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RESEARCH ARTICLE

Applying Combined Action Observation and Motor Imagery to Enhance Classification Performance in a Brain–Computer Interface System for Stroke Patients

NUTTAWAT RUNGSIRISILP AND YODCHANAN WONGSAWAT
Department of Biomedical Engineering, Faculty of Engineering, Mahidol University, Nakhon Pathom 73170, Thailand
Corresponding author: Yodchanan Wongsawat (yodchanan.won@mahidol.ac.th)

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ABSTRACT Motor imagery (MI) and action observation (AO) are mental practices commonly applied in brain–computer interface (BCI) systems for stroke rehabilitation. However, previous studies have reported that combined AO and MI (AOMI) is more effective than MI or AO alone in terms of enhanced event-related desynchronization (ERD), which expresses cortical excitability and improves the classification performance of the BCI system in healthy subjects. Nonetheless, evidence the use of this strategy in stroke patients is still lacking. Hence, this study aimed to investigate the effect of AOMI on ERD and classification performance in chronic stroke patients. Ten chronic stroke participants were recruited for this study. Each participant was asked to perform both MI (control condition) and AOMI (experimental condition) tasks. For the MI task, the participants requested to perform MI while gazing at a static arrow picture. For the AOMI task, the participants were given a video-guided movement while executing MI. An array of 16 Ag/AgCl electrodes were used to record electroencephalographic (EEG) data during the mental tasks to analyze ERD amplitudes. Common spatial patterns (CSPs) combined with support vector machines (SVMs) were employed to evaluate the classification performance (offline analysis) of the baseline and imagery classes under each condition. Our results indicated that the ERD values and classification accuracy in AOMI were significantly greater than those under MI conditions. Moreover, a significant negative correlation between ERD values and classification performance was also found. In other words, enhanced ERD values (more negative values) also increased classification performance.

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

I. INTRODUCTION

A stroke is a major cause of death worldwide. Most stroke survivors commonly experience hemiparesis on one side of the body [1]. Particularly, impairment of upper limb function greatly impacts their activities of daily living due to the inability to perform fine motor skills. Moreover, upper limb function rarely ever recovers completely. Hence, creating an effective therapeutic method to improve upper limb function is important for aiding stroke patients to resume normal life. [2]. Presently, constraint-induced movement therapy is a helpful therapeutic method that can enhance the recovery of upper limb function by encouraging the use of an affected upper limb. However, moderately to severely motor-impaired

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patients may not obtain sufficient benefits from this technique due to their incapacity to produce upper limb movement. Thus, other strategies to help these patients improve their upper limb function are needed [2], [3].

Motor imagery (MI) is a mental task that requires imagining a physical movement without performing the actual action. It is an alternate therapeutic method in which severely motor-impaired patients can access brain areas associated with motor execution without the need for voluntary movement [4]. Generally, there are two types of MI: kinesthetic MI and visual MI. Kinesthetic MI is an imagination of sensation perceived during executing real movement (such as muscle contraction, skin perceptions, proprioception), while visual MI creates a visual representation of movement in terms of the third-person view. Nevertheless, previous studies have indicated that kinesthetic MI was more effective than visual MI in activating brain areas related to motor execution [5], [6]. Therefore, kinesthetic MI appears to be more favorable to apply in stroke rehabilitation in conjunction with conventional therapy [4]. However, the main problem of applying MI training in stroke patients is the difficulty of evaluating the MI performance in these patients based on observation alone. Fortunately, brain–computer interface (BCI) technology currently exists to overcome this problem.

BCI is a system that can acquire brain signals while a stroke patient is executing MI. It can evaluate his/her MI performance using an algorithm to interpret that brain signal during the MI task [3]. According to electroencephalography (EEG) studies in healthy subjects, it is well known that executing MI produces a phenomenon called event-related desynchronization or synchronization (ERD/ERS). ERD is a decrease in EEG power, whereas ERS is an increase this power related to an event. Furthermore, they usually occur within specific frequency bands, including the alpha or mu and beta bands (8–13 Hz and 14–30 Hz, respectively). Normally, ERD appears over the contralateral sensorimotor areas of the imagined upper limb during MI. In contrast, ERS presents after MI termination. ERD refers to the activated cortical areas involved in sensory, motor, and cognitive processing, whereas ERS reflects inhibition of neural activity [7], [8]. Thus, ERD is usually used as a power spectrum feature in MI-based BCI systems to indicate that a stroke patient is performing MI.

In MI-based BCI training, a stroke patient is asked to perform kinesthetic MI while the system will monitor ERD. If ERD occurs, the system will provide useful feedback (i.e., functional electrical stimulation, haptic and visual feedback) back to the patient. In contrast, if ERD does not occur, the system will not give feedback to the patient. Hence, the patient can learn how to generate ERD by trial-and-error learning. Furthermore, neurofeedback in conjunction with ERD occurrence is a potential strategy for inducing neural plasticity that leads to improved motor function in stroke patients [3], [9], [10]. Moreover, previous studies have reported that MI-based BCI with neurofeedback could improve motor function in stroke patients [11]–[15].

In addition to MI, action observation (AO) is another way to trigger cortical areas involved in motor execution that passes through the mirror neural system [16]. AO carefully observe a movement performed by another person. It can recruit the same neural structures related to that observed movement as if he or she truly executed the observed action [17]. Hence, the idea of using AO for encouraging motor recovery in stroke patients has been proposed and is called AO therapy. AO therapy requires stroke patients to observe a specific object-directed action shown on a computer screen. The patients are then asked to perform the action that they observed [18]. Nevertheless, stroke patients who have severe motor impairment may not receive any benefits from this method because of their restricted ability to perform voluntary movement. Additionally, previous EEG studies revealed that ERD also occurred in AO and MI [19], [20]. Therefore, combining AO with the BCI system is another therapeutic training mode for enhancing motor recovery in severely motor-impaired stroke patients [21], [22].

Commonly, previous studies have examined the effect of MI- or AO-based BCI training on motor recovery in stroke patients separately. However, multimodal brain imaging studies have revealed that combined action observation and motor imagery (AOMI) could facilitate the brain areas associated with motor execution more effectively than MI or AO alone in healthy subjects [23]–[28]. AOMI is a movement imagination concurrent with watching the same imagined action shown on a computer screen [29], [30]. Previous research has reported that AOMI training could improve balance and muscle force and aiming performance in healthy subjects [31]–[33]. Although the AOMI concept is not a novel method, it is very rarely used in neurorehabilitation, particularly in stroke patients [29].

Few studies have investigated the effect of AOMI on motor recovery and cortical activity in stroke patients. Sun *et al.* [34] were the first to examine the effect of AOMI training on upper limb function and cortical activity in subacute stroke patients. In Sun's study, the patients were randomly allocated into experimental and control groups. In the experimental group, the patients were given AOMI training and conventional therapy, whereas the patients in the control group received asynchronous AOMI and conventional therapy. After four weeks of training, they found that the patients in the experimental group showed significantly greater improvement of upper limb function as evaluated by the Fugl–Meyer assessment compared to the patients in the control group. Furthermore, the patients in the experimental group also showed a significantly larger amplitude ERD in the alpha or mu band (7–12 Hz) at the C3 electrode (lesional sensorimotor area). In addition to Sun's study, Ichidi *et al.* [35] investigated the effect of AOMI on ERD patterns in stroke patients (no information on the stroke phase) during AOMI and MI tasks. In Ichidi's study, the patients were asked to execute three different cognitive tasks: MI with static hand pictures, MI with static words, and AOMI. They found that AOMI conditions demonstrated greater ERD amplitudes in the beta band (13–28 Hz) at C3 and C4 electrodes compared to MI conditions.

The common problem in EEG-based BCI systems is the variance of classification performance among subjects depending on the ability to generate ERD in each individual. In addition, stroke patients usually show weak ERD in the ipsilesional sensorimotor cortex during cognitive tasks, which negatively affects the classification performance [19], [36], [37]. According to the abovementioned studies, AOMI is likely to be a better strategy than MI and AO for producing ERD. Moreover, a previous study has reported that AOMI could lead to an improvement int the classification performance of the BCI system in healthy subjects [27].

Therefore, AOMI is probably also effective for improving classification performance in stroke patients. To verify this hypothesis, the present study aimed to investigate the effect of AOMI on cortical activity and classification performance in chronic stroke patients.

II. MATERIALS AND METHODS

A. PARTICIPANTS

In the present study, we recruited 10 chronic stroke patients with moderate to severe upper limb impairment, who were right-handed prior to stroke (one female, two right hemiparesis) from the Physical Therapy Center of Mahidol University. The inclusion criteria included several parameters: (1) first-ever stroke caused by ischemia or hemorrhage, (2) stroke onset more than six months, (3) age between 40 and 80 years, (4) normal vision, (5) Mini-Mental State Exam (MMSE) score $\geq$ 25, which means the participant must have normal cognitive status, (6) Fugl–Meyer Upper Extremity (FM-UE) $\leq$ 42, and (7) no previous experience with MI or AO. The participants were excluded if they had hemispatial neglect, aphasia, apraxia, and/or history of. Epilepsy. All participants signed written informed consents to participate in this study, which was approved by the Mahidol University Central Institutional Review Board (COA No. MU-CIRB 2020/097.3107). Participant details are presented in Table 1.

B. EXPERIMENTAL DESIGN

To evaluate the contribution of AOMI to classification performance, the MI task was used as the control condition. Before the participants participated in AOMI and MI, the researcher taught the participants how to execute kinesthetic MI. The researcher would perform passive movement of wrist and hand extension at the paretic hand and ask the participants to feel and memorize the sensation of movement (such as skin contraction, proprioception), which they had to imagine while performing kinesthetic MI.

In both AOMI and MI tasks, the participants started by watching a blank screen for 5 s after which a black cross appeared at the center of the display for 3 s to alert the participants to prepare themselves for performing the upcoming cognitive task. During this period, the participants were instructed to avoid any body movements, including eye blinking and saliva swallowing. Next, for the AOMI task, video-guided movement was shown on the computer screen for 5 s to demonstrate how to perform wrist and hand extensions. The video was presented from the first-person view on the same side as the paretic hand. The participants were then asked to concurrently perform kinesthetic MI while watching the video-guided movement. In contrast, for the MI task, the participants had to perform kinesthetic MI while watching the red arrow pointing in the direction of the paretic hand for 5 s. During the AOMI and MI periods, the participants were not allowed to produce any movement with the paretic hand. After that, the blank screen appeared again to inform the participants to relax. The relaxation time was randomly set between 5 and 8 s before the next trial started to avoid adaptation. A schematic of a trial in the AOMI and MI tasks is shown in Fig 1(a) and (b), respectively. In this study, each participant participated in the experiment for two days. On the first day, half of the participants were randomly assigned to perform the AOMI task, and the remaining participants were allocated to perform the MI task. On the second day, the participants who initially performed the AOMI task were assigned to participate in the MI task, whereas the participants who initially performed the MI task were assigned to participate in the AOMI task. On each experimental day, each participant was asked to perform the cognitive task for two sessions. A session was composed of 20 trials with 3-minute breaks between each session. Therefore, the total number of cognitive tasks was 40 trials for each condition (40 AOMI trials and 40 MI trials). The experimental trial was conducted for two days to prevent accumulated mental fatigue and reduce the effect of short-term memory from the prior task.

C. EEG DATA RECORDING

The participants were seated in a comfortable chair, and each participant placed his/her forearm of the affected side on a desk. A 14-inch laptop computer was set in front of them, and the display distance was proper for eyesight. A g. tec biosignal amplifier (g. USBamp, Graz, Austria) was used to acquire EEG data during the experiment. 16 electrode placements (FP1, FP2, FC3, FC4, C5, C6, C3, C4, C1, C2, CP3, CP4, P3, P4, O1, and O2 in accordance with the international 10–20 system), which are presented in Fig 2 were selected to record the EEG data at a sampling rate of 512 Hz. Electrodes on the AFz and the left earlobe were used as the ground electrode and reference electrode, respectively. The electrode impedances used to acquire the EEG data were below 5 KΩ. The graphical user interface for the participants to perform the AOMI and MI tasks was created by a Python script.

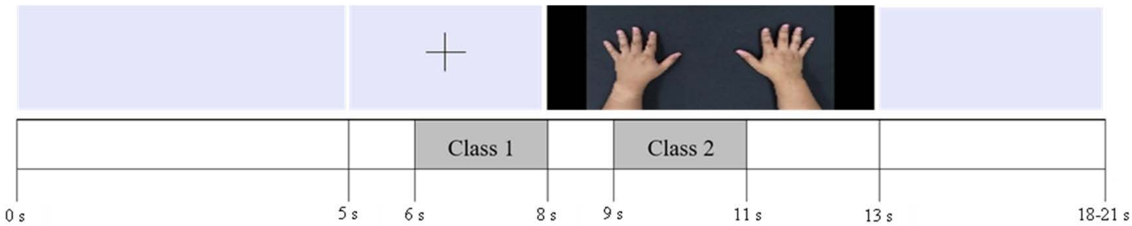
D. ERD/ERS AND TIME-FREQUENCY ANALYSES

In this study, we examined the cortical activity between AOMI and MI conditions by means of ERD/ERS and time-frequency analyses. The EEG data from C3 (for right-sided hemiparesis participants) or C4 (for left-sided hemiparesis participants) were selected, which were placed over the

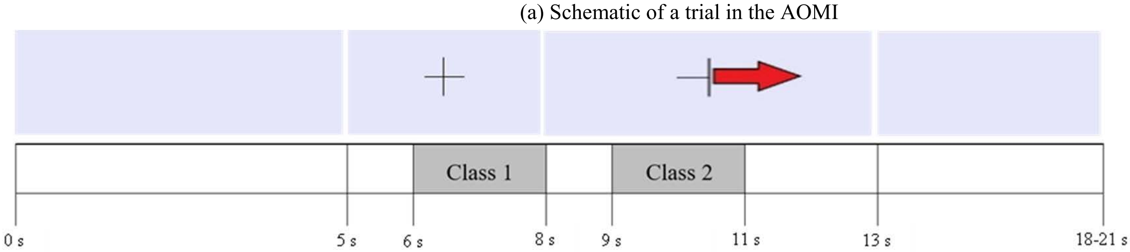
TABLE 1. Participant details.

Participant	Gender	Age (years)	Time since stroke (months)	Lesion type	Paretic side	MMSE score	FMA-UE score
P1	Male	53	144	Hemorrhage	Left	30	34
P2	Male	61	48	Ischemia	Right	25	29
P3	Female	68	14	Ischemia	Right	29	34
P4	Male	69	20	Ischemia	Left	28	13
P5	Male	54	24	Hemorrhage	Left	30	30
P6	Male	60	168	Ischemia	Left	27	42
P7	Male	56	96	Hemorrhage	Left	29	22
P8	Male	50	17	Ischemia	Left	29	20
P9	Male	74	36	Ischemia	Left	30	9
P10	Male	55	8	Ischemia	Left	30	28
Mean		60	57.5			28.7	26.1
SD		7.53	55			1.55	9.6

Abbreviation: MMSE = Mini-Mental State Exam, FMA-UE = Fugl–Meyer Upper Extremity



(a) Schematic of a trial in the AOMI



(b) Schematic of a trial in the MI

FIGURE 1. Schematic of a trial in the AOMI and MI task. (a) The participants started by watching a blank screen for 5 s after which a black cross appeared at the center of the screen for 3 s. Next, the participants were asked to perform kinesthetic MI while concurrently watching the video-guided movement for 5 s. Finally, the blank screen appeared again to inform the participants to relax. The relaxation time was randomly set between 5 and 8 s. (b) The participants started by watching a blank screen for 5 s after which a black cross appeared at the center of the screen for 3 s. Next, the participants were asked to concurrently execute kinesthetic MI while watching at a red arrow pointing in the direction of the paretic hand for 5 s. Finally, the blank screen appeared again to inform the participants to relax. The relaxation time was randomly set between 5 and 8 s.

primary sensorimotor area of the hand to calculate % ERD/ERS values and plot time–frequency maps. First, the EEG data were sliced into 8-s epochs (starting at 5 and 13 s in Fig 1a, b) after which they were bandpass filtered from 5–35 Hz, and an independent component analysis (ICA) was used to reject eye blinking artifacts [38]. Finally, the preprocessed data were used to compute ERD/ERS values and plot time–frequency maps.

Normally, ERD/ERS values are presented in terms of percentage change, and equation (1) was used to obtain % ERD/ERS values [8]:

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

$\boldsymbol{A}$ indicates the power spectrum values in a given frequency band (such as alpha and beta bands) while the participants were performing the cognitive tasks. $\boldsymbol{R}$ represents the power spectrum value before the participants executed the cognitive task. The EEG data from 1 to 5 s after the video-guided movement or red arrow appeared (i.e., from 9 to 13 s in Fig 1a, b) and from 2 to 3 s after the black cross presented on the screen (i.e., from 7 to 8 s in Fig 1a, b) were used to compute $\boldsymbol{A}$ and $\boldsymbol{R}$, respectively. Welch's method with a Hamming window (nonoverlapping) was employed to estimate the power spectrum values of $\boldsymbol{A}$ and $\boldsymbol{R}$ in each epoch. Then, we averaged $\boldsymbol{A}$ and $\boldsymbol{R}$ across epochs, and put these values into equation (1) to obtain % ERD/ERS values. If the value of % ERD/ERS was a negative number, it indicated the presence of ERD (activated neural activity). In contrast, if the value of % ERD/ERS was a positive number, it indicated the presence of ERS (inhibited neural activity) [7], [8]. In this study, the % ERD/ERS values was computed in four frequency bands, including the alpha (8–13 Hz), lower beta (14–20 Hz), upper beta (21–30 Hz), and whole bands

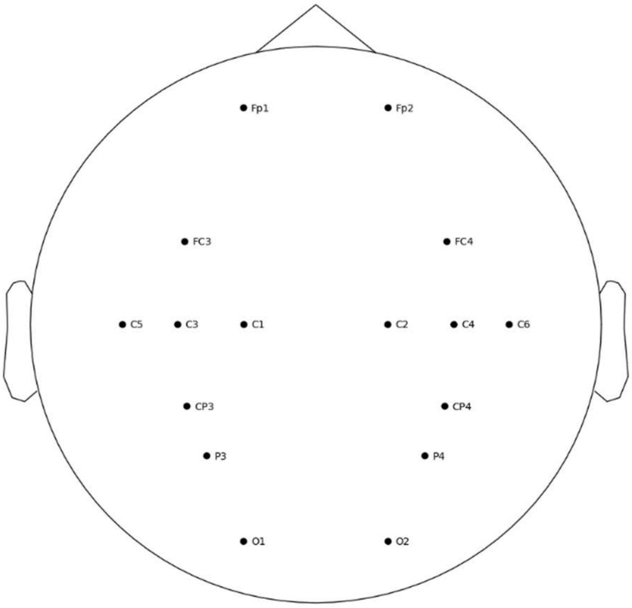


FIGURE 2. The 16-electrode placements used to record EEG data.

(8–30 Hz) to compare cortical activity between AOMI and MI conditions.

For time–frequency analysis, the mean event-related spectral perturbation (ERSP) was plotted to express the activity in the affected sensorimotor area of the hand (C3 or C4). ERSP presented cortical activity in terms of spectral power change relative to the baseline due to a cognitive task. Eight-second epoch data (starting at 5 and 13 s in Fig 1a, b) were applied to compute ERSP for plotting time–frequency maps, and the mean ERSP was obtained using equation (2).

$$\boldsymbol{ERSP}\,(\boldsymbol{f},\boldsymbol{t})=\frac{\boldsymbol{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i}\mathcal{D}\boldsymbol{1}}^{\boldsymbol{N}}(\boldsymbol{F_i}(\boldsymbol{f},\boldsymbol{t})^{\boldsymbol{2}}) \tag{2}$$

$\boldsymbol{N}$ is the number of trials. $\boldsymbol{F_i}(\boldsymbol{f},\boldsymbol{t})$ is the spectral estimation of the $\boldsymbol{i}$th trial, which was estimated by short-time Fourier transform using a Hanning-tapered window. $\boldsymbol{f}$ and $\boldsymbol{t}$ are the frequency (i.e., 5–35 Hz) and time (i.e., from 5 to 13 s in Fig 1a, b), respectively. ERSP values were normalized by subtracting the baseline (i.e., from 7 to 8 s in Fig 1a, b) and presented in log-transformed values. The whole process of ERD/ERS and time-frequency analyses were conducted with MATLAB (R2020a) and the EEGLAB (v2020.0) toolbox [38]. The results of the time-frequency analysis of all participants during AOMI and MI tasks are shown in Fig 3.

E. CLASSIFICATION PERFORMANCE

In this study, an offline classification analysis was used to evaluate the classification performance between AOMI and MI conditions. The preprocessed data in the section on ERD/ERS and time-frequency analyses were continually applied to establish the classification model. After that,

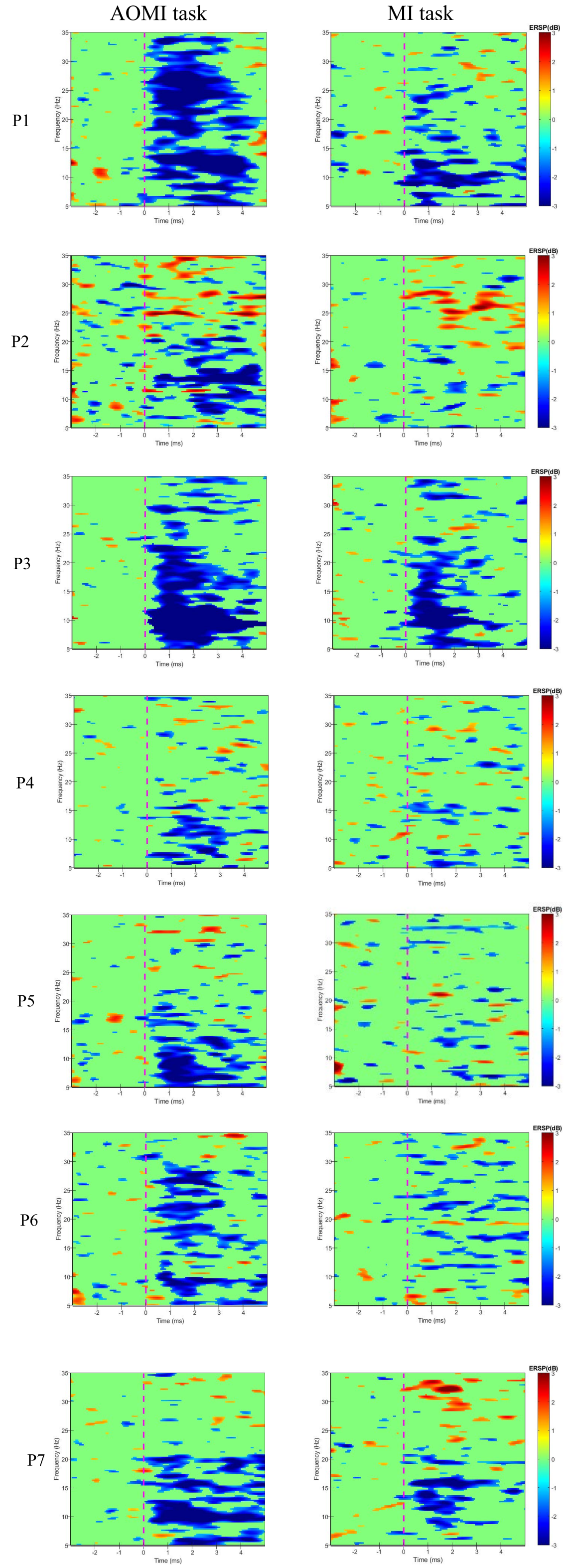


FIGURE 3. Event-related spectral perturbation (ERSP) maps at the C3 or C4 channel between AOMI and MI tasks of all participants. The blue color refers to a decrease in EEG power (activated neural activity), and the red color indicates an increase in EEG power (inhibited neural activity) relative to the baseline. The results of ERSP map exhibited that AOMI was more effective than MI tasks in terms of activating the neural activity of the primary sensorimotor area of the hand.

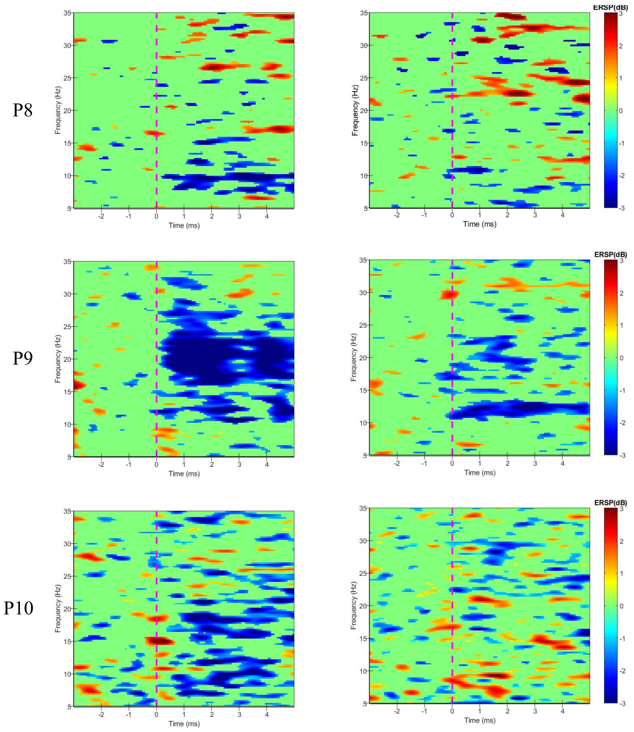


FIGURE 3. ***(Continued.)*** **Event-related spectral perturbation (ERSP) maps at the C3 or C4 channel between AOMI and MI tasks of all participants. The blue color refers to a decrease in EEG power (activated neural activity), and the red color indicates an increase in EEG power (inhibited neural activity) relative to the baseline. The results of ERSP map exhibited that AOMI was more effective than MI tasks in terms of activating the neural activity of the primary sensorimotor area of the hand.**

the EEG data from five channels placing over the affected sensorimotor areas (FC3, C5, C3, C1, CP3 for right-sided hemiparesis and FC4, C6, C4, C2, CP4 for left-sided hemiparesis) were selected. Next, the EEG data were sliced into 2-s epochs to create the data for a 2-class condition. The 6–8 and 9–11 s periods (Fig 1a, b) were represented as 2-s epochs for class 1 (baseline class) and class 2 (imagery class), respectively. The two classes were differentiated because they are commonly used in EEG-based BCI systems for stroke rehabilitation [27], [39]–[41]. In the present study, the participants were asked to perform each AOMI and MI task for two sessions, and each session was composed of 20 trials. Thus, we obtained the EEG data for 40 trials, in which each trial comprised 2 classes. Therefore, 40 epochs of data for each class (40 epochs for the baseline class and 40 epochs for the imagery class in each AOMI and MI condition) were obtained. The epoch data were separately bandpass filtered into four frequency bands: (1) alpha (8–13 Hz), (2) lower beta (14–20 Hz), (3) upper beta (21–30 Hz), and (4) whole bands (8–30 Hz). The EEG data were filtered into four bands to compare the classification performance based on each band power feature between the AOMI and MI conditions. Afterwards, a common spatial pattern (CSP) filter was used to increase the difference between the two classes by projecting the CSP filter matrix into the original datasets, which could concurrently maximize the variance for one class and minimize the variance for another class [42]. Later, mean band powers extracted from the filtered data were used as the feature vectors, and a support vector machine (SVM) was applied to create the classifier [43]. Finally, a 5-fold cross validation (80% for training and 20% for testing) was used to obtain the mean accuracy results. The whole process of offline classification analysis was provided by MNE, SciPy, and Scikit-learn python packages.

F. STATISTICAL ANALYSIS

PASW Statistics software version 18.0 (formerly SPSS Statistics, Chicago) was adopted for statistical analysis in this study. Due to the small sample size, the Wilcoxon signed-rank test was used to compare the mean classification accuracy and % ERD/ERS values between AOMI and MI conditions in each frequency band. Statistical significance was defined when p values were < 0.05.

III. RESULTS

A. % ERD/ERS of C3/C4

In the present study, % ERD/ERS values from the C3 (left-sided hemiparesis participants) or C4 (right-sided hemiparesis participants) channels were used to compare AOMI and MI conditions, and we found significant differences in % ERD/ERS values in the alpha ($p = 0.005$), lower beta ($p = 0.013$), upper beta ($p = 0.022$) and whole bands ($p = 0.007$). The % ERD/ERS results in all participants are presented in Table 2.

B. CLASSIFICATION PERFORMANCE

When comparing the mean classification performance in four band power features between AOMI and MI conditions, we found significant differences in mean classification performance in the alpha ($p = 0.005$), lower beta ($p = 0.011$), upper beta ($p = 0.021$) and whole bands ($p = 0.005$). The classification accuracy results for all participants are shown in Table 3.

In addition to evaluating the mean classification accuracy, false positive and false negative (FP and FN, respectively) values were analyzed. According to a 5-fold cross validation, each confusion matrix result consisted of 16 test datasets. Hence, the summation of confusion matrix from the 5-fold cross validation in each participant was composed of 80 test datasets. Then, the summation of confusion matrix across all participants was averaged to obtain the mean of confusion matrix between the AOMI and MI conditions in each frequency band. We found that the AOMI task produced lower FP and FN values compared to the MI condition for all frequency bands. The means of all participant's confusion matrix results between the AOMI and MI conditions are shown in Table 4.

In the present study, five channels (i.e., FC3/FC4, C5/C6, C3/C4, C1/C2, and CP3/CP4) were selected to establish the classification model, but % ERD/ERS values were analyzed only for a single channel (C3 or C4). To clarify whether

TABLE 2. % ERD/ERS values in four frequency bands for all participants between the AOMI and MI conditions.

Participant	% ERD/ERS values of C3/C4							
	Alpha band (8-13 Hz)		Lower beta band (14-20 Hz)		Upper beta band (21-30 Hz)		Whole band (8-30 Hz)	
	AOMI	MI	AOMI	MI	AOMI	MI	AOMI	MI
P1	-31.07	-23.56	-37.57	-18.76	-26.85	-11.15	-32.35	-19.36
P2	-21.72	20.38	-29.97	2.6	-5.67	-2.34	-22.4	10.42
P3	-58.81	-17.68	-32.42	-21.91	-18.67	-7.88	-45.85	-17.35
P4	-20.31	-11.79	-2.79	-7.11	2.76	-8.61	-8.85	-9.93
P5	-20.04	-1.43	-18.58	-8.55	-10.35	10.52	-17.76	0.56
P6	-19.51	-4.07	-28.5	-11.63	-23.54	-21	-22.56	-9.36
P7	-44.58	-7.84	-21.35	-24.2	-5.55	26.79	-33.58	-8.06
P8	-28.47	-6.15	-0.31	25.9	5.9	35.29	-9.32	11.48
P9	-26.95	-16.69	-34.08	-5.16	-21.15	-9.15	-27.62	-10.1
P10	-16.54	7.73	-35.51	-19.95	-15.29	-12.1	-21.98	-6
Mean	-28.8	-6.11	-24.11	-8.88	-11.84	0.037	-24.23	-5.77
SD	12.63	12.27	12.62	14.11	10.56	17.35	10.70	9.86
*p value*s	0.005*		0.013*		0.022*		0.007*	

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

TABLE 3. Mean classification accuracy in four band power features for all participants between the AOMI and MI conditions.

Participant	% Mean classification accuracy							
	Alpha band (8-13 Hz)		Lower beta band (14-20 Hz)		Upper beta band (21-30 Hz)		Whole band (8-30 Hz)	
	AOMI	MI	AOMI	MI	AOMI	MI	AOMI	MI
P1	86.25	73.75	93.75	67.5	98.75	73.75	92.5	77.5
P2	85	68.75	75	76.25	85	68.75	70	57.5
P3	87.5	78.75	83.75	70	78.75	71.25	87.5	81.25
P4	76.25	65	72.5	65	52.5	58.75	73.75	71
P5	83.75	68.75	80	71.25	67.5	65	82.5	55
P6	80	61.25	72.5	70	87.5	75	82.5	70
P7	91.25	82.5	97.5	82.5	87.5	76.25	91.25	80
P8	80	58.75	68.75	68.75	58.75	58.75	71.25	56.25
P9	70	67.5	83.75	71.25	88.75	76.25	80	68.75
P10	77.5	68.75	78.75	75	82.5	77.5	83.75	63.75
Mean	81.75	69.375	80.625	71.75	78.75	70.125	81.5	68.125
SD	5.92	6.94	8.86	4.75	13.86	6.741	7.47	9.27
*p value*s	0.005*		0.011*		0.021*		0.005*	

* represents significance in Wilcoxon signed-ranks test (p value < 0.05).

TABLE 4. The means of all participant's confusion matrices between the AOMI and MI conditions.

Frequency band	Condition	True positive	False positive	True negative	False negative
Alpha band (8–13 Hz)	AOMI	31.8 ± 3.12	8.2 ± 3.12	33.6 ± 2.94	6.4 ± 2.94
	MI	25.5 ± 5.6	14.6 ± 5.75	30 ± 2.45	9.9 ± 2.43
Lower beta band (14–20 Hz)	AOMI	31.5 ± 4.18	8.5 ± 4.18	33 ± 4.31	7 ± 4.31
	MI	27 ± 4	13 ± 4	30.4 ± 2.11	9.6 ± 2.11
Upper beta band (21–30 Hz)	AOMI	31.9 ± 6.04	8.1 ± 6.04	31.1 ± 6.02	8.9 ± 6.02
	MI	27.8 ± 3.87	12 ± 3.87	28.3 ± 3.93	11.9 ± 4.01
Whole band (8–30 Hz)	AOMI	32 ± 4.1	8 ± 4.1	33.2 ± 2.96	6.8 ± 2.96
	MI	27 ± 3.85	13 ± 3.85	27.5 ± 4.3	12.5 ± 4.3

increased ERD in C3 or C4 contributed to improving the classification performance, Spearman's correlation was used to examine the correlation between % ERD/ERS values of C3/C4 and mean classification performance in each frequency band. The correlation results indicated that there were significant negative correlations between % ERD/ERS values and mean classification performance in the alpha ($r = -0.729$; $p = 0.000$), lower beta ($r = -0.625$; $p = 0.003$), upper beta ($r = -0.661$; $p = 0.002$), and whole bands ($r = -0.817$; $p = 0.000$). Hence, increased ERD values (more negative values) at the C3 or C4 channel based on AOMI contributed to improving the classification performance. In other words, stronger ERD at the C3 or C4 channel (the primary sensorimotor area of the hand) correlated with higher classification performance. The results of the correlation analysis between %ERD/ERS (C3/C4) values and classification performance in each frequency band are shown in Fig 4.

IV. DISCUSSION

A. MAIN RESULTS

This study aimed to examine the effects of AOMI on cortical activity and classification performance in chronic stroke patients. Our results indicate that AOMI is a more robust strategy than MI in terms of enhanced ERD values in the affected sensorimotor area and classification performance. Significant differences in ERD values and classification performance between AOMI and MI conditions were found in the alpha (8–13 Hz), lower beta (14–20 Hz), upper beta (21–30 Hz), and whole bands (8–30 Hz). Moreover, a significant negative correlation between ERD values and classification performance was found. In other words, increased ERD values (more negative values) also led to an improvement in classification performance.

B. EFFECT OF AOMI ON ERD

ERD is an electrophysiological phenomenon expressed in terms of decreased EEG power at a specific frequency band (such as alpha and beta bands) that is related to a specific event. Generally, ERD is interpreted as an increase in cortical excitability or activated cortical neurons involved in the processing of sensory and cognitive information or motor behaviors. In healthy subjects, motor execution (ME) in addition to MI and AO can manifestly produce ERD in a specific brain area [8], [44]. For instance, observation of hand movement can elicit ERD (alpha band) in the occipital lobe. Hand MI can provoke ERD (alpha and beta bands) in the contralateral sensorimotor areas of the imagined hand [5]. However, in stroke patients, ERD during MI or ME is commonly reduced or absent in the affected hemisphere due to damaged neurons [8], [37].

In the present study, according to the results of %ERD/ERS of C3/C4 and time-frequency analyses, the ERD magnitudes significantly increased compared to MI condition when participants were given the video-guided movement while performing MI (AOMI condition). These findings are in line with previous studies that examined ERD magnitudes in healthy and stroke subjects [24], [27], [35], [45]. However, when considering only the effect of AOMI on ERD in the alpha band as described in previous studies, variation in the results were found. In experiments conducted in healthy subjects, Eaves *et al*. [45] reported no significant difference in ERD in the alpha band between AOMI and MI tasks, whereas the studies from Bian *et al*. [27] and Nagai *et al*. [24] found significant differences in ERD in the alpha band between AOMI and MI conditions. In the experiments conducted in stroke subjects, Ichidi *et al*. [35] also reported that no significant differences were noted in ERD in the alpha band between AOMI and MI conditions in stroke patients. Although, our results indicate that AOMI is superior to MI in producing ERD in the alpha band. The factors that may influence the results in this study and previous works incongruently include the differences between participants (healthy or stroke subjects), stroke phase (subacute or chronic phases), and/or mental tasks (AOMI of simple or complex movements). Additionally, our study conducted the experiment with only ten chronic stroke patients. Therefore, further studies should clarify the effect of AOMI on ERD in the alpha band in a large sample size of stroke patients. For the results of ERD in the beta band, our result is in line with previous studies [24], [27], [35], [45] in which AOMI was reported to be more effective than MI for enhancing ERD in the beta band.

In summary, it may be concluded that AOMI is more effective than MI in terms of producing an increase in cortical activity involved in motor function. The increased ERD during AOMI may be induced by the spontaneous activation of the mirror neuron system that is automatically stimulated by observation of body movement [19], [20], [27]. Moreover, applying video-guided movement while performing MI may increase task attention and lead to enhanced ERD [8]. For clinical applications, Sun *et al.* [34] demonstrated that using AOMI training along with conventional therapy was more effective than MI training for improving upper limb function in subacute stroke patients. However, its effect on improving upper limb function in chronic stroke patients is still unclear. Thus, future research should investigate this hypothesis.

C. EFFECT OF AOMI ON CLASSIFICATION PERFORMANCE

The common problem of MI-based BCI systems is the variation in classification performance among subjects depending on the capability of generating ERD in each individual. Particularly, stroke patients who usually have less ability to elicit ERD due to brain lesions commonly show lower classification performance [19], [36], [37]. To improve classification accuracy, some studies have proposed novel mathematical algorithms or classifiers to overcome this problem [42], [46], [47]. On the other hand, some studies focus on a strategy that could enhance ERD by using sensory stimulation (such as vibration, electrical stimulations, and/or visual-guided movements) during MI and has led to increased classification accuracy [27], [48], [49]. In this study, the latter method was used to improve classification performance in chronic stroke patients. Our results indicate that adding video-guided movement during MI could improve classification accuracy even in stroke patients. Furthermore, FP and FN values in the AOMI condition were lower than in the MI condition. In addition, it was also found that increased ERD values

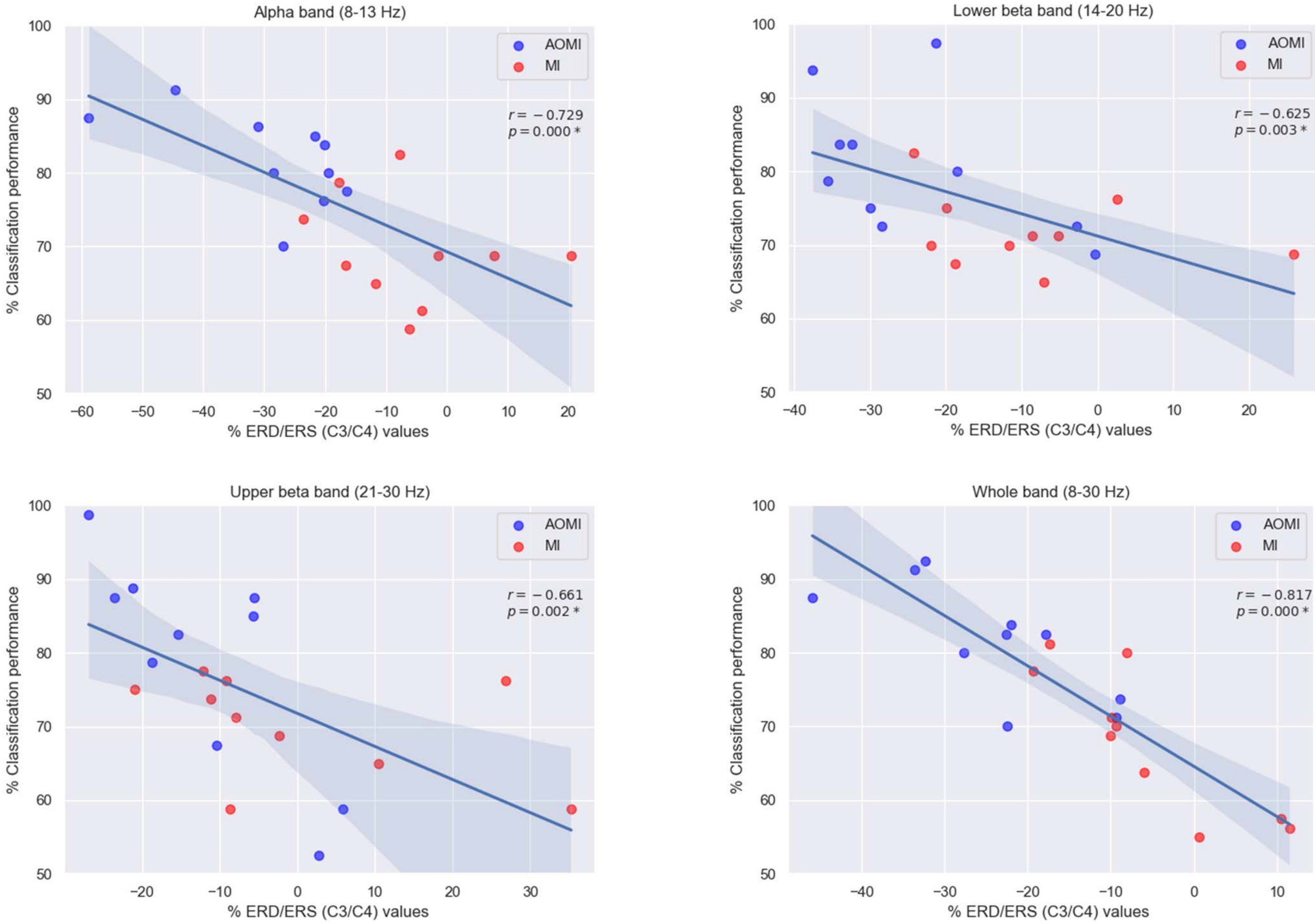


FIGURE 4. **Correlation analysis between % ERD/ERS (C3/C4) values and classification performance in each frequency band.**

significantly correlated with improved classification performance. These findings are in line with Bian's study which examined the effect of AOMI on classification performance in healthy subjects [27].

Although AOMI is not a new strategy, evidence of the use of AOMI-based BCI systems for stroke rehabilitation is still lacking. In the present study, we only provided videos that showed simple movement of the wrist and hand to stroke patients during MI. However, simple movement could lead to a significant improvement in classification performance and ERD in the affected sensorimotor area. It is well known that ERD represents a decrease in EEG power in a specific frequency band (8–30 Hz) during MI relative to the baseline or idle state [7], [8]. Our classification models, which are based on ERD features, were used to classify the EEG data between imagery and baseline states. Hence, it is straightforward that increasing ERD due to AOMI could make the classification model to discriminate which EEG data were imagery or baseline state easier compared to MI. Thus, AOMI is a more appropriate method for stroke patients who are new patients and are unfamiliar with classical MI to allow them to participate in EEG-based BCI training. In addition, the benefits of using video clips to improve MI efficacy are low cost and easy to implement in BCI systems; therefore, our findings may offer an alternative strategy for improving the effectiveness of BCI systems for stroke rehabilitation. However, our study only demonstrated AOMI advantages in an offline classification analysis. To confirm its advantage in terms of improving the efficacy of BCI training for stroke rehabilitation, future studies should compare the effect of AOMI and MI-based BCI training with neurofeedback (such as functional electrical stimulation or robotic hands) on motor recovery in stroke patients. Furthermore, our study used video-guided movement to improve classification accuracy between baseline and imagery classes. Nevertheless, using AOMI to improve classification performance between right- and left-hand classes or hand and foot classes is still debatable. Further studies should investigate this hypothesis.

D. LIMITATIONS

Even though a small sample size of 10 participants was involved in this study, the increased cortical activity and classification performance were found to be significant. Future studies should validate our results by conducting experiments in a large population of stroke patients. In addition, we do not know the type of lesions in each participant (such as cortical, subcortical, and/or mixed lesions). A previous study reported that different lesion locations affected the ERD amplitude during MI, especially in supratentorial lesions, including primary motor cortex damage, which negatively impacted the production of ERD in the affected hemisphere [50]. Thus, further studies should verify the effect of AOMI on stroke patients who present with this lesion.

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