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Short communication

Neurofeedback-based motor imagery training for brain–computer interface (BCI)

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ABSTRACT

In the present study, we propose a neurofeedback-based motor imagery training system for EEG-based brain–computer interface (BCI). The proposed system can help individuals get the feel of motor imagery by presenting them with real-time brain activation maps on their cortex. Ten healthy participants took part in our experiment, half of whom were trained by the suggested training system and the others did not use any training. All participants in the trained group succeeded in performing motor imagery after a series of trials to activate their motor cortex without any physical movements of their limbs. To confirm the effect of the suggested system, we recorded EEG signals for the trained group around sensorimotor cortex while they were imagining either left or right hand movements according to our experimental design, before and after the motor imagery training. For the control group, we also recorded EEG signals twice without any training sessions. The participants' intentions were then classified using a time–frequency analysis technique, and the results of the trained group showed significant differences in the sensorimotor rhythms between the signals recorded before and after training. Classification accuracy was also enhanced considerably in all participants after motor imagery training, compared to the accuracy before training. On the other hand, the analysis results for the control EEG data set did not show consistent increment in both the number of meaningful time–frequency combinations and the classification accuracy, demonstrating that the suggested system can be used as a tool for training motor imagery tasks in BCI applications. Further, we expect that the motor imagery training system will be useful not only for BCI applications, but for functional brain mapping studies that utilize motor imagery tasks as well.

1. Introduction

There are a great numbers of disabled individuals who cannot freely move or control specific parts of their body because of serious neurological diseases such as amyotrophic lateral sclerosis (ALS), brainstem stroke, and so on. Brain–computer interfaces (BCIs) can help them to drive and control external devices using only their brain activity, without the need for physical body movements (Wolpaw et al., 2002).

Diverse types of electrical brain activities have been used to realize electroencephalography (EEG)-based BCI systems, e.g., mu rhythm (Blankertz et al., 2007; Chatterjee et al., 2007; Kamousi et al., 2007; Pfurtscheller et al., 2006; Pineda et al., 2003), slow cortical potential (Birbaumer et al., 1999), event-related p300 (Bayliss, 2003; Hoffmann et al., 2008), and steady-state visual evoked potential (Lalor et al., 2005; Middendorf et al., 2000). Among these activities, the one most widely used to monitor brain activities for BCI applications has been the mu(μ) rhythm, which is related to motor actions (Blankertz et al., 2007; Galan et al., 2008; Neuper et al., 2003; Pfurtscheller et al., 2003). The mu rhythm can be voluntarily modulated by individuals unlike event related brain activities.

Motor imagery, defined as mental simulation of a kinesthetic movement (Decety and Inqvar, 1990; Jeannerod and Frak, 1999), can also modulate mu rhythm activities in the sensorimotor cortex without any physical movements of the body. It has been well established that the imagination of each left and right hand movement results in event-related desynchronization (ERD) of mu-band power in the contralateral sensorimotor areas, which is also the case for physical hand movements (Lotze et al., 1999; Pfurtscheller and Neuper, 2001). Brain activities modulated by motor imagery of either the left or right hand are regarded as good features for BCIs, because such activities are readily reproducible and show consistent EEG patterns on the sensorimotor cortical areas (Hollinger et al., 1999; Pfurtscheller and Neuper, 1997). Moreover, thanks to the contralateral localization of the oscillatory activity, the activities evoked from left and right hand motor imagery are, comparatively, readily discriminated (Ince et al., 2006; Kamousi et al., 2007; Model and Zibulevsky, 2006). However, many individuals have difficulty in getting used to the feel of motor imagery , since most people do not easily recognize how they can have a concrete feeling of motor imagery and tend to imagine the images of moving their hands or legs instead (Neuper et al., 2005). Therefore, one of the challenging issues in the EEG-based BCI studies has

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been how one can efficiently train individuals to perform motor imagery tasks.

Over the last decade, various feedback methods for motor imagery training have been proposed, most of which are based on visual (Blankertz et al., 2007; Leeb et al., 2006; Pineda et al., 2003) or auditory feedbacks (Hinterberger et al., 2004; Nijboer et al., 2008). For example, suppose that a participant is instructed to perform a motor imagery task involving their left or right hand. Then, reference features of brain activities evoked from the left and right hand motor imagery are extracted and the participant's intentions are classified by comparing the reference features with the current features. The participants are then provided with visual or auditory feedback according to the classification results. However, some participants cannot generate more useful features in their sensorimotor cortex after motor imagery training processes, compared to the features extracted before the training (Blankertz et al., 2007; Hoffmann et al., 2008; Nijboer et al., 2008). One typical reason to explain the wrong motor imagery is that participants tend to imagine visual images of the movement (visual-motor imagery: VMI), which generates a type of brain activity pattern completely different from that of actual motor imagery (Neuper et al., 2005). Therefore, even when participants attempt the same motor imagery task, individual differences are often observed, because the results are dependent on their feelings and perception on the motor imagery task, as described by Annett (1995).

The goal of the present study was to develop a motor imagery training system that can help individuals easily get the feel of motor imagery. To this end, we developed a kind of neurofeedback systems to train motor imagery by presenting participants with time-varying activation maps of their brain, using a real-time cortical rhythmic activity monitoring system that we recently introduced in a previous study (Im et al., 2007). The real-time cortical activity monitoring system could visualize spatiotemporal changes of cortical rhythmic activity of a specific frequency band on a subject's cortical surface, rather than the subject's scalp surface, with a high temporal resolution. In our experiment, half of 10 human volunteers, who had no prior experience of BCI experiments, were asked to imagine either left or right hand movement while they were watching their cortical activation maps through the real-time monitoring system. During the experiment, the participants were asked to continuously try to increase their mu rhythm activations (8–12 Hz) around the sensorimotor cortex areas. We then investigated changes in the EEG signals recorded before and after motor imagery training to demonstrate the effect of our motor imagery training system. The other five control subjects did not had any motor imagery training and the changes in the EEG signals recorded before and after a 30-min break were investigated.

2. Materials and methods

Our experiments consisted of two sessions: motor imagery training session and EEG recording sessions. In the motor imagery training session, the participants were trying to increase their mu rhythm activations around the sensorimotor cortex while they were watching their cortical activation maps through the real-time rhythmic activity monitoring system. Two EEG recordings were performed each before and after the motor imagery training session to demonstrate the effect of our neurofeedback-based motor imagery training system.

2.1. Subjects and environment of experiments

Ten healthy volunteers (all male, all right handed, age 25.1 ± 1.97 years) took part in this study. None of the participants had a previous history of neurological, psychiatric, or other severe disease that may otherwise influenced the experimental results. We gave a fully detailed summary of the experimental procedures and protocols to each of the participants before the experiment. All participants gave written consent and received adequate reimbursement for their participation. The study protocol was approved by the Institutional Review Board (IRB) committee of Yonsei University in Korea. None of the participants had previous background knowledge or experience with BCIs, nor had they ever participated in any EEG experiment. All experiments were conducted in the Bioelectromagnetics and Neuroimaging Laboratory of Yonsei University.

Electrodes were attached on the participants' scalp according to the extended international 10–20 system. In the motor imagery training session, the EEG signals were acquired at 16 electrode locations (AF3, FC3, C3, CP3, PO3, FCz, Cz, CPz, AF4, FC4, C4, CP4, PO4, T7, T8, and Oz) using a multi-channel EEG acquisition system (WEEG-32, Laxtha Inc., Daejeon, Korea) in a dimly lit, soundproof room. In the EEG recording sessions, the EEG signals were recorded at 15 electrode locations (Cz, C1, C2, C3, C4, CPz, CP1, CP2, CP3, CP4, FCz, FC1, FC2, FC3, and FC4) covering the sensorimotor area, using the same recording system. The sampling rate was set at 256 Hz in all experiments with a sensitivity of 7 μV. Facial EMG and EOG were also recorded during the EEG recordings and used as references in artifact rejection process.

We used different electrode configurations for the motor imagery training and the EEG recording sessions. In the training session, we used 16 electrodes broadly attached on the participants' scalp because we needed to monitor their brain activity patterns in the whole brain areas including the sensorimotor cortex. On the other hand, in the EEG recording sessions, 15 electrodes were focally attached around their sensorimotor cortex as we were only interested in EEG signals related with motor functions.

2.2. Motor imagery training

During the motor imagery training session five volunteers (EK, GS, DK, KS, and JN) were made to sit on a comfortable armchair facing a 17″ monitor and were presented with time-varying maps of their cortical rhythmic activity that were updated every 350 ms while they were attempting either left or right hand motor imagery. Fig. 1 shows screenshots of the experiment, where the subject EK activated his motor cortex without any physical movements of his hands (see Supplementary movie file). Before the training, we explained to the participants the locations of the sensorimotor cortex and provided them with a movie that explained the expected cortical activation changes. The participants were then instructed to continuously attempt to generate cortical activations around the sensorimotor cortex. In the beginning of the training session, all participants failed to generate brain activities around the sensorimotor cortex; however, through repetitive trials, all participants succeeded in generating brain activity on their sensorimotor cortex without any physical movements. Participants were given 30 min for the motor imagery training.

2.3. An EEG-based real-time cortical rhythmic activity monitoring system

An EEG-based real-time cortical rhythmic activity monitoring system (Im et al., 2007), which was used in the training session, consisted of pre-processing and real-time processing parts. In the pre-processing part of the experiment, an inverse operator was constructed in which the subject's anatomical information was reflected. In the present study, a standard brain atlas (Evans et al., 1992) provided by the Montreal Neurological Institute (MNI) and a standard configuration of electrodes were utilized, since individual magnetic resonance imaging (MRI) data for the subjects were not available. Once the linear inverse operator had been constructed and saved to a data-storage unit, spatiotemporal changes of cortical

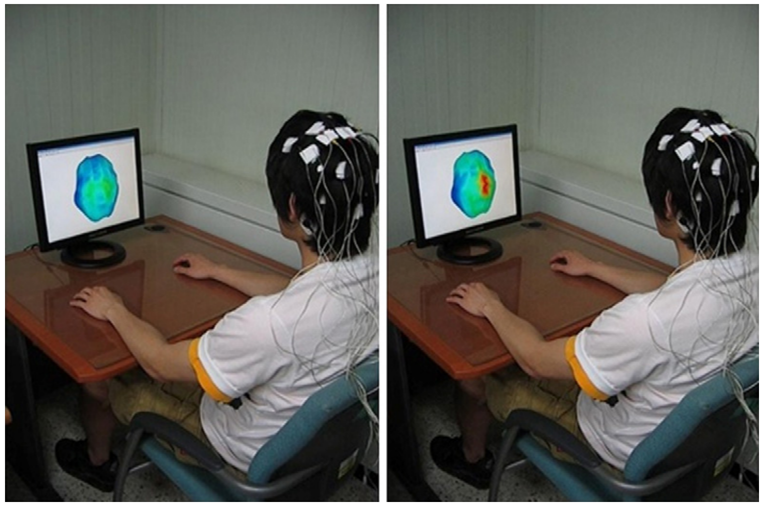

Fig. 1. Screenshots of real-time cortical mu rhythm activity (8–12 Hz) monitoring. The participant (EK) was instructed to continuously attempt to generate cortical activations around the sensorimotor cortex by imagining his left or right hand movement (see Supplementary movie). A cortical activation map at rest state (left) and when the participant was performing motor imagery (right).

rhythmic activates were monitored in real-time by means of a unified processing scheme consisting of three independent programs: an FFT program, a frequency domain minimum norm estimation (FD-MNE) solver, and a 3D visualization program, which were all executed sequentially at each time slice (Im et al., 2007).

2.4. EEG data acquisition

EEG data were acquired before and after the training session to confirm the effect of our motor imagery training system. The whole experiments including the neurofeedback training and the two EEG recordings were conducted on the same day. For the control group participants (JI, BK, HJ, TI, and SJ), EEG data were recorded twice with a 30-min break time. Fig. 2 shows the experimental paradigm used for the EEG recordings in the present study. First, we used a gray (RGB: 132, 132, 132) background, and after presenting a blank screen for 3 s, a circle with a black-and-white checkerboard pattern appeared randomly on either the left or right side of the screen for next 0.25 s, indicating which hand movement the participant was to imagine. After a 1 s preparation time (blank screen), the letter 'X' appeared at the center of the screen for 0.25 s, at which time, the participant was asked to perform either the left or right hand motor imagery as indicated. This procedure was repeated 180 times: when 90 trials were performed for the right hand motor imagery, the other 90 trials were performed for the left hand motor imagery.

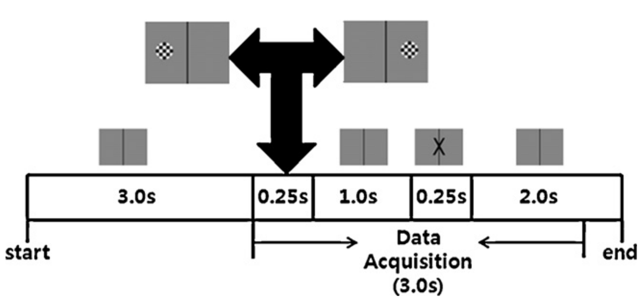

Fig. 2. The experimental paradigm used for EEG recording: after presenting a blank screen for 3 s, a circle with a black-and-white checkerboard pattern appeared randomly on either the left or right side of the screen for the next 0.25 s, indicating which hand movement the participant was to imagine. After a 1 s preparation time (blank screen), the letter 'X' appeared at the center of the screen and lasted for 0.25 s. At that time, the participant was to being performing either left or right hand motor imagery. The time period used for the data analysis (3.0 s) is depicted in the figure.

To confirm if the participants physically moved their hands, we also recorded an electromyogram (EMG) from electrodes attached on the participants' both forearms (Wolpaw and McFarland, 2004) during the EEG recording sessions. Fig. 3 shows the changes of EMG powers recorded both before and while the participants of the trained group were performing the motor imagery task. No significant difference between the two EMG data sets (less than 10% variations) were found for all five participants, indicating that they did not move their hands when they were attempting to perform the motor imagery task.

2.5. EEG data analysis

We used the 3.0 s time segment marked in Fig. 2 for the data analysis because the participant might start the motor imagery before the letter 'X' appeared (Ince et al., 2006, 2007; Kamousi et al., 2007). After data acquisition, the raw EEG signals were converted to a common average reference (CAR) to compensate for common noise components. The CAR method has been shown to produce good performance in noise reduction along with surface Laplacian filtering (Hjorth, 1975; McFarland et al., 1997). EEG epochs highly contaminated by facial muscle movements were rejected manually by inspecting the simultaneously recorded facial EMG signals. EOG artifacts were not removed since the influence of eye blinks or eyeball movements upon the EEG channels around the sensorimotor area was not significant.

For the time–frequency analysis we used fourth order Butterworth band-pass filters in which the span of the frequency band was 2 Hz with a 50% overlapping. The selected frequency bands were 6–30 Hz, including mu and beta bands, which are related to limb movements. After calculating the envelopes of the signals at each frequency bin, a moving average filter was applied to the time domain signals at 400 ms intervals (50% overlapping) to smooth the envelopes. After all, the frequency band and time series were evenly divided into 23 frequency bins and 14 time segments, respectively. We then obtained a time–frequency pattern map by integrating the enveloped signals at each time segment and frequency bin. Two-tailed t-tests were then applied to every possible combination of frequency bins, time segments, and electrodes in order to find combinations that produced significant differences ($p < 0.05$) between left and right hand motor imagery.

To evaluate the classification accuracy, the two time–frequency combinations that had the smallest p-value in the time–frequency

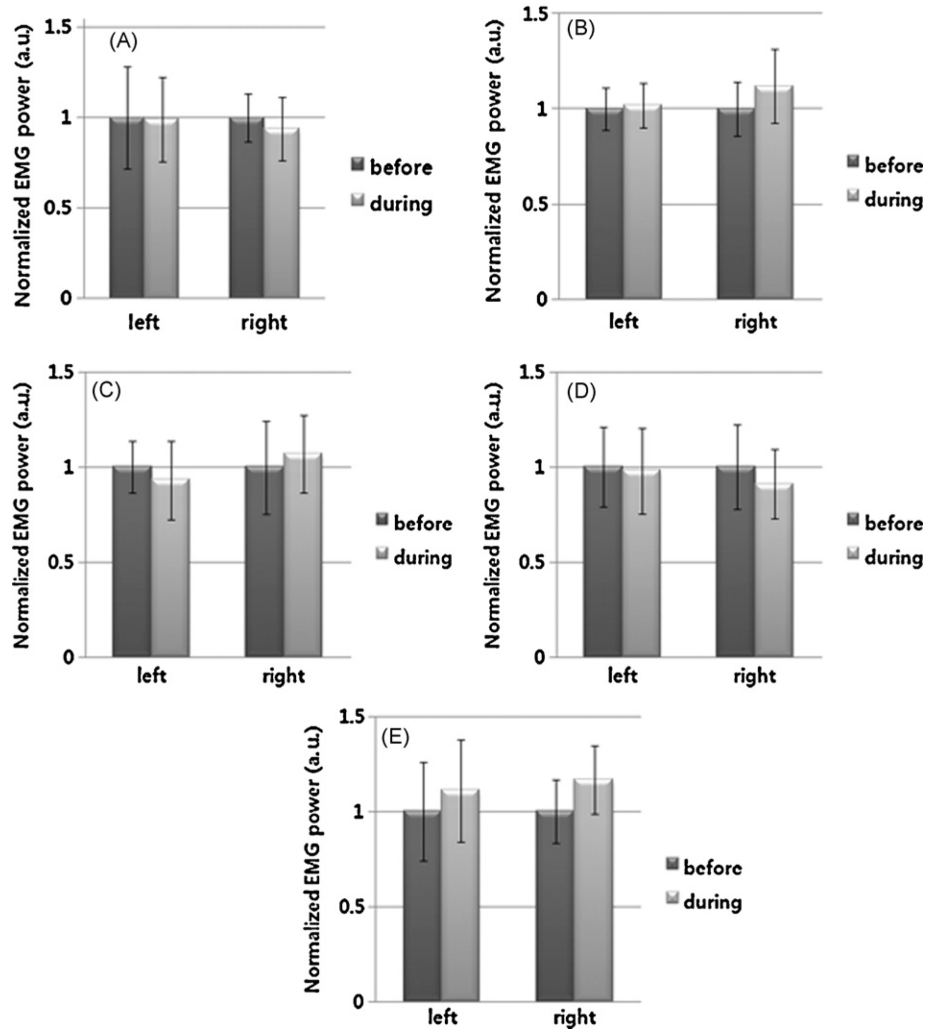

Fig. 3. Changes in EMG power recorded at both of the participants' forearms before and during performing the motor imagery task. No statistically significant difference between the two EMG data sets (two-tailed paired t-test, $p < 0.05$) was found for all five participants of the trained group, indicating that the participants did not move their hands when they were attempting to perform the motor imagery task. A, B, C, D, and E indicate the EMG power changes of each participant, EK, GS, DK, KS, and JN, respectively. In the figures, 'before' and 'during' represent 'before the motor imagery' and 'during the motor imagery,' respectively.

pattern maps were selected for each participant. Among the 180 trials (90 each for right and left hand motor imagery), 90 trials (45 each for right and left hand motor imagery) were randomly selected and used as a training set, while the remaining motor imagery trials were used as a test set for calculating the classification accuracy. For each trial of the test set, Euclidean distances from the two average feature vectors computed on the reference data sets (45 right and 45 left hand motor imagery trials each) were compared and the trial was assigned to a class based on whichever had the shorter distance.

3. Results

3.1. Changes in brain activity after motor imagery training

Fig. 4 shows the time–frequency pattern maps for the trained group participants, where the black colored blocks represent time–frequency combinations that showed significant differences ($p < 0.05$) between left and right hand motor imagery. As seen in the figures, where two featured electrodes were selected for each participant, the time–frequency pattern maps did not show any distinguished features before the training session. On the contrary, we observed that the number of the 'black' blocks was increased and the blocks were clustered around the sensorimotor rhythm (around 10 and 20 Hz) after the training session. Table 1 shows the number of time–frequency combinations that showed significant difference between left and right hand motor imagery, demonstrating that meaningful changes of brain activities occurred in all participants of the trained group after the training session. On the other hand, for the control group, we could not observe any consistent changes in the number of significant time–frequency combinations between

Table 1
The total number of time–frequency combinations showing a significant difference between left and right hand motor imagery.

Trained group			Control group		
Participant	Before	After	Participant	First	Second
EK	220	300	JI	219	207
GS	280	308	BK	269	217
DK	183	275	HJ	379	384
KS	297	446	TI	508	312
JN	275	349	SJ	412	547

'Before' and 'After' represent the number of significant features obtainable before the motor imagery training and after the motor imagery training, respectively. 'First' and 'Second' represent the number of significant features obtainable in the first and second EEG recording sessions, respectively.

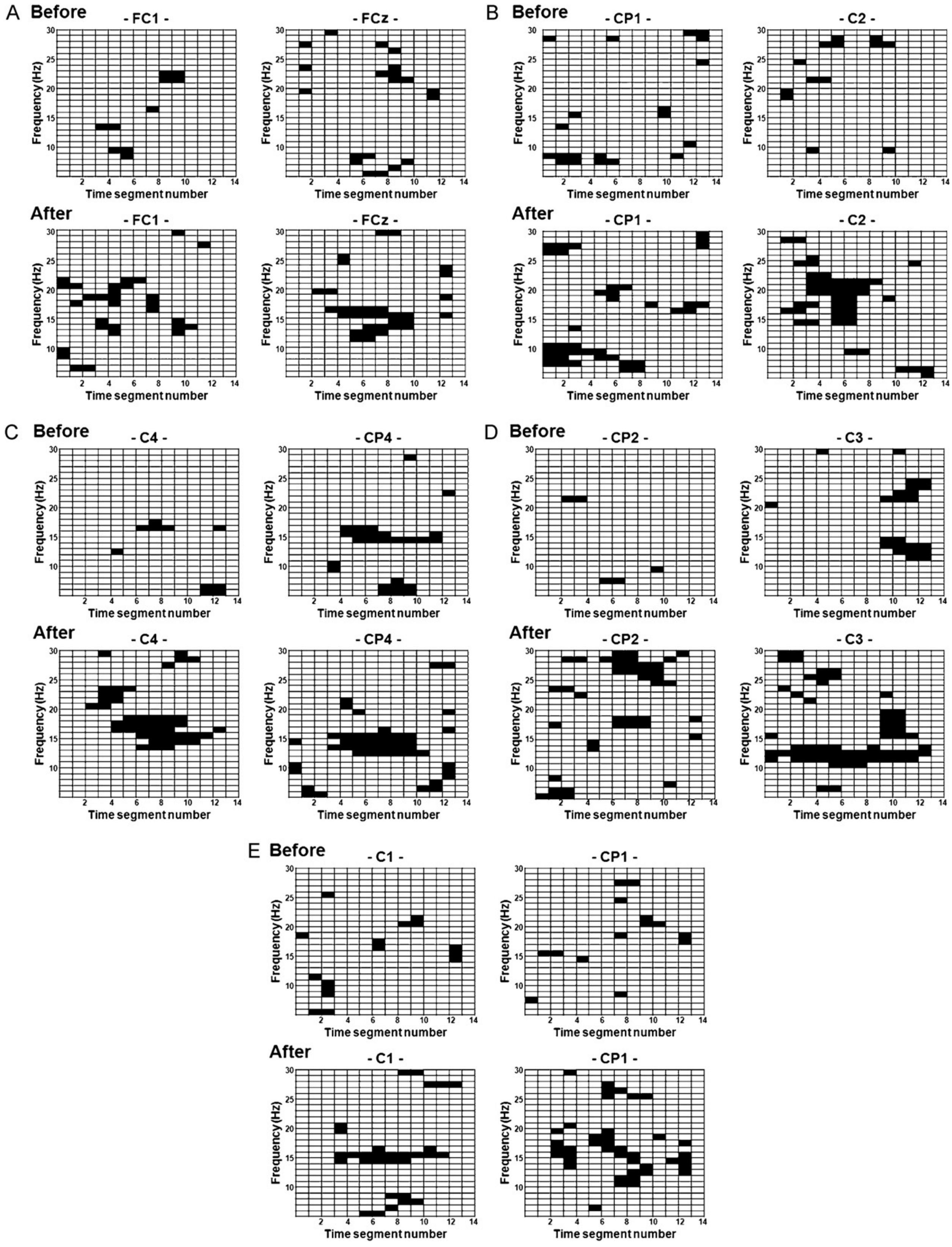

Fig. 4. Time–frequency pattern maps at the two electrode locations. The black colored blocks represent the time–frequency combinations that showed statistically significant difference ($p < 0.05$) between left and right hand motor imagery tasks. The time–frequency pattern maps did not show any distinguishable features before the training session, while the number of the 'black' blocks increased and the blocks were clustered around the mu rhythm (around 10 and 20 Hz) after the training session. 'Before' and 'after' represent the time–frequency patterns calculated before the training session and those calculated after the training session, respectively.

the first and second EEG data sets. From these results, we confirmed that it was possible to train participants to generate specific brain activity patterns on the sensorimotor cortex using the proposed system.

3.2. Classification accuracy before and after the motor imagery training

We also investigated the changes in classification accuracy before and after motor imagery training. Table 2 shows the accuracy of classifying left and right hand motor imagery of all participants. Since small *p*-values in the time–frequency pattern maps meant that there were significant differences between the left and right hand motor imagery, we selected two time–frequency combinations having smallest *p*-values as the features for classifying left and right hand motor imagery. We found that most of the extracted features corresponded to the mu rhythm which had been used in the neurofeedback training session (frequency bin and electrode in each subject of the trained group—EK: 11–13 Hz in FC1 and 11–13 Hz in C4; GS: 10–12 Hz in FC1 and 9–11 Hz in FC2; DK: 13–15 Hz in FC4 and 13–15 Hz in C2; KS: 12–14 Hz in C3 and 11–13 Hz in C2; JN: 7–9 Hz in C2 and 9–11 Hz in CP3).

A simple Euclidean distance algorithm was then used to estimate classification accuracy. Analysis of the results indicated that the classification accuracy was enhanced considerably for all five individuals in the trained group after the motor imagery training; while the analysis results for the control EEG data set did not show consistent increment in the classification accuracy, demonstrating that the proposed motor imagery training system could be used to enhance the performance of motor-imagery-based BCI systems. These results have a thread of connection with those of the previous time–frequency analysis, in that the individuals of the trained group were able to generate distinguishable brain activity patterns between the left and right hand motor imagery after a short training session that lasted for 30 min.

To test if the number of features affects the computed classification accuracy, we applied different numbers of features to the same classification algorithm (from 3 to 5 features). The use of more features enhanced the classification accuracy in most cases, but the difference was not significant and did not affect the findings of our study.

4. Discussions and conclusions

For motor imagery training we used a real-time cortical rhythmic activity monitoring system (Im et al., 2007) that visualizes source activation maps on the cortical surface, rather than the scalp surface, to show the subjects their time-varying brain activities. The main reason why we chose to use the 'cortical' activity monitoring system was that EEG topographies cannot be directly attributed to the underlying cortical regions. In BCI applications, different types of EEG topographies can be observed even for identical motor imagery tasks (McFarland et al., 2000) because the EEG topography is dependent on neuronal source orientations. Since most participants of motor imagery experiments are not familiar with EEG topographies, the use of inverse solutions could help them easily perform motor imagery training.

Many studies have reported the importance and usefulness of motor imagery in various applications such as learning complex motor skills in sports (Murphy, 1994) and re-learning motor skills in clinical applications (Dijkerman et al., 2004). Ever since Jastrow's first study of mental simulation (Jastrow, 1892), motor imagery, a kind of mental process, has been widely used for learning motor skills and enhancing players' performance in sports science. Indeed, mental imagery, including motor imagery, has been demonstrated to be a central factor for motor skill acquisition and execution (Murphy, 1994). Motor imagery has been also been used to diagnose and rehabilitate brain-injured patients (Owen et al., 2006; Tamir et al., 2007). For example, Tamir et al. (2007) applied motor imagery to patients with Parkinson's disease for improving their motor function, and found that the combination of motor imagery and physical practice is more effective than conventional physical training methods, especially for reducing bradykinesia. Although in the present study we applied our proposed motor imagery training system to a noninvasive BCI application, we expect that it can be applied to other applications, including those described above, in order to help the individuals get the feel of the motor imagery task and consequently, thereby enhancing efficiency of the relevant studies.

The average classification accuracy in the trained group was 71.4% after the motor imagery training, which, although relatively low compared to values reported in the literatures concerning similar motor imagery classification (Ince et al., 2006, 2007; Kamousi et al., 2007; Leeb et al., 2006; Wang et al., 2004) was still thought to be an acceptable level for practical BCI applications according to Perelmouter and Birbaumer's report (Perelmouter and Birbaumer, 2000). Nonetheless, the increment of the classification accuracy was thought to be meaningful enough to confirm the effect of our neurofeedback-based motor imagery training, considering that the main purpose of the classification was not to obtain a high classification accuracy, but rather to show how efficiently we were able to train subjects, who were unable to have a concrete feeling of motor imagery, to perform the motor imagery task.

In the present study, we focused on training motor imagery of both hands. According to the literature, imagery of feet and tongue (or mouth) movements can be also used as effectors in EEG-based BCI systems (Pfurtscheller et al., 2006). Further, it has been reported that the mu rhythm is blocked or desynchronized at sensorimotor cortex during hand movement imagery, whereas it increases during foot or tongue motor imagery (Pfurtscheller et al., 2006). In the same study, it was also reported that EEGs recorded during left hand, right hand, foot, and tongue motor imagery are classifiable. Based on the previous report, it seems that subjects should be able generate distinguishable brain activity patterns of four or more effectors using our motor imagery training system, an exciting prospect that we will focus on in future studies.

In our neurofeedback-based motor imagery training system, we confined mu rhythm to 8–12 Hz frequency band, but the frequency band of mu rhythm may vary from one individual to another. Fortunately, in our experimental study, all participants succeeded in generating brain activity around their sensorimotor cortex in the neurofeedback training session with the typical frequency band. However, if the training session fails, the experimenter can adjust the frequency band (e.g. 13–15 Hz) and repeat the training session.

In the present study, we confirmed the effect of our neurofeedback-based motor imagery training system by comparing

Table 2
Changes in classification accuracy before and after motor imagery training (or first and second EEG recordings in control group). We first selected the two time–frequency combinations that had the smallest *p*-values as the features for classifying left and right hand motor imagery. A Euclidean distance algorithm was then used to estimate the classification accuracy.

Trained group			Control group		
Participant	Before (%)	After (%)	Participant	First (%)	Second (%)
EK	60	77	JI	57	52
GS	62	67	BK	60	54
DK	59	72	HJ	73	70
KS	58	72	TI	67	75
JN	55	69	SJ	64	66
Mean	58.8	71.4	Mean	64.2	63.4

two EEG data sets each recorded with a cue-based (or synchronized) BCI paradigm before and after the motor imagery training. Since asynchronous (or self-paced) BCI systems are becoming popular in recent years, we will apply our motor imagery training system to such systems in our future studies. In addition, we are planning to compare our training method with other conventional training methods in the near future.

In summary, we developed a type of neurofeedback systems that can help individuals to get the feel of motor imagery by presenting them with real-time cortical activation maps on their sensorimotor cortex. Importantly, all of the study participants succeeded in generating brain activation around the sensorimotor cortex during the training session. The EEG data recorded after the motor imagery training showed significant enhancement in both the number of meaningful features and the classification accuracy, demonstrating the efficiency of our motor imagery training system. Lastly, we expect that the proposed motor imagery training system will be useful not only for BCI applications, but also for functional brain mapping studies relevant to motor imagery tasks.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jneumeth.2009.01.015.

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