], [60].

To compare the cortical excitation of the affected sensorimotor hand region during the BCI training in this study, ERD analysis was conducted. ERD typically refers to activated cortical neurons involved in sensory, motor, and cognitive processing [13], [14]. In the current study, we showed that the AOMI-based BCI training produced a higher ERD compared to MI-based BCI training, which was similar to a previous study [40]. Additionally, we also found that AOMI-based BCI training was more effective than MI-based BCI training in terms of encouraging the participants to produce more ERD over time. The increased ERD during AOMI-based

BCI training may be caused by the automatic activation of the mirror neuron system, which is spontaneously excited by observation of body movement [24], [25], [33], [34]. Furthermore, the use of video-guided movement during the MI task may boost task attention and guide participants to execute MI more easily, resulting in a significant increase in ERD [14], [34]. Moreover, our previous study involving chronic stroke patients revealed that AOMI was superior to MI in terms of enhancing ERD, resulting in improved offline classification performance [34]. Similarly, the classification model in this study was based on ERD features. Therefore, the greater ERD during the AOMI task may advocate that the AOMI-based BCI group manifested higher online classification accuracy than the MI-based BCI group. The greater online classification accuracy indicated a higher number of activated FES that could further augment ERD [61]. Consequently, the greater ERD during the AOMI task coincided with the higher number of activated FES may promoted more activated neurons in the affected sensorimotor hand region, which contributed to the greater improvement of upper limb function.

Notwithstanding, AOMI-based BCI training seemed to be more effective than MI-based BCI training in terms of promoting motor recovery. The FMA-UE score of one participant (AOMI9) in the AOMI-based BCI group did not improve following the intervention. Nonetheless, this did not imply that she received no therapeutic benefit from the training. At the onset of the intervention, she was completely incapable of wrist extension. After completing the training, she could perform wrist extension with a small degree of range of motion. However, the degree of movement (less than 15 degrees) did not meet the FMA-UE evaluation threshold to obtain a point. In addition, she was the only participant in this study who had sleepless symptoms prior to stroke onset that continued until now. A previous meta-analysis revealed that sleep disorders negatively impact stroke rehabilitation [62]. Therefore, it is hypothesized that this factor might have negatively impacted her upper limb recovery in the present study. Further research is required to determine whether sleepless symptoms influence the therapeutic effect of BCI training on motor recovery in stroke patients.

Moreover, we compared Δ FMA-UE scores due to AOMI-based BCI training to a similar study in which chronic stroke patients received MI-based BCI training. We discovered that the Δ FMA-UE scores in our study were lower. The mean Δ FMA-UE score caused by MI-based BCI training with FES feedback was 6.6 in the study by Biasiucci et al. [51], whereas our score was 5.67. The differences in the score could be due to the substantial difference in online classification accuracy between the two studies. The online classification accuracy in Biasiucci et al. [51] was 85.95 $\pm$ 8.40%, whereas our outcome was 74.67 $\pm$ 8.60%. In the present study, the classification model was based on EEG data from five channels and band power features in the frequency range of 8–30 Hz, whereas the classification model in Biasiucci et al. [51] was built on EEG data from 16 channels and specific band power features for each participant. Consequently, these variables may explain why their online classification accuracy was higher. As stated previously, the higher online classification performance was correlated with, the higher number of patients receiving FES feedback, which led to the expansion of more activated neurons and greater improvements in motor function. In addition, the number of participants in Biasiucci et al. [51] (n = 14) was greater than that in our study (n = 9); consequently, these variables may have influenced to the inconsistency of the results. To confirm our findings and reduce the bias due to the classification model, future studies should compare the effect of AOMI and MI-based BCI training on motor recovery in a larger sample size and use a classification model based on specific band power for each participant.

In summary, the current study showed that AOMI-based BCI training was superior to MI-based BCI training with respect to improving upper limb function, cortical excitation of the affected sensorimotor hand region, and cognitive task performance in chronic stroke patients. Implementing AO (video-guided movement) during the MI task is inexpensive and straightforward in BCI systems. Our hope is that these results will promote the widespread use of AOMI in BCI systems for stroke rehabilitation. For instance, AOMI-based BCI training can be applied to promote lower limb recovery in stroke patients. As mentioned previously, the small sample size was a limitation of this study. Additionally, in the current study, we did not have a sham group to ensure that the improvement in upper limb function in the participants was not by chance. In addition, this study was conducted as a clinical trial in parallel. To reduce the variation in MI ability among participants, additional research should verify our findings using a clinical crossover trial. In addition, we did not monitor how long the therapeutic effect lasted, and we evaluated upper limb function using only FMA-UE, which may not be sensitive enough to detect a small motor gain. Therefore, future research should address these issues and reexamine our findings.

V. CONCLUSION

Both AOMI and MI-based BCI training could improve upper limb function in chronic stroke patients. However, AOMI-based BCI training presented significantly greater therapeutic effect than MI-based BCI training. Moreover, AOMI-based BCI training also encouraged greater cortical excitation of the affected sensorimotor hand region and cognitive task performance than MI-based BCI training. Higher cognitive task performance during AOMI-based BCI training may promote greater cortical excitation of the affected sensorimotor hand region, which contributes to greater motor improvement compared to MI-based BCI training, as indicated by the correlation analysis.

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