Improving Performance of Motor Imagery-Based Brain–Computer Interface in Poorly Performing Subjects Using a Hybrid-Imagery Method Utilizing Combined Motor and Somatosensory Activity

Sangin Park, Jihyeon Ha, and Laehyun Kim

***Abstract*—The phenomena of brain-computer interface-inefficiency in transfer rates and reliability can hinder development and use of brain-computer interface technology. This study aimed to enhance the classification performance of motor imagery-based brain-computer interface (three-class: left hand, right hand, and right foot) of poor performers using a hybrid-imagery approach that combined motor and somatosensory activity. Twenty healthy subjects participated in these experiments involving the following three paradigms: (1) Control-condition: motor imagery only, (2) Hybrid-condition I: combined motor and somatosensory stimuli (same stimulus: rough ball), and (3) Hybrid-condition II: combined motor and somatosensory stimuli (different stimulus: hard and rough, soft and smooth, and hard and rough ball). The three paradigms for all participants, achieved an average accuracy of 63.60±21.62%, 71.25±19.53%, and 84.09±12.79% using the filter bank common spatial pattern algorithm (5-fold cross-validation), respectively. In the poor performance group, the Hybrid-condition II paradigm achieved an accuracy of 81.82%, showing a significant increase of 38.86% and 21.04% in accuracy compared to the control-condition (42.96%) and Hybrid-condition I (60.78%), respectively. Conversely, the good performance group showed a pattern of increasing accuracy, with no significant difference between the three paradigms. The Hybrid-condition II paradigm provided high concentration and discrimination to poor performers in the motor imagery-based brain-computer interface and generated the enhanced event-related desynchronization pattern in three modalities corresponding to different types of somatosensory stimuli in motor and somatosensory regions compared to the Control-condition and Hybrid-condition I. The hybrid-imagery approach can help improve motor imagery-based brain-computer interface performance, especially for poorly performing users, thus contributing to the practical use and uptake of brain-computer interface.**

***Index Terms*—BCI inefficient, brain-computer interface, motor imagery, motor imagery training, somatosensory stimuli.**

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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 Korea Institute of Science Technology, Seoul, South Korea, under Approval No. 2021-012.

Sangin Park is with the Industry-Academy Cooperation Team, Hanyang University, Seoul 04763, South Korea (e-mail: sipark84@hanyang.ac.kr).

Jihyeon Ha is with the Center for Bionics, Korea Institute of Science and Technology, Seoul 02792, South Korea (e-mail: hj910410@kist.re.kr).

Laehyun Kim is with the Center for Bionics, Korea Institute of Science and Technology, Seoul 02792, South Korea, and also with the Department of HY-KIST Bio-Convergence, Hanyang University, Seoul 04763, South Korea (e-mail: laehyunk@kist.re.kr).

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I. Introduction

BRAIN-COMPUTER interfaces (BCIs) are computer-based systems that enable control of external devices and applications directly through brain signals [1], [2]. BCI systems independent of external stimuli are fully controlled by self-initiation, and motor imagery (MI) is a well-known stimulus independent BCI [3], [4]. MI is a cognitive process in which mental stimulation of body movements occurs without execution [5], [6], [7]. MI-based BCI can efficiently control external devices based on intuitive mapping between interfaces and control commands and is widely used in various applications [8], [9]. However, MI-based BCI reveals lower transfer rates and reliability in the recognition of a subject's intent than other BCI methods, and this phenomenon is prominent in poorly performing users [9]. Low transfer rates and reliability due to errors are major factors that disincentivize the use of BCI systems [10]. To improve MI-based BCI transfer rates, methods have been proposed to respond to errors using error-related potentials or negativity [11], [12], [13], [14], [15]. However, this approach provides only a temporary solution, instead of a resolution [9]. Generally, 15-30% of users who try to control an external device or system using BCI systems cannot show a sufficient level of accuracy (<70% after BCI training). The phenomenon is known as "BCI illiteracy" [16], [17] or "BCI inefficiency" [18], [19]. A performance of 70% is the minimum classification accuracy required for reliable communication with external devices or systems by BCI [20]. The cause of BCI illiteracy and inefficiency remains unknown [18]. BCI inefficiency can hinder the development and wide use of BCI technology; therefore, it is necessary to alleviate this problem [9], [21]. Moreover, a large proportion of stroke patients are struggling due to BCI-inefficiency [22]. Understanding the BCI-inefficiency phenomenon can contribute to the clinical application of BCI-based motor function rehabilitation [23], [24].

Improving the performance of poorly performing users in MI-based BCI is divided into technological (improving feature extraction or classification algorithms) and human factors (generating good quality EEG patterns via improvement in training or feedback [i.e., visual, tactile, and neurofeedback]) [25]. Studies have attempted to enhance the performance of MI-based BCI for poorly performing users by improving the algorithm for feature extraction or classification [18], [26], [27], [28], [29]. Although the average classification performance of MI-based BCI has been enhanced by improving algorithms, such as feature extraction or classification, poorly performing users still do not reach a sufficient level of communication with external devices or systems [18]. Reducing the percentage of BCI-inefficient subjects requires the development of effective experimental paradigms and training protocols [19]. BCI requires learning or training [30], and its success is a major determinant of performance [31].

Thus, many studies have focused on improving performance by training and have reported a noticeable positive effect. There has been research on (1) training using vibrotactile feedback [32], [33] and an augmented reality environment [34], (2) enhancement of brain activity (i.e., theta, alpha, and beta oscillations) by neurofeedback in the resting state [35], [36] and a real-time biofeedback mechanism [29], and (3) enhancement of cortical activity (i.e., event-related desynchronization) by transcranial magnetic stimulation [24], [37]. Researchers have also tried to enhance a user's cortical activity using training methods with stimuli to improve the performance of BCI-inefficient users. A hybrid training approach combining MI and somatosensory stimuli reported improvements in the performance of subjects in the hybrid training group than that in MI alone [3], [32]. A hybrid training method combining two or more modalities can potentially enhance the patterns of MI features caused by BCI paradigm and improve performance in poorly performing users [38]. Our previous study also confirmed that combining brain activity from the motor and somatosensory cortex by hybrid training using tangible objects (i.e., hard and rough balls) demonstrated improved classification performance of MI-based BCI (three-class) in the poorly performing group [9]. Compared to our previous studies, this study is consistent with our previous study in terms of using hybrid imagery combining motor and somatosensory sensation from tangible objects. However, while past studies have used the same type of tangible objects for the three modalities (i.e., both hands and right foot), the present study proposes using different types of tangible objects for each modality.

This study aimed to improve the MI-based BCI performance (three-class: left hand, right hand, and right foot) of poor performers using a hybrid training method that combined motor and somatosensory activity. We focused on hybrid training for three-class MI using independent somatosensory stimuli from each modality. This approach was divided into execution and imagery sessions. The execution session involved hybrid training in the use of motor execution (ME) and sensations from tangible objects with characteristics of different types in each modality (i.e., right hand: hard and rough ball; left hand: soft and smooth ball; right foot: soft and rough ball). The imagery session required participants to imagine trained sensations in both the motor and somatosensory systems simultaneously. The proposed method in this study, which focused on poorly performing users, was compared with MI and our previous hybrid method. In a previous study, we confirmed that hybrid training methods using somatosensory stimuli improved the classification accuracy by activating both the somatosensory and motor cortices. We believe that hybrid training using somatosensory stimuli with different characteristics will increase discrimination for MI-commands and increase concentration for the imagery paradigm.

II. Materials and Methods

A. Subjects

Twenty healthy subjects participated in the experiments (10 women, all right-handed, average age 26.4 ± 3.9 years) and were paid 120,000 KRW each. All subjects had prior experience with the MI experiment. Before participation, all subjects were informed of the experimental protocol and signed informed consent forms. This study was approved by the ethics committee of the Korea Institute of Science Technology, Seoul, South Korea (approval number: 2021-012).

B. EEG Recordings

A BioSemi ActiveTwo system with 64 channels (BioSemi BV, Amsterdam, Netherlands) mounted on an EEG electrode cap arranged in an international 10–20 montage was used to record EEG signals. Two additional electrodes, a common mode sense active electrode and a driven right leg passive electrode, were used as reference and ground, respectively, according to BioSemi's design. The EEG signals were measured at a sampling rate of 2048 Hz and down sampled to 256 Hz. The common average reference was used for offline analyses.

C. Experimental Protocol

This experiment consisted of three paradigms: MI, hybrid-condition paradigm I (HC_I), and hybrid-condition paradigm II (HC_{II}). All paradigms involved execution and imagery sessions. The experimental protocol composition was the same among the three paradigms, but the BCI task applied to execution and imagery sessions was different. Each paradigm started with an execution session and proceeded to an imagery session. The subjects were divided into two groups, good and poor performers (BCI inefficient), to determine the effect of the proposed hybrid-imagery paradigm on poor performers. BCI inefficient subjects had a classification performance of $<70\%$ for three classes in the MI paradigm based on previous studies [18], [39], and the remaining subjects were good performers ($>70\%$ accuracy).

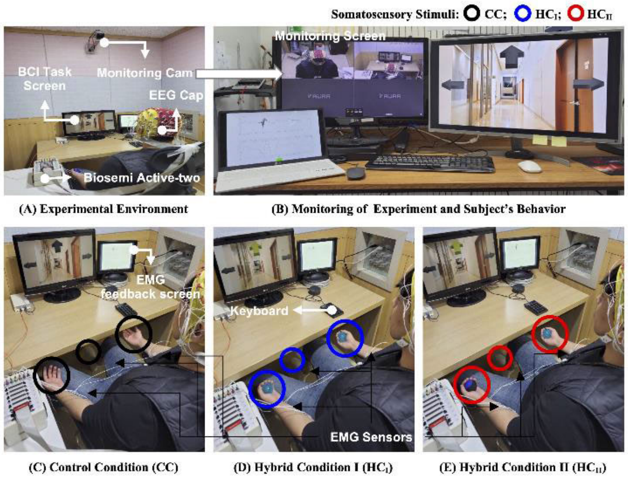

Fig. 1. Overview of experimental environment. (A) Experimental environment. (B) Control room: monitoring of experimental procedure and subject's behavior, and measuring EEG signals. (C) Control condition (CC): kinesthetic imagery without somatosensory stimuli. (D) Hybrid condition I (HC$_I$): somatosensory stimuli of same type (hard and rough ball). (E) Hybrid condition II (HC$_{II}$): somatosensory stimuli of different type (soft and smooth ball: left hand; hard and rough ball: right hand; soft and rough half-ball: right foot).

The subjects comfortably sat a meter away from the monitor screen in an electrically shielded room. They were asked to perform a task. The screen presented cues as follows: At the beginning of each trial (T=0 s), a fixation cross ("+") appeared at the center of the screen for 2 s. At T=2 s, a video of the telepresence robot moving to a three-way crossroad was presented until the rest period of each trial. Five types of videos were presented at a count-balanced random. The video involved a visual cue of arrow type in the left, right, and forward directions. The target cue was highlighted when the telepresence robot reached the three-way crossroad (T=4 s), and the subjects were asked to perform execution or imagery tasks for 3 s. The left, right, and forward arrows indicated the left hand, right hand, and right feet, respectively. The classes were presented at a count-balanced random. At T=7 s, the subjects were instructed to relax until they received feedback using a keypress. Each block consisted of 50 trials with an inter-block interval of 60 s. The entire execution and imagery task consisted of 150 trials (three blocks) and 300 trials (six blocks), respectively. The subjects were asked to restrict eye and body movements related to muscle contraction during the imagery session but not during the training session. Finally, we conducted a post-experimental interview. Subjects were instructed to report their feelings or experiences for each paradigm and the differences between them using the following questions: (1) Question 1: Which method in each paradigm is better for conducting a BCI-task? (2) Question 2: Why do you think this method is better compared to others? (open-ended questions). The experimental environment and protocol are illustrated in Figs. 1 and 2, respectively.

1) Control-Condition Paradigm (CC): For the ME session, subjects were instructed to perform clenching of the left and right hands or step on the right foot according to the cue on the screen. In the MI session, the subjects were asked to mentally simulate their physical movements performed in the ME session (i.e., kinesthetic imagery).

2) Hybrid-Condition Paradigm I (HC$_I$): For HC$_I$, same somatosensory stimuli of ball type were applied to both hands and the right foot (i.e., hard and rough tangible balls) (Fig. 2(B)). During the execution of HC$_I$ (HC$_I$E), the subjects were instructed to clench hard and rough tangible balls in their left or right hands or step on a hard and rough half-ball. In the imagery task of HC$_I$ (HC$_I$I), subjects were required to imagine both the motor and somatic sensory sensations from tangible objects (i.e., hybrid-imagery) trained in HC$_I$E even when there was no physical movement or somatosensory stimuli.

3) Hybrid-Condition Paradigm II (HC$_{II}$): Execution and imagery sessions in HC$_{II}$ (HC$_{II}$E and HC$_{II}$I) were consistent with HC$_I$ but differed in the somatosensory stimuli applied in both hands and the right foot. The left hand, right hand, and right foot used hard and rough balls, soft and smooth balls, and hard and rough half balls, respectively (Fig. 2(C)).

This study used a "within-subjects" design and all participants performed the CC, HC$_I$, and HC$_{II}$ paradigms. The three paradigms were conducted on consecutive days, at the same time of day for three days (e.g., first day, CC; second day, HC$_I$; third day, HC$_{II}$), and the order between the three paradigms was randomly assigned. Moreover, this work attempted to minimize individual differences in the force or speed of movements. The force and speed of hand clenching involving mental simulation could affect brain activities [40], [41]. Electromyogram (EMG) signals were recorded from the left hand, right hand, and right foot during the execution session. Subjects were asked to control the force at 50% of their maximum voluntary contraction (MVC). It was trained by feedback of force and speed results of each trial using a sub-screen in only the execution session, and they were required to maintain consistency in the imagery paradigm. EMG signals were measured at 2048 Hz using a BioSemi ActiveTwo system. MVC was calculated by: (1) Down-sampling at 256 Hz. (2) DC component removal using a 0.5 Hz high-pass filter. (3) Signal smoothing using a 1 Hz low-pass filter. (4) Root-mean-square processing (Fig. 3). EMG signal processing was performed using MATLAB toolbox (2020b, Mathworks Inc., Natick, MA, United States).

D. Feature Extraction and Classification

In this study, our goal is enhancing the performance of MI-BCI in poorly performing users using the hybrid-imagery method. We used the filter bank common spatial pattern algorithm (FBCSP) [42]. FBCSP is the generally recognized benchmark method in the MI-BCI field and also serves as the baseline for comparison in most papers. Thus, we selected a widely used feature extraction method to compare the practical effect of the proposed method in this study with that of previous studies. To obtain optimization results for feature extraction and classification, we used "scikit-learn" (ver. 0.24.2) in Python (ver. 3.6.9.).

We used thirty EEG channels that measured activation of the supplementary motor area and both motor and somatosensory cortices (FT9, FC5, FC1, C3, T7, TP9, CP5, CP1, TP10, CP6, CP2, Cz, C4, T8, FT10, FC6, FC2, FT7, FC3, C1, C5, TP7, CP3, CPz, CP4, TP8, C6, C2, FC4, FT8) [3], [43]. An infinite impulse response filter (4–40 Hz) was applied to the selected EEG signals, and the EEG artifacts were removed

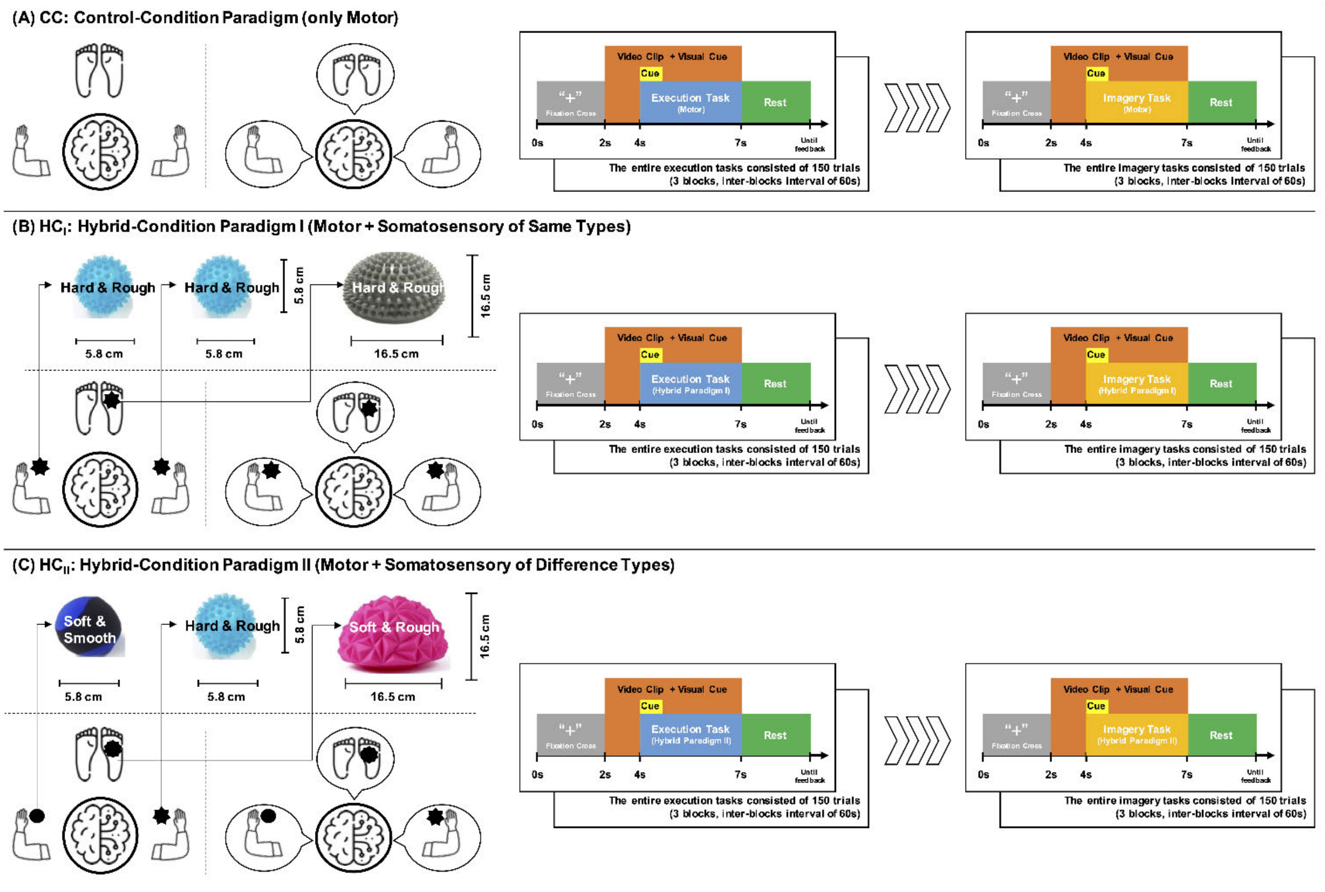

Fig. 2. Overview of experimental protocol for the three paradigms. (A) Control-Condition Paradigm (CC): motor execution and imagery tasks without somatosensory stimuli. (B) Hybrid-Condition Paradigm I (HC$_I$): execution and imagery tasks using both motor and somatosensory stimuli of same type (i.e., hard and rough ball). (C) Hybrid-Condition Paradigm II (HC$_{II}$): execution and imagery tasks using both motor and somatosensory stimuli of difference type (i.e., soft and smooth ball, hard and rough ball, and soft and rough half-ball).

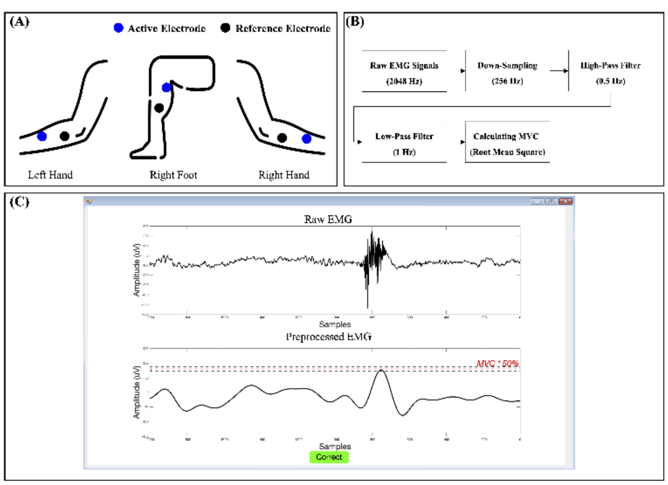

Fig. 3. (A) Electrode positions of the three channels in the electromyogram (EMG) to control the force and speed of movements (i.e., left hand, right hand, and right foot) using feedback. (B) Signals processing of EMG. (C) Monitoring screen for results of EMG.

using a wavelet-based neural network (WNN) [44]. The WNN is widely used in electrooculogram artifact removal algorithms. This algorithm combined the approximating capability of both neural network and wavelet transform to locate and eliminate artifacts.

Preprocessed EEG data were extracted from the time window of the MI task (2.4–4.4 s). The time window was determined by considering about 0.4 s was required for the motor response preparation after the cue [45], [46]. For feature extraction, FBCSP was conducted as follows [47], [48], [49]. We used a filter bank that decomposes the EEG signal into multiple frequency pass bands using a total of 9 band-pass filters, namely, 4 to 8 Hz, 8 to 12 Hz, 12 to 16 Hz, 16 to 20 Hz, 20 to 24 Hz, 24 to 28 Hz, 28 to 32 Hz, 32 to 36 Hz, and 36 to 40 Hz. We performed common spatial pattern (CSP) spatial filtering, whereby each pair of band-pass and spatial filters computes the CSP features that are specific to the band-pass frequency range by linearly transforming the EEG signal. We selected discriminative CSP features for the subject's task using the mutual information-based best individual feature algorithm (MIBIF). Finally, we used support vector machine to classify the selected CSP features [42]. We conducted this procedure using 5-fold cross-validation.

E. Statistical Analysis

Repeated measures of classification performance of BCI task on three paradigms were taken (i.e., CC, HC$_I$, HC$_{II}$) for each participant within the same experiment. Thus, in the statistical analysis, one-way repeated measures analysis of variance (RM-ANOVA) was applied. RM-ANOVA (also

TABLE I
CLASSIFICATION ACCURACY FOR THREE-CLASS MI-BASED BCI IN THREE PARADIGMS (CC, HC_I, AND HC_{II})

Subjects	Accuracy (kappa)					
	CC	HC_I	HC_{II}	HC_I - CC	HC_{II} - CC	HC_{II}- HC_I
Sub. 1	45.5 (0.18)	54.4 (0.31)	90.0 (0.85)	8.9 (0.13)	44.5 (0.67)	35.6 (0.54)
Sub. 2	81.8 (0.73)	53.5 (0.30)	89.9 (0.85)	-28.3 (-0.43)	8.1 (0.12)	36.4 (0.55)
Sub. 3	39.2 (0.09)	69.2 (0.54)	98.8 (0.98)	30.0 (0.45)	59.6 (0.89)	29.6 (0.44)
Sub. 4	37.5 (0.06)	89.5 (0.84)	95.7 (0.94)	52.0 (0.78)	58.2 (0.88)	6.2 (0.10)
Sub. 5	79.3 (0.69)	76.0 (0.65)	74.0 (0.61)	-3.3 (-0.04)	-5.3 (-0.08)	-2.0 (-0.04)
Sub. 6	40.4 (0.11)	84.8 (0.77)	95.7 (0.94)	44.4 (0.66)	55.3 (0.83)	10.9 (0.17)
Sub. 7	39.1 (0.09)	34.7 (0.01)	68.0 (0.52)	-4.4 (-0.08)	28.9 (0.43)	33.3 (0.51)
Sub. 8	80.3 (0.70)	78.3 (0.68)	83.3 (0.74)	-2.0 (-0.02)	3.0 (0.04)	5.0 (0.06)
Sub. 9	37.7 (0.07)	42.3 (0.13)	95.4 (0.93)	4.6 (0.06)	57.7 (0.86)	53.1 (0.80)
Sub. 10	64.6 (0.47)	45.4 (0.18)	91.1 (0.87)	-19.2 (-0.29)	26.5 (0.40)	45.7 (0.69)
Sub. 11	46.0 (0.18)	56.0 (0.32)	63.3 (0.45)	10.0 (0.14)	17.3 (0.27)	7.3 (0.13)
Sub. 12	44.3 (0.16)	43.2 (0.15)	60.9 (0.41)	-1.1 (-0.01)	16.6 (0.25)	17.7 (0.26)
Sub. 13	90.8 (0.86)	89.7 (0.85)	95.1 (0.93)	-1.1 (-0.01)	4.3 (0.07)	5.4 (0.08)
Sub. 14	35.3 (0.02)	88.3 (0.83)	59.3 (0.39)	53.0 (0.81)	24.0 (0.37)	-29.0 (-0.44)
Sub. 15	89.5 (0.84)	73.1 (0.60)	85.7 (0.79)	-16.4 (-0.24)	-3.8 (-0.05)	12.6 (0.19)
Sub. 16	80.0 (0.70)	80.4 (0.71)	71.4 (0.57)	0.4 (0.01)	-8.6 (-0.13)	-9.0 (-0.14)
Sub. 17	88.8 (0.83)	82.8 (0.74)	92.3 (0.88)	-6.0 (-0.09)	3.5 (0.05)	9.5 (0.14)
Sub. 18	87.0 (0.81)	98.8 (0.98)	84.1 (0.76)	11.8 (0.17)	-2.9 (-0.05)	-14.7 (-0.22)
Sub. 19	85.9 (0.79)	98.8 (0.98)	98.8 (0.98)	12.9 (0.19)	0.0 (0.00)	-60.0 (-0.90)
Sub. 20	79.0 (0.69)	85.7 (0.79)	89.0 (0.79)	6.7 (0.10)	10.0 (0.10)	3.3 (0.00)
Avg.	63.60 (0.47)	71.25 (0.62)	84.09 (0.74)	7.65 (0.11)	20.49 (0.31)	12.85 (0.19)
SD	21.62 (0.33)	19.53 (0.30)	12.79 (0.19)	21.54 (0.32)	22.47 (0.34)	20.21 (0.31)

CC-HC_I, CC-HC_{II}, and HC_I-HC_{II} represent the accuracy differences between paradigms. The participant numbers of "poor performers" are in ***bold*** and italicized.

known as within-subjects ANOVA) was used to determine whether three or more group measurements were significantly different for the same participant in each group [50]. If the distribution did not pass the normality test, the Friedman test was conducted. It is a nonparametric alternative to a one-way RM-ANOVA, repeated measures design whose distribution is not normal [51]. To identify the statistical significance of pairwise groups, post-hoc analyses were conducted using a paired samples t-test (i.e., RM-ANOVA) and the Wilcoxon signed-rank test (i.e., Friedman test) according to the normality. Additionally, this study provides information on the effect size to confirm the practical significance of RM-ANOVA and Wilcoxon signed-rank test based on the

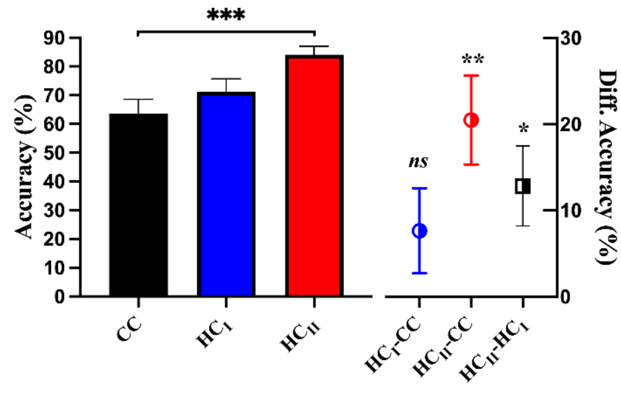

Fig. 4. Comparison of classification accuracy for three-class between CC, HC_I, and HC_{II} paradigms with RM-ANOVA results. Error bars indicate standard errors (ns: non-significant; $^{**}p < 0.01$; $^{***}p < 0.001$).

partial eta-squared value ($\eta p2$) and the r statistic, respectively. The standard values for practical significance of 0.01, 0.06, and 0.14 in $\eta p2$ were regarded as small, medium, and large, respectively [52]. The effect size for the r values of 0.1, 0.3, and 0.5 was defined as small, medium, and large, respectively [53]. All statistical data analyses were conducted using IBM SPSS Statistics 21.0 for Windows (SPSS Inc., Chicago, IL, USA).

III. RESULTS

A. Classification Accuracy for Three-Class

We compared the classification performance of CC, HC_I, and HC_{II} paradigms in distinguishing between the three classes of MI-based BCI. CC, HC_I, and HC_{II} for all participants, achieved the average accuracy (kappa) of 63.60±21.62% (0.45±0.33), 71.25±19.53% (0.57±0.30), and 84.09±12.79% (0.76±0.19) using FBCSP, respectively. All data were subjected to the Shapiro–Wilk normality test with a p-value (p) of 0.05, at the 5% significance level ($p > 0.05$). One-way Rm-ANOVA with Greenhouse–Geisser correction revealed statistically significant differences between the three paradigms ($F_{1971,37.444} = 8.877$, $p < 0.001$, $\eta p2 = 0.200$). Post-hoc analysis with Bonferroni adjustments revealed a statistically significant difference between the three paradigms: HC_I and HC_{II} ($M = -12.845$, $SE = 4.635$, $p < 0.05$) and CC versus HC_{II} ($M = -20.490$, $SE = 5.154$, $p < 0.01$). No significant differences were found between CC and HC_I paradigms ($M = -7.645$, $SE = 4.941$, $p > 0.05$) (Fig. 4). The HC_{II} paradigm achieved 9.13% and 7.51% larger CC and HC_I paradigms, respectively (Table I).

B. Comparison of Classification Accuracy Between Good and Poor Performers for the Three Paradigms

Good and poor performers were defined based on 70% classification accuracy in CC paradigm (i.e., poor performer > 70% ≥ good performer) [18], [39]. The subjects were divided into two groups: (1) Good performer group (4 women, average age 27.3±4.2 years): Sub. 2, 5, 8, 13, 15, 16, 17, 18, 19, and 20. (2) Poor performer group (6 women, average age 24.9±2.1 years): Sub. 1, 3, 4, 6, 7, 9, 10, 11, 12, and 14.

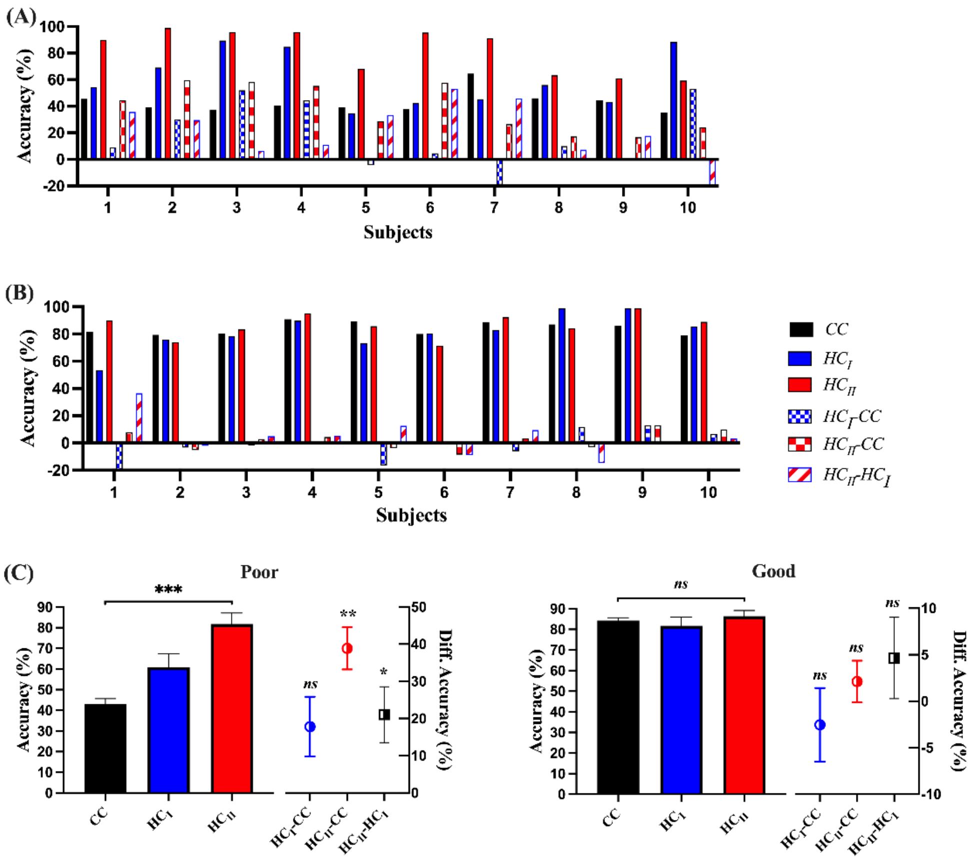

Fig. 5. Comparison of classification accuracy (three-class) for CC, HC_I, and HC_{II} paradigms between poor (A) and good performer groups (B) with Friedman test results (C). Error bars indicate standard errors (ns: non-significant, $^*p < 0.05$; $^{**}p < 0.01$, $^{***}p < 0.001$).

TABLE II
CLASSIFICATION AVERAGED ACCURACY FOR THREE-CLASS MI-BASED BCI IN THREE PARADIGMS (CC, HC_I, AND HC_{II}) BETWEEN GOOD AND POOR PERFORMER GROUPS

Group	Accuracy (kappa)					
	CC	HC_I	HC_{II}	HC_I-CC	HC_{II}-CC	HC_{II}-HC_I
Good performer (10 subjects)	84.24	81.71	86.36	-2.53	2.12	4.65
	(0.76)	(0.73)	(0.79)	(-0.04)	(0.03)	(0.06)
Poor performer (10 subjects)	42.96	60.78	81.82	17.82	38.86	21.04
	(0.14)	(0.41)	(0.73)	(0.27)	(0.59)	(0.32)

Fig. 5 and Table II summarize the classification performances of the good and poor performer groups in the three paradigms. In the poor performer group, the HC_{II} paradigm achieved an accuracy of 81.82%, showing an increase of 38.86% and 21.04% in accuracy compared to CC (42.96%) and HC_I (60.78%) paradigms, respectively. In the good performer group, the HC_{II} paradigm achieved an accuracy of 86.359%, showing an increase of 2.12% and 4.65% in accuracy compared to CC (84.24%) and HC_I (81.71%) paradigms, respectively. Data from all groups did not pass the Shapiro–Wilk normality test ($p < 0.05$), and we conducted the Friedman test. In the poor performer group, the Friedman test showed a statistically significant difference among the three paradigms ($X^2(2) = 13.40$, $p < 0.001$). The Wilcoxon signed-rank test demonstrated significant differences in classification accuracy between CC and HC_{II} ($T = -2.803$, $p < 0.01$, $r = 0.84$), and HC_I and HC_{II} ($T = -2.293$, $p < 0.05$, $r = 0.51$). However, no significant difference was found between CC and HC_I ($T = -1.886$, $p < 0.05$, $r = 0.51$). In the good performer group, no significant difference was found using the Friedman test ($X^2(2) = 1.28$, $p > 0.05$).

We analyzed the power spectrum on mu- (8-12 Hz) and beta-bands (18-25 Hz) to show event-related desynchronization/synchronization (ERD/ERS) patterns (Fig. 6 and Fig. 7). For time series plots for ERD with respect to each class (right hand, left hand, and right foot), we used C3, C4, and Cz, respectively. The topographies during right hand task in all conditions are shown in Fig. 6 (A) and Fig. 7 (A). Desynchronization at the contralateral motor area was noticeable. In time series plots (Fig. 6 (A) and Fig. 7 (A)), ERD was also noticeable (i.e., lower EEG power). In each group, however, the desynchronization pattern of poor performers on CC was weak relative to HC_I and HC_{II}. As shown in time series plots during left hand task in all conditions in Fig. 6 (B) and Fig. 7 (B), ERD at the contralateral motor area was also noticeable. In each group, however, ERD of poor performers on CC was weak relative to HC_I and HC_{II}. As shown in Fig. 6 (C) and Fig. 7 (C), ERS at Cz is apparent for all conditions, but ERD at C3 and C4 were more noticeable in HC_{II}. In Fig. 6 and Fig. 7, the topographies in HC_{II} in all groups showed the strongest deactivation pattern in the primary somatosensory area (CPz).

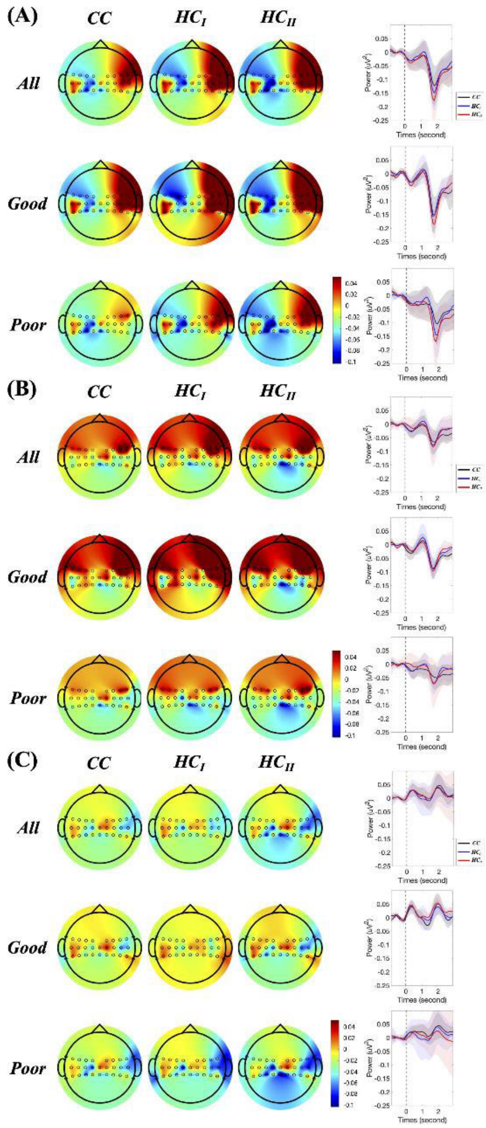

Fig. 6. Topographies and time series plots on mu-band (8-12Hz) power in all trials among the three groups (all participants, good performers, and poor performers) with respect to three conditions (CC: control condition, HC_I: hybrid condition I, and HC_{II}: hybrid condition II). (A) Topographies and time series plots during right hand, (B) left hand, and (C) right foot conditions.

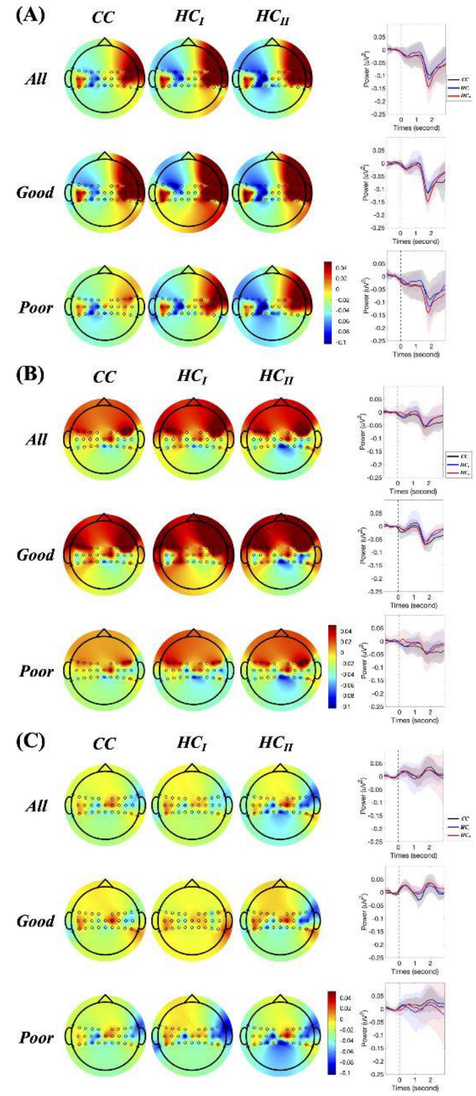

Fig. 7. Topographies and time series plots on beta-band (18-25Hz) power in all trials among the three groups (all participants, good performers, and poor performers) with respect to three conditions (CC: control condition, HC_I: hybrid condition I, and HC_{II}: hybrid condition II). (A) Topographies and time series plots during right hand, (B) left hand, and (C) right foot conditions.

C. Classification Accuracy for Two-Class

For right and left hands, CC, HC_I, and HC_{II} for all participants achieved the average accuracy (kappa) of 72.32±19.69% (0.45±0.39), 78.75±15.19% (0.58±0.30), and 87.59±15.35% (0.75±0.31), respectively. In the good performer group, the HC_{II} achieved an accuracy of 90.81%, showing an increase of 0.98% and 5.64% in accuracy compared to CC (89.84%) and HC_I (85.17%), respectively. In the poor performer group, the HC_{II} achieved an accuracy of 84.36%, showing an increase of 29.55% and 12.03% in accuracy compared to CC (54.81%) and HC_I (72.33%), respectively, as shown in Figure 8(A).

For right hand and right foot, CC, HC_I, and HC_{II} for all participants, achieved the average accuracy (kappa) of 76.68±22.06% (0.53±0.44), 80.79±17.50% (0.62±0.35), and 94.12±5.60% (0.88±0.11), respectively. In the good performer group, the HC_{II} achieved an accuracy of 92.80%, showing a decrease of 1.24% and an increase 2.86% in accuracy compared to CC (94.04%) and HC_I (89.93%), respectively. In the poor performer group, the HC_{II} achieved an accuracy of 95.45%, showing an increase of 36.12% and 23.81% in accuracy compared to CC (59.33%) and HC_I (71.64%), respectively, as shown in Figure 8(B).

For left hand and right foot, CC, HC_I, and HC_{II} for all participants achieved the average accuracy (kappa) of 74.08±19.57% (0.48±0.39), 80.60±17.58% (0.61±0.35), and 89.42±13.89% (0.79±0.28), respectively. In the good performer group, the HC_{II} achieved an accuracy of 91.06%, showing an decrease of 2.28% and an increase 2.30% in accuracy compared to CC (88.77%) and HC_I (88.75%), respectively. In the poor performer group, the HC_{II} achieved an accuracy of 87.78%, showing an increase of 28.39% and 15.32% in accuracy compared to CC (59.39%) and HC_I (72.46%), respectively, as shown in Figure 8(C).

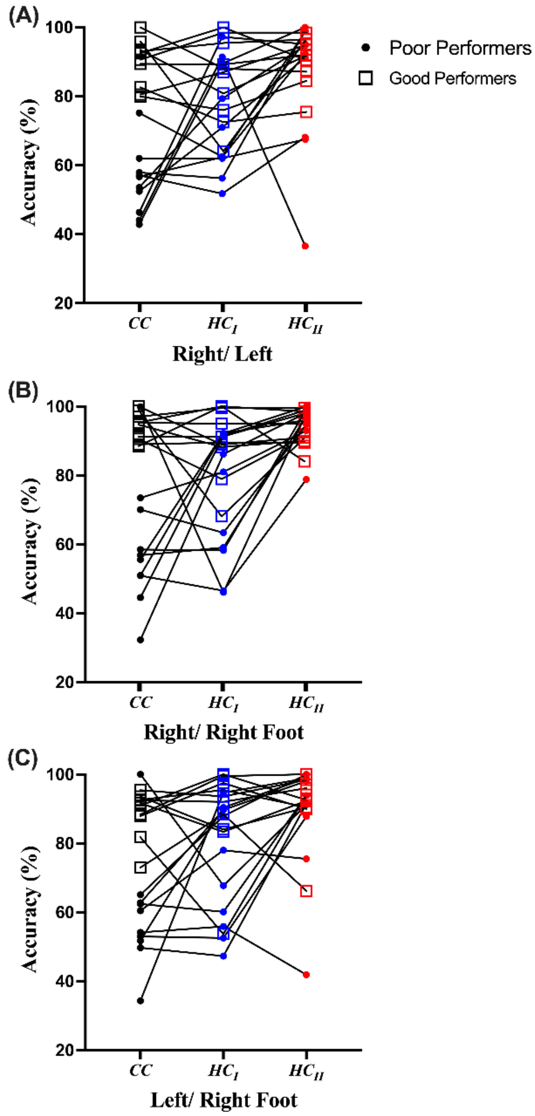

Fig. 8. For CC, HC_I, and HC_{II} paradigms, comparison of classification accuracy (two-class) between right and left hands (A), right hand and right foot (B), and left hand and right foot (C). Filled circles denote poor performers and squares denote good performers.

TABLE III
RESULTS OF SUBJECTIVE INTERVIEW FOR EXPERIENCE BETWEEN THREE PARADIGMS

Subjects	Q1	Q2
Sub. 1	HC_{II}	The hybrid paradigms were more helpful to imagine compared to MI. HC_{II} has different stimuli, making it easier to imagine.
Sub. 2	HC_{II}	HC_{II} made me more focused
Sub. 3	HC_{II}	HC_{II} made recall the feel for sensation of objects together
Sub. 4	HC_{II}	MI felt difficult to me. In HC_{II}, different stimuli made me more comfortable to imagine.
Sub. 5	CC	Hybrid paradigms felt confusing for me MI was more familiar to me.
Sub. 6	HC_{II}	HC_{II} is more comfortable to perform kinesthetic MI
Sub. 7	HC_I	I don't know clearly
Sub. 8	CC	MI was more familiar for me than other methods
Sub. 9	HC_{II}	HC_{II} is more comfortable to perform kinesthetic MI
Sub. 10	HC_{II}	HC_{II} is more comfortable to perform kinesthetic MI because stimuli were different
Sub. 11	HC_{II}	HC_{II} made me more focused
Sub. 12	HC_{II}	HC_{II} is more comfortable to perform kinesthetic MI
Sub. 13	HC_I	HC_I made me more focused HC_I and HC_{II} did not make much difference to me.
Sub. 14	HC_{II}	HC_{II} made recall the feel for sensation of objects together
Sub. 15	CC	MI was more familiar to me than other methods
Sub. 16	CC	Hybrid paradigms felt confusing to me
Sub. 17	CC	HC_{II} made me more focused
Sub. 18	CC	HC_I and HC_{II} did not make much difference to me
Sub. 19	CC	Hybrid paradigms felt confusing to me
Sub. 20	CC	HC_I and HC_{II} did not make much difference to me

The participants classified as "poor performers" are in ***bold*** and italicized. Q1: Which method in each paradigm is better for conducting a BCI-task? Q2: Why do you think this method is better compared to others?

D. Results of Subject's Interviews

1) Question 1: Which Method in Each Paradigm Is Better for Conducting a BCI-task?: For question 1, the response rates for CC, HC_I, and HC_{II} paradigms in the good performer group (10 subjects) were reported as 8 (80%), 1 (10%), and 1 (10%), respectively. Conversely, the response rates for CC, HC_I, and HC_{II} paradigms in the poor performer group (10 subjects) were 0 (0%), 1 (10%), and 9 (90%), respectively. The good and poor performer groups had the highest percentage of choosing the CC and HC_{II} paradigms, respectively.

2) Question 2: Why Do You Think This Method Is Better Compared to Others?: For question 2, many subjects in the good performer group reported that previously experienced CC paradigms were more familiar and helpful than hybrid paradigms, and the hybrid paradigms felt confusing. Conversely, the poor performer group reported that hybrid paradigms were more useful and helpful in performing kinesthetic MI because of the somatosensory stimuli. They also experienced difficulties with MI. Further, HC_{II} was more helpful in specifying kinesthetic MI than HC_I because it had high discrimination by independence of somatosensory stimuli applied to each modality (Table III).

IV. DISCUSSION

A. Summary of Findings

This study had aimed to improve the performance of MI-based BCI in a poor performer group (i.e., BCI inefficient subjects). Thus, this study proposes a unique approach based on hybrid training and imagery paradigms using somatosensory stimuli. The proposed approach (HC_{II} paradigm) achieved an average accuracy of 84.09% for all participants, which was 20.49% and 12.85% greater than that of CC (63.60%) and HC_I (71.25%) paradigms, respectively. In the poor performer group, the average classification performance of HC_{II} was 38.86% and 21.04% higher than that of CC and HC_I, respectively. However, the good performer group showed a slight increase (2.12% and 4.65%) in performance in HC_{II} compared with CC and HC_I, respectively. This study confirmed that hybrid training and imagery paradigms using different types of somatosensory stimuli could improve the performance of MI-based BCI, particularly in the poor performer group.

B. Improving the Classification Performance by Hybrid Paradigms Compared to MI

Previous studies have reported that the hybrid-imagery approach using motor and somatosensory stimuli could enhance the performance of BCI compared to using only motor function. A study [32] showed that the hybrid modality group combined with motor and somatosensory attentional orientation (SAO) (i.e., vibration stimulus) achieved an average accuracy for two-class BCI 11.13% and 10.45% higher than MI and selective sensation groups, respectively. Another study reported that a hybrid modality (MI and SAO) achieved an average classification accuracy for two classes that was 7.70% and 7.21% larger than that of MI and SAO alone, respectively [3]. Our previous study also confirmed that a hybrid method of imagery that combines ME and somatosensory sensation using a tangible object of the same type (i.e., a hard and rough ball) could enhance the average classification performance by 10.73% compared to MI alone [9]. The hybrid-imagery approach can help generate quality EEG patterns because somatosensory stimuli are strongly related to consistent imagining [9]. BCI-inefficient subjects reported difficulties in specifying their imaginations in MI tasks [9], [17], and inconsistent MI can adversely affect the quality of EEG patterns [54], [55]. Furthermore, SAO and MI have distinctive neurophysiological origins, such as the somatosensory and motor cortices, respectively [3], [56]. The hybrid-imagery approach induces activation of both the somatosensory and motor cortices and can have a positive effect on the EEG pattern's quality [3], [9]. MI-based BCI alone probably has already reached the limit of enhancement of classification performance [9], [57]; thus, a new approach is needed to improve performance (i.e., BCI-inefficient users) [58]. This approach complements previous research based on technological factors in MI, which has improved the performance of BCI-inefficient subjects exclusively by feature extraction and classification algorithms [59], [60].

C. Novel Hybrid-Approach to Enhance BCI Performance in BCI-Inefficient Subjects

This study proposes a development approach from our previous study [9] to enhance the three-class BCI performance of BCI inefficient users by hybrid-imagery activating both the motor and somatosensory cortices using the sensation of tangible objects. We attempted to increase discrimination for three modalities (i.e., both hands and right foot) by differentiating the somatosensory stimuli applied to each modality (i.e., tangible objects: hard and rough, soft and smooth balls, and hard and rough types), including the effect of the hybrid-imagery paradigm. The proposed method (HC_{II}) significantly increased classification performance by 8.01% and 13.09% compared to our previous research (HC_{I}) and CC, respectively, in the poorly performing group. Conversely, the good performer group showed an increasing trend in performance with no significant difference between the three paradigms.

We believe that there are multiple reasons for the enhanced classification performance in the poor performer group. The first is the materialization of the imagery procedure and high concentration on the BCI task by different types of somatosensory stimuli. Different stimuli applied to each modality increased the discrimination of the subject's imagination process for tasks of the three classes. We believe that HC_{II} positively helped poorly performing subjects who had difficulty conducting MI alone and specified and discerned the object of imagination. Our interpretation is supported by the results of the post-experiment interviews on the subject's experience with the experimental paradigms. Subjects in the poor performer group preferred the hybrid paradigm compared to MI alone; moreover, HC_{II} had different types of somatosensory stimuli that helped them focus and specify their imagery procedure. The good performer group reported that the established MI approach was more familiar among the hybrid paradigms and felt confused about the new approach. Second, the different types of somatosensory stimuli generated a quality EEG pattern in both the motor and somatosensory area by discrimination enhancement. That is, different types of stimuli applied to each modality of three-class caused enhanced ERD patterns of mu- and beta-bands in the primary motor area. As shown in Fig. 6 and Fig. 7, EEG activities of good performers were naturally the same as in previous studies, regardless of condition [61], [62]. However, EEG activities of poor performers were different than those of the good performers. As shown in topographies and time-series plots for the right hand of poor performers, ERD patterns appeared strongly at HC_{II}. These trends were similar to those of good performers. Similarly, in other classes (left hand and right foot), EEG activities of poor performers were similar to those of good performers. Previous studies reported that somatosensory stimuli, which differs in its pattern or type, induces other patterns of cortical activity [63], [64], [65], [66]. In addition, imagery and execution of somatosensory stimulation can facilitate cortical excitability [67], [68]. In this study, our results for HC_{II} also indicated that the EEG activities (deactivation) at somatosensory area (CPz) appeared strong not only in poor performers, but also good performers. We believe that the activity pattern in the somatosensory area can be influenced by different types of tangible objects, which lead to improved classification performance in HC_{II} compared to that in HC_{I} by increasing discrimination and generating quality EEG patterns.

D. Limitations

MI-based BCIs are used in neurorehabilitation therapy to restore impaired motor function in stroke patients [69]. Because a large proportion of stroke patients is closely related to BCI-inefficiency users [22], the proposed approach may help those who are unable to perform voluntary movements, restoring motor function by applying passive movement using external devices. However, this study recruited only healthy participants. The limitations of validation for stroke patients need to be considered in further studies. Moreover, the MI-BCI familiarity of subjects might have influenced the conclusion of this study, because this study only recruited subjects who had prior experience in MI experiments. The performance enhancement of MI-BCI on new users who have no or little experience cannot be guaranteed by the findings of this work, and this needs to be considered in further studies.

V. Conclusion

Using a modality-independent somatosensory stimulus and the hybrid-imagery paradigm to simulate both motor and somatosensory stimuli significantly enhanced the three-class BCI performance in the poor performer group. A modality-independent somatosensory stimulus provided high concentration and discrimination to poor performers during MI-based BCI and generated a quality EEG pattern to represent MI. This improved classification accuracy compared to MI alone and a previous approach. The hybrid-imagery approach can help improve MI-BCI performance, address BCI illiteracy, and will be applicable to neurorehabilitation research to restore impaired motor functions. Our findings can contribute to the practical use and uptake of BCI. We believe that various types of somatosensory stimuli or modalities combinations may significantly improve BCI performance and should be investigated in the future.

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