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Improving performance in motor imagery BCI-based control applications via virtually embodied feedback

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ABSTRACT

Objective: Brain-computer interfaces (BCIs) based on motor imagery (MI) are commonly used for control applications. However, these applications require strong and discriminant neural patterns for which extensive experience in MI may be necessary. Inspired by the field of rehabilitation where embodiment is a key element for improving cortical activity, our study proposes a novel control scheme in which virtually embodiable feedback is provided during control to enhance performance.
Methods: Subjects underwent two immersive virtual reality control scenarios in which they controlled the two-dimensional movement of a device using electroencephalography (EEG). The two scenarios only differ on whether embodiable feedback, which mirrors the movement of the classified intention, is provided. After undergoing each scenario, subjects also answered a questionnaire in which they rated how immersive the scenario and embodiable the feedback were.
Results: Subjects exhibited higher control performance, greater discriminability in brain activity patterns, and enhanced cortical activation when using our control scheme compared to the standard control scheme in which embodiable feedback is absent. Moreover, the self-rated embodiment and presence scores showed significantly positive linear relationships with performance.
Significance: The findings in our study provide evidence that providing embodiable feedback as guidance on how intention is classified may be effective for control applications by inducing enhanced neural activity and patterns with greater discriminability. By applying embodiable feedback to immersive virtual reality, our study also serves as another instance in which virtual reality is shown to be a promising tool for improving MI.

1. Introduction

For brain-computer interface (BCI) applications that require active control, it is crucial for the neural activity patterns of different intentions to be distinguishable [1–4]. Without discriminability, BCIs are unable to deliver the user's intentions to the devices they are connected to. Motor imagery (MI) is the go-to paradigm for such applications, as it not only focuses on active intentions unlike other BCI paradigms, which utilize reactive responses, but also promotes discriminability by inducing changes in neural patterns [5–8]. These changes, located in activated regions within the sensorimotor cortex, exhibit themselves in two distinct patterns: event-related desynchronization (ERD), or a blocking of oscillatory neural activity, and event-related synchronization (ERS), a recovery of oscillatory activity shortly after desynchronization [9–11].

With MI playing such an important role in BCI applications, much research on ways to enhance MI has been conducted. One such way is applying visual imagery in the form of action observation (AO), or the visualization of a virtual body part executing the imagined movement, to kinesthetic MI to enhance cortical activity [12–15]. Previous studies in the field of rehabilitation have not only suggested that AO may excite cortical activity corresponding to the visualized action due to the mirror neuron system, which is activated by perceiving or imitating the visualized action, but also claimed that AO may help stroke patients induce rhythmical patterns such as ERD of the corresponding brain region [16–19]. AO has therefore been widely used along with kinesthetic MI to induce greater brain activity in patients as well as in healthy subjects who use BCI applications [20–23]. For example, Nagai et al. compared three different protocols for kinesthetic MI training: AO of the subject's own hand executing a grasping movement, AO of someone else's hand executing the movement, and no AO [24]. The protocols that provided

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AO resulted in greater ERD compared to the no AO protocol. Another interesting result was that AO of the subject's own hand resulted in even greater ERD compared to AO of someone else's hand.

Similar findings were also discovered for feedback methods, which inform subjects on how their neural activity is being classified during MI. Ono et al. experimented with four different feedback methods for binary classification of resting or movement of the dominant hand during MI training: no feedback, standard bar feedback, incongruent feedback in which a virtual hand executing the classified movement was shown at eye level, and congruent feedback in which the virtual hand was provided as an overlay over the subjects' hands [25]. The congruent feedback exhibited the greatest improvement in MI performance in terms of both ERD ratio and classification accuracy. Various studies have investigated this phenomenon and concluded that ownership over visualized movement may influence MI performance, providing evidence that improvements in performance result from embodiment of the mirrored movement [26,27].

Consequently, there have been recent attempts to increase body ownership and enhance MI performance by providing both AO and feedback in virtual reality (VR) environments [28–31]. With their ability to realistically present virtual scenarios while concealing the real surrounding environment, immersive head-mounted displays have proven to be a useful tool for increasing embodiment [32–35]. For instance, Škola and Liarokapis found that using an immersive head-mounted display during training to provide AO of and feedback on forward arm movement led to a higher ERD ratio and classification accuracy than when training with the standard bar paradigm through a monitor display [36].

However, with current research mainly focusing on applications to rehabilitation or MI training, no evidence of whether embodiable feedback is also effective for control scenarios yet exists. Unlike rehabilitation applications, which mainly focus on the presence of cortical activity during scenarios within a fixed, static environment, control scenarios not only exhibit dynamic changes in the surrounding environment while the device is controlled but also require multiple degrees of freedom in movement mapped to different MI tasks, resulting in greater perceptual complexity. Whether utilizing embodiable feedback for an unembodiable device is appropriate and how the usage of embodiable feedback in the context of greater perceptual complexity may affect desired neural activation are other warranted questions that have not been answered by current literature. Although some studies have used virtual reality environments for control applications [37,38], our study further investigates the actual effect that immersive VR-based embodiable feedback has on controlling devices.

In this study, we therefore propose a novel control scheme in which virtually embodiable feedback is provided not only during MI training, but also while controlling unhuman devices. To verify the hypothesis that our control scheme improves performance, we constructed a VR control scenario in which the subject controls the two-dimensional movement of a virtual device with MI in first-person perspective. Repeated left hand grasping MI, repeated right hand grasping MI, and resting state were mapped to left rotation, right rotation, and forward movement, respectively. Subjects participated in two experimental sessions, with each session consisting of three different phases: a training phase using AO followed by two control phases, both of which used our control scenario. Electroencephalography (EEG) was used to analyze neural activity and patterns during the three phases, and with the data collected during the training phase, a machine learning classifier was created to predict the subjects' intentions during the control phases. The two control phases differ solely on whether embodiable feedback is given: one only provides information on the device's movement, while the other provides not only information on the device's movement but also embodiable feedback in the form of virtual hand movements, which mirror the classifier's predictions of the subjects' intentions.

2. Experiment

2.1. Subjects

Fourteen healthy subjects aged between 21 and 30 were recruited for this experiment. Twelve of these subjects were right-handed, while the remaining two were left-handed. Six subjects had prior experience with MI-based studies, while the rest did not. None of the subjects had experience with BCI-based control applications. All subjects had prior experience with using immersive head-mounted displays. All subjects went through two experimental sessions, where each session consisted of a training phase followed by two consecutive control phases. All subjects were warned that each session would take more than an hour and were therefore also recommended to get enough rest before each session. This study was approved by the Korea Advanced Institute of Science and Technology Institutional Review Board. All subjects gave their written consent prior to the experiment.

2.2. Experiment design

Our immersive virtual reality scenario was implemented using the Unity game engine (Unity Technologies, San Francisco, CA, USA). As seen in Fig. 1, the scenario setting is a track containing seven forward stretches, three left turns, and three right turns, with the starting and end positions colored in red. The subject starts off at the track's starting position, facing forward in first-person perspective. The subject's perspective is fixed relative to a drone-shaped virtual device that is above and slightly ahead of them. Two virtual hands, which are shoulder-width apart from each other, are also below and slightly ahead of the subject such that they would have similar positions to the subject's actual hands when resting while seated. Three signs, one each of a left arrow, a right arrow, and a cross, are also placed in front of the subject, with at most one of them visible at a time to indicate that the subject is expected to perform left hand grasping, right hand grasping MI, or resting imagery, respectively.

2.3. Training phase

In the training phase, subjects were instructed to complete 20 consecutive MI trials, with each trial consisting of three tasks in randomized order: one repeated left hand grasping, one repeated right hand grasping, and one resting task.

Each task was a sequence of a 3-s preparation period, a subsequent 10-s MI period, and finally a 3-s resting period. During the preparation period, subjects were shown one of the three signs to notify them of which task they were undergoing. During the MI period, the virtual hands executed the movement corresponding to the task. Subjects were instructed to observe the movement of the virtual hands and to imagine them to be their own as if they were executing the actions themselves. During the resting period, subjects were expected to stop the corresponding MI and were permitted to make slight movements such as eye blinking. EEG signals were recorded throughout the entire training phase in order to analyze the elicited brain patterns and construct a classification model for the two control phases.

2.4. Control phases

After the training phase, a classification model was created with the acquired EEG data. Subjects then underwent two control phases in which they were instructed to control a virtual device. For both phases, the device followed the same predetermined route on the track, with indicator signs informing the subject of how the device should move throughout the phases. The device moved if and only if the model classified the subjects' neural signals to be the MI task mapped to the required movement of the device. Repeated left hand grasping and right hand grasping MI were mapped to left rotation and right rotation of the

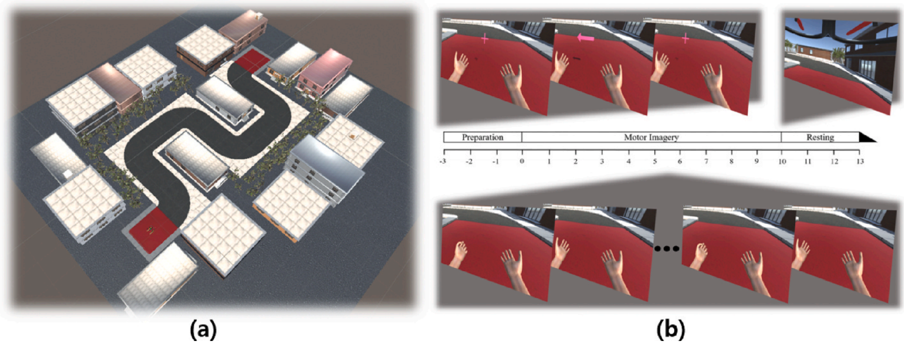

Fig. 1. Setup and design of the experiment. (a) Our VR scenario in which a simulated device is controlled on a track with left turns, right turns, and forward stretches. (b) A timeline of a single task during the training phase.

device, respectively. Resting imagery was mapped to forward movement of the device, as a substantial amount of resting state data is required for computing the ERD ratios as well as for increasing user performance [39–41]. The virtual device moved asynchronously based on the real-time EEG signals as shown in Fig. 2, with the signals continuously classified every second throughout the whole control phase from start to finish. Prior to the control phases, subjects were made aware that the interface may misclassify their intentions.

The two control phases only differ on whether they provide embodiable feedback. In one phase, virtual hands are shown and execute the movement that is classified (embodied feedback control scheme, referred to as EFCS). The other phase does not show the virtual hands (standard control scheme, referred to as SCS). Thus, the performances from the two control phases can be compared by analyzing each subjects' classification accuracy and time to completion [42]. To prevent the possibility of the order of the two control phases affecting results, the treatments were randomized such that in one experimental session the EFCS came prior to the SCS and in the other session the SCS came prior to the EFCS, with the order of the two sessions randomized.

2.5. Experimental setup

The experiments were conducted in a dark, soundproof room to prevent distractions. Subjects were seated in a comfortable chair, wore an EEG cap and an Oculus Go (Oculus VR, Menlo Park, CA, USA), and were asked to place their hands on the desk in front of them as shown in Fig. 3. To maximize embodiment, subjects were asked to place their hands such that the virtual hands were in appropriate positions for embodiment.

EEG data was obtained with BrainProducts' actiChamp and actiCAP (BrainProducts, Munich, Germany) at a sample rate of 500 Hz. Including ground (AFz) and reference (Fz), a total of 16 electrodes were used (F3, F4, FC5, FC1, FC2, FC6, C3, C4, CP5, CP1, CP2, CP6, P3, P4) according to the international 10–20 system. The impedance of each electrode was kept under 10 kΩ. The electrodes were carefully placed under the Oculus Go such that slight head movements could not cause significant noise in the data. The data was band-pass filtered between 8 and 36 Hz.

2.6. Questionnaires

After each experimental session, subjects were asked to complete a questionnaire, which aimed to gather information on the subjects' experiences and their opinions on how helpful virtual hand feedback was for MI performance. The full questionnaire is shown in Table 1.

The questionnaire included measures of embodiment (body ownership) and presence (spatial), which were prepared based on previous

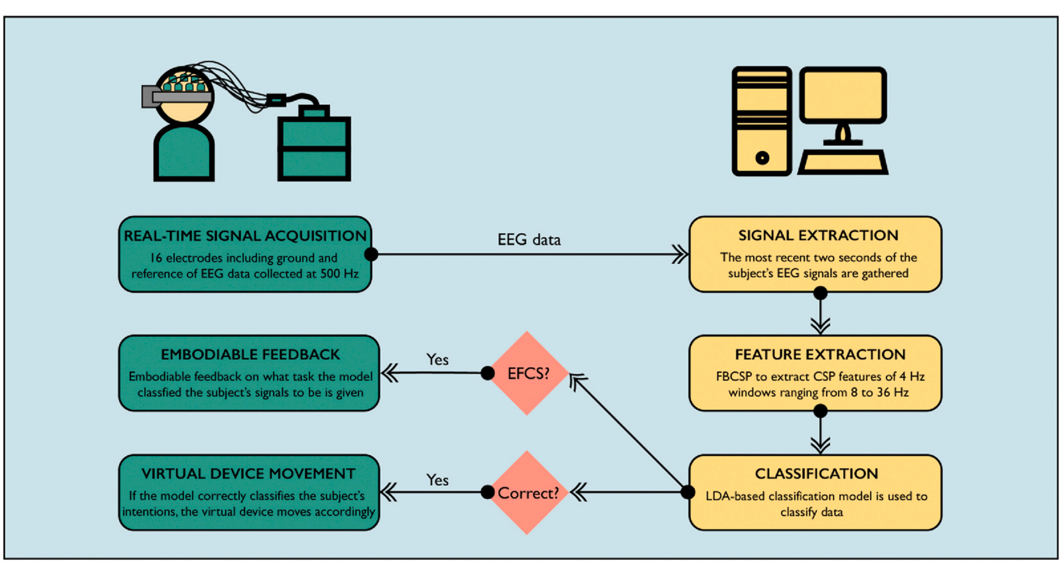

Fig. 2. An overall flow chart of the two control phases. The EEG signals were classified real-time, resulting in an asynchronous BCI control of a virtual device.

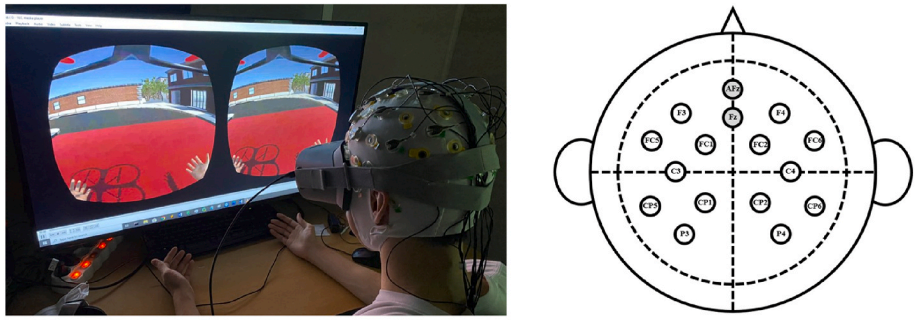

Fig. 3. (a) Experimental setup of subjects using the head-mounted display. (b) Electrode positions used in the experiment to measure EEG data.

Table 1
Questionnaire for self evaluation.

Category	Question
Embodiment	During training, to what extent did you feel the virtual hands to be your own?
Presence	To what extent did you feel surrounded by the simulated virtual environment?
Evaluation (MI)	Disregarding the results, please self-rate how well you could imagine movements during the control phase without virtual hand feedback.
Evaluation (MI)	Disregarding the results, please self-rate how well you could imagine movements during the control phase with virtual hand feedback.
Survey (AO)	Did the virtual hands help you imagine hand movements during the training phase?
Evaluation (AO)	Please answer the above question with a numeric scale.
Survey (EF)	Did the virtual hands help you imagine hand movements during the control phase?
Evaluation (EF)	Please answer the above question with a numeric scale.
Survey (EF)	Did the virtual hands help you control the device during the control phase?
Evaluation (EF)	Please answer the above question with a numeric scale.

studies regarding measures of different perceptions of virtual reality environments [33,43,44], along with self-evaluations related to subjects' MI performances, action observation, and the provided feedback.

The responses to embodiment, presence and MI performance were measured on a 11-point numeric scale (0: extremely negative response and 10: extremely positive response). The responses to the survey and the evaluation questions regarding action observation and embodied feedback were multiple choice (was rather distracting, neither, was helpful) and a 11-point numeric scale (−5: was very distracting and 5: was very helpful), respectively.

3. Methods

3.1. Classification model for control scheme

Prior to constructing the classification model, we first preprocessed the acquired data from the training phase by applying data augmentation: each 10-s EEG data from the MI period of each trial was augmented by splitting it into 2-s time windows with a stride of 0.1 s, resulting in 81 samples. With 20 trials, there was therefore a total of 1620 samples per task. A Filter-Bank Common Spatial Pattern (FBCSP) was then used on these samples to extract the CSP features of 4 Hz windows ranging from 8 to 36 Hz, which resulted in 7 different filter bands with 4 components each [45]. The multi-class classification model was then constructed using the Bayesian formulation of Fisher's linear discriminant analysis (LDA) on the features [46].

3.2. Control performance

Subjects' performances during the two control phases were compared in terms of both the time to completion and the classification accuracy. Classification accuracy was determined by the percentage of times that the classification model correctly predicted the subjects' signals to be the task corresponding to the indicator sign shown to the subject. We first applied a two-way ANOVA, with the usage of embodiable feedback and the order of control phases as the two factors, on the time to completion to investigate whether the performances between the two control phases were statistically different and whether the order of the control phases influenced performance.

To measure the performances of subjects during the training phase, which were considered as baseline measures for their performances during the two control phases, we performed 4-fold cross-validation using FBCSP on the training phase data. To analyze and compare the classification accuracies during each phase, we applied the Mann-Whitney U test along with Bonferroni correction for multiple comparison tests. Furthermore, the classification accuracies for each MI task during the two control phases were separately examined and compared using the same procedure.

3.3. ERD performance

To investigate ERD performance of subjects for both left hand and right hand grasping MI, data from electrode positions C3 and C4 were analyzed to measure the ERD ratio [47,48]. For all three phases, we first categorized the EEG data into the three imagery tasks and computed the mean power spectrum of each task using the following equation:

$$PSD(task) = \frac{1}{n_{task}} \sum_{t=1}^{n_{task}} P(task, t) \qquad (1)$$

$$task \in \{left, right, rest\}$$

where *task* is one of the three MI tasks (left, right, and resting), n_{task} represents the number of times that task was performed during a single phase, and $P(task, t)$ represents the power spectrum of the tth time the task was performed.

To measure the ERD ratios of subjects for each phase, the mean power spectrum of the resting task was used as a baseline. Thus, the ERD ratios of left hand and right hand MI were calculated with the following equation:

$$ERD(m) = \frac{PSD(rest) - PSD(m)}{PSD(rest)} \times 100(\%) \qquad (2)$$

$$m \in \{left, right\}$$

where *m* indicates left or right hand MI, and *rest* represents resting state. As previous studies have indicated that each individual's brain activities vary between different frequency bands [49,50], the frequency band

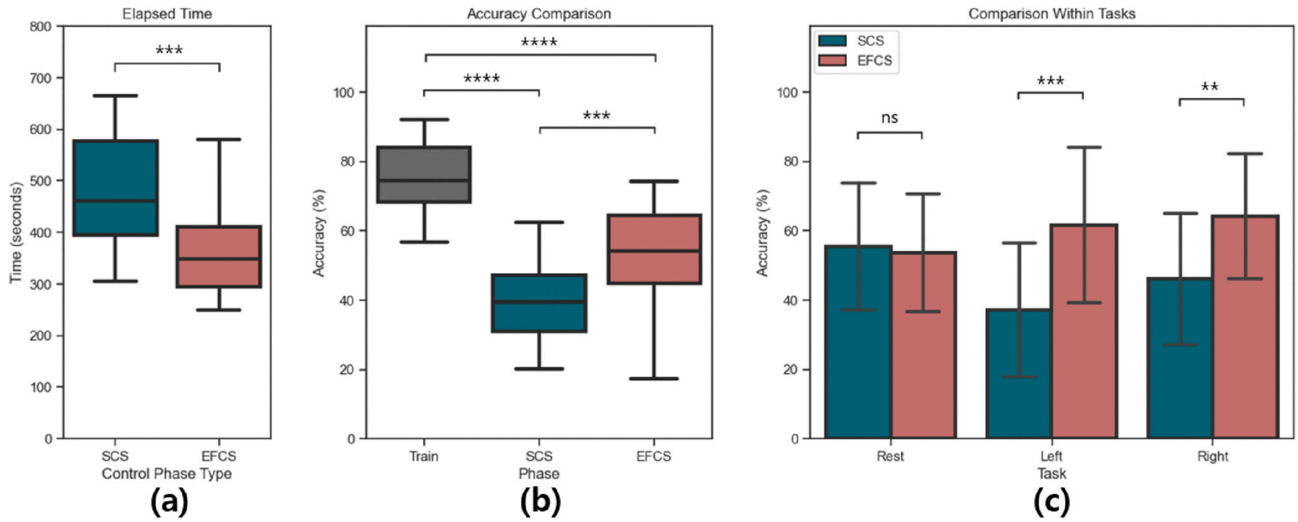

Fig. 4. Control scheme results. (a) Time to completion during the two control phases. (b) Comparison of 4-fold cross-validation training accuracy and classification accuracy results of the two control phases. (c) Comparison of classification accuracy of each task between the two control phases (**$p < 0.01$, ***$p < 0.001$, ****$p < 0.0001$, ns indicates no significance, error bars in bar plots represent standard deviation).

used in FBCSP that had the maximum elicited ERD ratio from the two experimental sessions was selected for each subject for analysis.

As left hand and right hand MI are two distinguishable tasks, the ERD ratios from the two hand grasping MI were separately investigated. To compare the changes in ERD ratios between the training phase and the two control phases, we applied Mann-Whitney *U* test and Bonferroni correction for multiple comparisons.

4. Results

4.1. Control performance and classification results

As shown in Fig. 4, three comparisons were made to analyze control performance: time to completion between the two control phases, classification accuracies of all three MI tasks between each phase, and the classification accuracies of each task between the two control phases.

The two-way ANOVA showed that the EFCS exhibited a significantly lower time to completion (F (1,26) = 18.096, $p < 0.001$) compared to the SCS (387.26 ± 152.20 s with embodiable feedback and 492.66 ± 131.43 s without). On the other hand, no statistical significance was observed for the order of the two phases (F (1,26) = 1.690, $p > 0.2$).

The classification accuracies from the two control phases (53.27 ± 13.21 for the EFCS and 39.99 ± 10.47 for the SCS) both exhibited a significant degradation in performance compared to the cross-validated accuracies of the training phase (75.04 ± 11.11). Statistical analysis

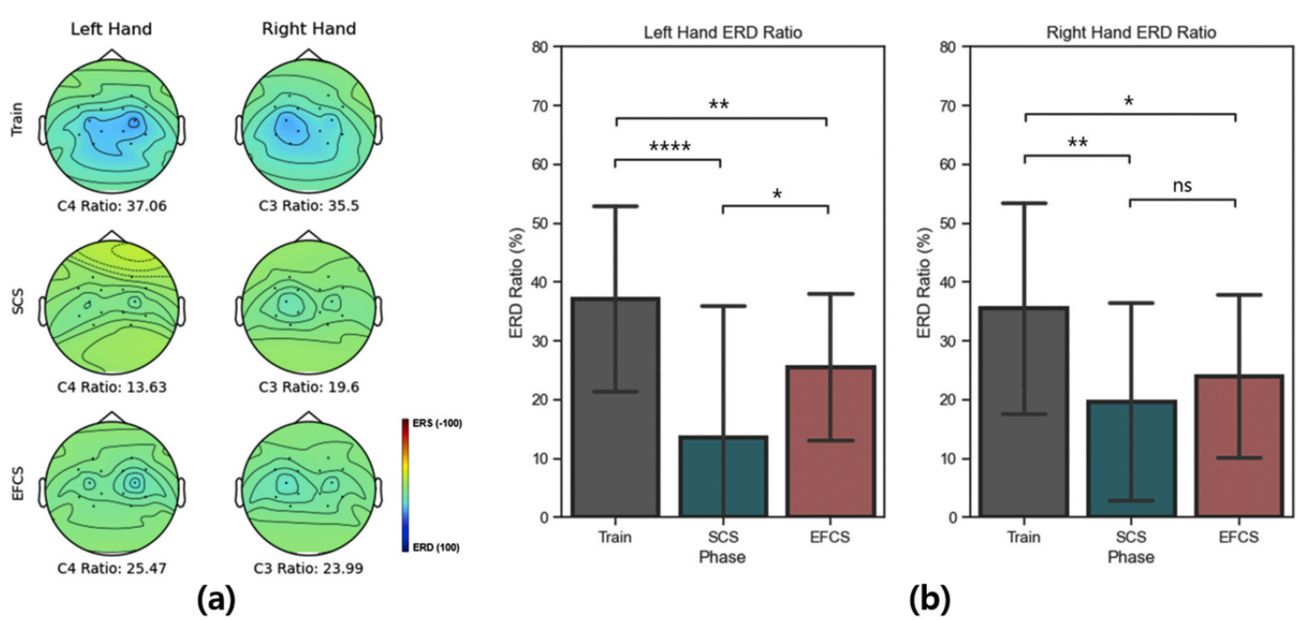

Fig. 5. ERD ratio results for the three phases. (a) Averaged topomap of per-subject best ERD ratios for left hand and right hand MI from each phase. (b) Comparison of per-subject best ERD ratios of left and right hand MI between the phases (*$p < 0.05$, **$p < 0.01$, ****$p < 0.0001$, ns indicates no significance, error bars in bar plots represent standard deviation).

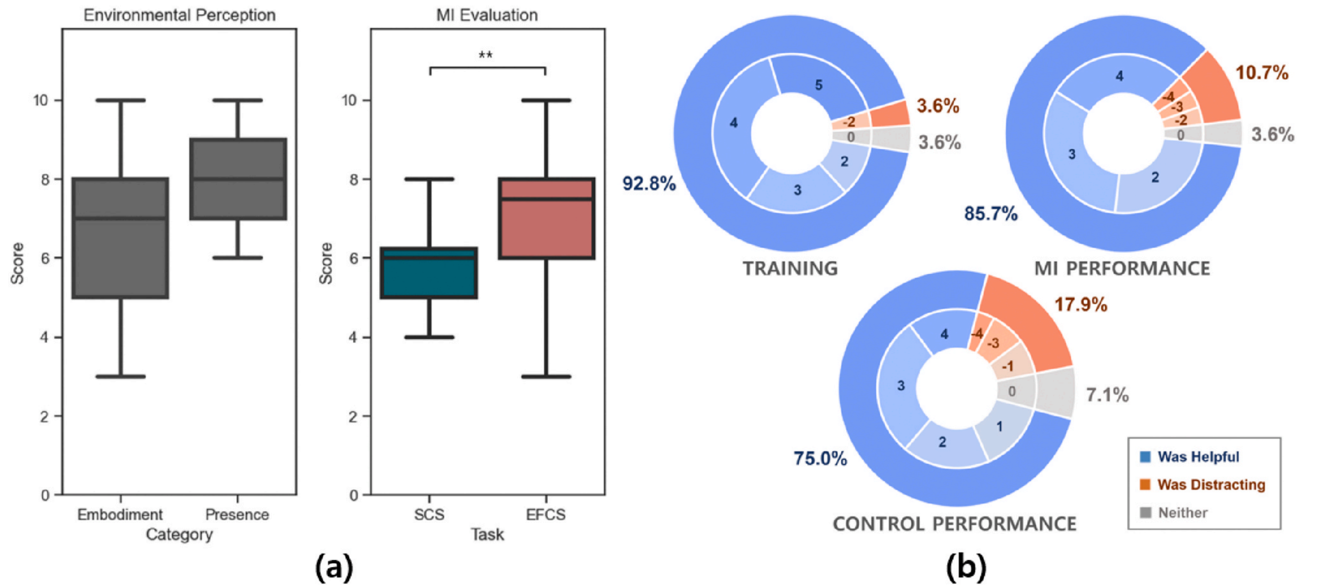

Fig. 6. Questionnaire results. (a) Responses regarding embodiment, presence, and self-rated MI performance while within our immersive virtual reality environment ($^{**}p < 0.01$). (b) Results from the evaluation of action observation and embodied feedback in the form of virtual hands.

using the Bonferroni-corrected Mann-Whitney U test further showed that the SCS had a greater effect size on the decrease in performance ($p-adj <$ 1e-08, $u = 769$) compared to the EFCS ($p-adj <$ 1e-06, $u = 711$). There were also significant differences in accuracy between the two control phases themselves, with the EFCS having significantly higher accuracy than the SCS ($p-adj < 0.001$, $u = 165$).

No significant difference was observed for resting performance between the two control phases using the Bonferroni-corrected Mann-Whitney U test ($p-adj > 0.9$, $u = 414$), with the accuracies of the EFCS and SCS at 53.59 $\pm$ 16.99 and 55.39 $\pm$ 18.24, respectively. However, significant differences were observed for the other two MI tasks ($p-adj < 0.001$, $u = 167$ for left hand and $p-adj < 0.01$, $u = 183$ for right hand MI), with the EFCS exhibiting a much greater accuracy (61.65 $\pm$ 22.45 and 64.25 $\pm$ 17.98 for left and right hand, respectively) than the SCS (37.21 $\pm$ 19.26 and 46.08 $\pm$ 18.99 for left and right hand, respectively).

4.2. ERD ratio results

Fig. 5 shows the averaged ERD topomap of all subjects for left hand and right hand MI across all three phases. The topomap indicates that the ERD ratios were observed mostly from the electrode positions C4 and C3 of each individual's representative frequency band.

Fig. 5 also shows the comparisons between the ERD ratios from electrodes C4 and C3 during left and right hand MI, respectively, of each phase. The ERD ratios were much greater during the training phase than during either of the control phases for both left hand and right hand MI (37.06 $\pm$ 15.73 and 35.50 17.89, respectively). Statistical analysis further showed that for both left hand and right hand MI, the SCS (13.63 $\pm$ 22.28, $p-adj < 0.0001$, $u = 652$ and 19.60 $\pm$ 16.76, $p-adj < 0.01$, $u = 588$ for left hand and right hand, respectively) has a greater effect size on the decrease in ERD ratio than the EFCS (25.47 $\pm$ 12.44, $p-adj < 0.01$, $u = 576$ and 23.99 $\pm$ 13.87, $p-adj < 0.05$, $u = 547$ for left hand and right hand, respectively). A significantly greater ERD ratio was observed for the EFCS compared to the SCS for left hand MI ($p-adj < 0.05$, $u = 238$), while a greater but not significant ERD ratio for the EFCS ($p-adj > 0.82$, $u = 325$) was observed for right hand MI.

4.3. Questionnaire results

The questionnaire results are described in Fig. 6. With scores out of 10, subjects expressed the extent to which they were able to embody the virtual hands with a score of 6.71 $\pm$ 1.89, and the extent to which they felt immersed in the virtual reality environment with a score of 8.14 $\pm$ 1.12. Furthermore, subjects reported that they were able to perform MI better during the EFCS in which embodiable feedback was provided (7.00 $\pm$ 1.87) than during the SCS in which feedback was absent (5.714 $\pm$ 1.31) with statistical significance ($p < 0.01$, $u = 573.5$).

The questionnaire further shows that over 90% and over 85% of the subjects found the virtual hands to be helpful for performing MI during the training phase and during the EFCS, respectively. About 75% of the subjects reported that they found the virtual hands to be helpful for controlling the drone during the EFCS. The average scores for the above three questions regarding the virtual hands were 3.46, 2.29, and 1.5, respectively, indicating that the embodiable feedback provided in the form of virtual hands was, on average, beneficial to the subjects for performing MI as well as for completing the EFCS.

5. Discussion

Previous research has shown that providing embodiable feedback that mimics the MI task during rehabilitation or clinical treatments may improve brain activity [25,27,36]. However, such cases have limited complexity, as they mostly focus on enhancement of cortical activation during training while performing MI in a static environment. To the best of our knowledge, we are the first to explore the usage of embodiable feedback in control scenarios to enhance performance. Furthermore, although many studies have used virtual reality environments for their visual scenarios, few have used immersive head-mounted displays to display them. In this study, we hypothesized that virtually embodiable feedback, provided through immersive VR head-mounted displays, may also improve cortical activation as well as spatial discrimination during MI in control scenarios despite their increased complexity relative to rehabilitation applications. We tested this by creating an immersive virtual reality scenario in which subjects had to control a device in first-person perspective either with or without virtual hand feedback.

The results from our experiments indicate that subjects were able to finish the control scenario faster when provided with virtual hand feedback. To investigate how such feedback influenced performance, we analyzed the classification accuracy as well as the ERD ratios obtained during the experiments. Out of the three phases, the training phase had

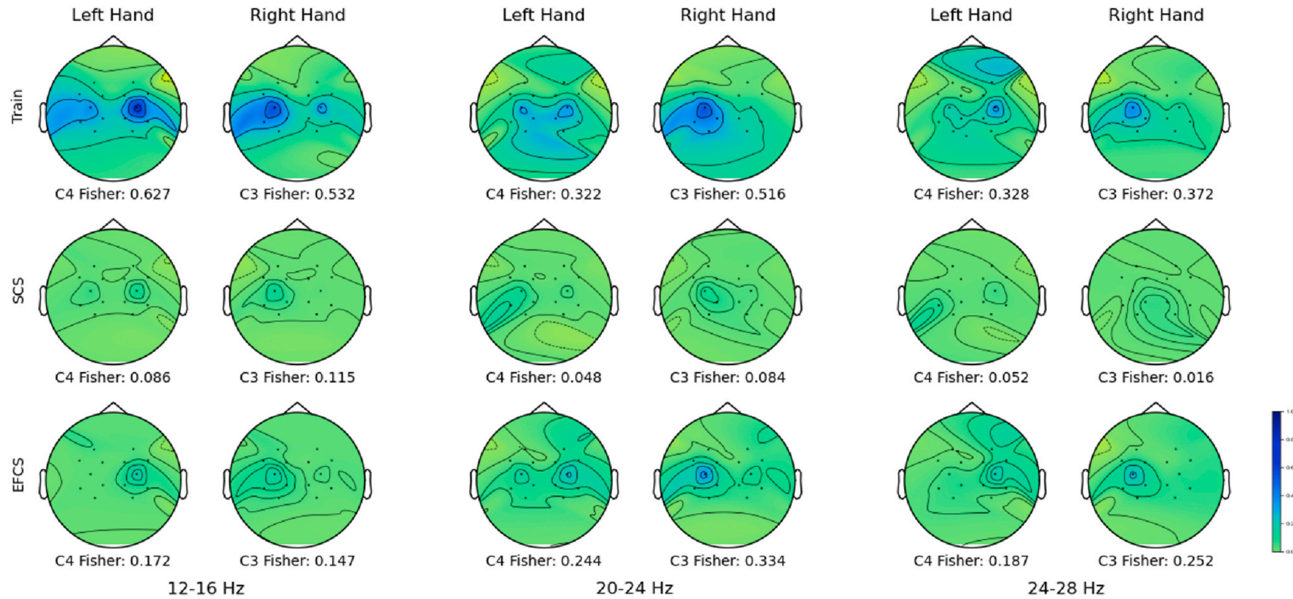

Fig. 7. Topomaps of Fisher ratios from the ERD ratio of all subjects on representative frequency bands.

subjects both inducing the highest ERD ratio and achieving the highest classification accuracy for MI. Such results corroborate the claim of many preceding studies that action observation along with MI may amplify cortical activation of corresponding movement [14,21–23]. On the other hand, the two control phases both exhibited a decrease in ERD ratio as well as accuracy from the training phase baseline. Although both control phases resulted in a decrease in performance, a smaller decrease was observed for the control phase that provided feedback, indicating that users were able to better control the simulated device when virtual hands were present. With the classification model also classifying left hand and right hand MI more accurately in the EFCS than in the SCS, we have confirmed that subjects undergoing a control scenario were able to induce brain activity patterns of greater discriminability when virtual embodiable feedback was provided. To alleviate concerns that these results were due to other factors outside of MI such as noise, we further plotted Fisher ratios to verify that MI was the main influence of classification accuracy. As shown in Fig. 7, we have confirmed that for all the three phases, the electrode positions that majorly affected the classification of the different MI tasks were C3 and C4, which are known to be the positions corresponding to right and left hand MI, respectively.

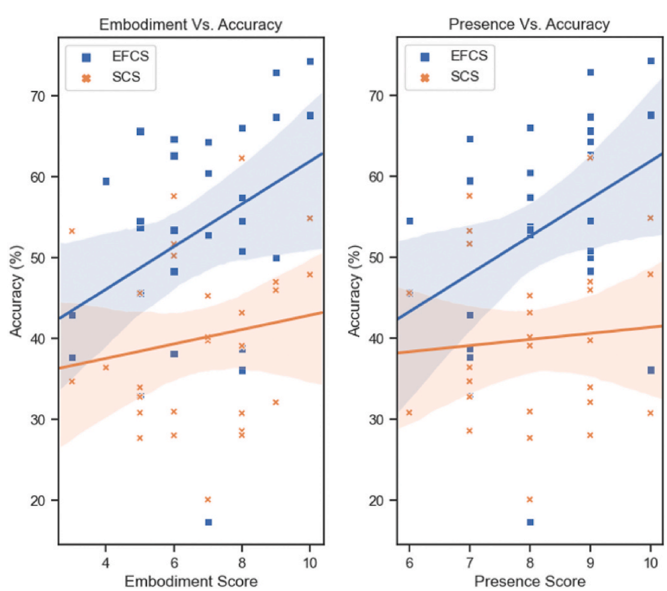

Fig. 8. Effect of embodiment and presence on control performance.

As seen from the questionnaire results, our subjects showed varying degrees of perceived embodiment and presence, with some perceiving the provided scenario to have negatively affected their performance. To investigate whether such differences of perception from each subject, despite their exposure to the same environment, may have correlated with their control performances, we further analyzed the effect of embodiment and presence on MI performance. As shown in Fig. 8, statistically significant positive linear relationships between classification accuracy and both embodiment and presence were shown for device control with virtual hand feedback ($r = 0.377$, $p = 0.048$ for embodiment and $r = 0.396$, $p = 0.036$ for presence), while no statistically significant positive relationships were shown from device control without virtual hand feedback ($r = 0.160$, $p > 0.415$ for embodiment and $r = 0.081$, $p > 0.681$ for presence). The difference in significance for presence was especially surprising, as the question only asked about the surrounding environment and not about the virtual hands. With previous studies concluding that immersion is positively correlated with both embodiment and presence [51–53], we can infer that the increase in performance is due to increased immersion, which increased both embodiment and presence as well. A future study should be conducted to verify this inference.

Although we have shown that users have greater control over a simulated device when provided with virtually embodiable feedback, our small sample size may have skewed results. A future study should investigate the effects of virtually embodied feedback on a larger sample of subjects. Furthermore, there is no guarantee that virtually embodiable feedback will positively affect device control in the real world. Real-world tests were avoided due to the potential of environmental factors adversely affecting results, but the difference in immersion between a virtual reality environment and the real world or some augmented reality cannot be ignored. To address this, we attempted to make our scenario as realistic as possible by making the virtual hands and environment realistic while also allowing subjects to move their head around freely to view the environment. Our control scheme also stops the device when the classification model determines the subjects' intentions to be different from the required movement, which differs from navigation in the real world in which the device always moves in the classified direction. If we were to allow the control scheme to directly follow the classifications made by the classification model, there would exist the possibility of subjects never finishing the control phase, which we wanted to avoid. With the main focus of our study being the effect of embodiable feedback on MI during control scenarios, we thought a predetermined route would be the fairest way to compare times to completion to analyze the effect on MI. We also mapped the resting MI task to the forward movement of the device, which is unusual for control scenarios. This was done to (1) gather enough resting state data between turns, which is a requirement for accurately calculating the ERD ratios, and (2) shorten training time for subjects by minimizing the number of classes such that subjects would be less affected by fatigue while using the head-mounted displays. Nevertheless, our study is the first to reveal the promising potential of virtually embodiable feedback to improve performance for real-life control applications.

6. Conclusion

In our study, we applied embodiable feedback to an immersive virtual reality environment to improve the performance of MI-based BCI, specifically in the case of control applications in which users are exposed to a dynamically changing environment and greater perceptual complexity. Our results suggest that embodied feedback may both enhance discriminability of spatial brain patterns and improve cortical activation of the desired MI when users use BCIs to control devices. Such findings could contribute to MI-based BCI systems by providing accessibility to users who may not have the extensive MI experience that was required for traditional systems and helping them learn to elicit desired neural patterns.

Declaration of competing interest

None declared.

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