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.

Keywords: Brain-computer Interface (BCI); EEG; Motor Imagery; Real-time Cortical Activity Monitoring;

1. Introduction

Brain-computer interfaces (BCIs) can help disabled individuals to drive and control external devices using only their brain activities [Wolpaw et al., 2002]. Up to now, 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], slow cortical potential [Birbaumer et al., 1999], event-related p300 [Bayliss, 2003] and steady-state visual evoked potential [Lalor et al., 2005]. Among these activities, the one most widely used to monitor brain activities for BCI applications has been the mu rhythm which is related to motor actions [Blankertz et al., 2007; Neuper et al., 2003; Pfurtscheller et al., 2003].

Motor imagery, defined as mental simulation of a kinesthetic movement [Decety and Inqvar, 1990; Jeannerod and Frak, 1999], can modulate mu rhythm activities in the sensorimotor cortex without any physical movements of the body. Brain activities modulated by motor imagery of either the left or right hand are regarded as good features and readily discriminated for BCIs [Ince et al., 2006; Kamousi et al., 2007; Model and Zibulevsky, 2006], because such activities are readily reproducible and show consistent EEG patterns on the sensorimotor cortical areas [Hollinger et al., 1999; Pfurtscheller and Neuper, 1997]. 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. Therefore, one of the challenging issues in the EEG-based BCI studies has 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] or auditory [Hinterberger et al., 2004; Nijboer et al., 2008] feedbacks. 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 tasks, as described by Annett [1995].

The goal of the present study was to develop a new motor imagery training system that can help individuals easily get the feel of motor imagery. To this end, we developed a kind of neurofeedback system to train motor imagery by presenting participants with time-varying activation maps of their brain, using a real-time cortical rhythmic activity monitoring system [Im et al., 2007]. We trained half of 10 human volunteers using the suggested system and recorded EEG signals before and after the motor imagery training. We then investigated changes in the EEG signals recorded before and after the motor imagery training. 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. Material and Methods

2.1. Participants and environment of experiments

Ten healthy volunteers (all male and right handed, age 25.1 ± 1.97y) took part in this study. None of them had a previous history of neurological, psychiatric or other severe diseases. 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. All experiments were conducted in the Bioelectromagnetics and Neuroimaging Laboratory of Yonsei University.

In the motor imagery training sessions, 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, C4, 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.

2.2. Motor imagery training

During the motor imagery training session five participants 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. 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. 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. Fig.1 shows screenshots of the experiment, where the subject EK activated his motor cortex without any physical movements of his hands.

![Figure 1](screenshots.jpg)

*Figure 1. Screenshots of real-time cortical mu-rhythm activation monitoring: (left) normal cortical activation map, (right) cortical activation map during motor imagery.*

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 (Evanse et al., 1992) provided by the Montreal Neurological Institute (MNI) and a standard configuration of electrodes were utilized, since 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 rhythmic activities 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 executed sequentially at each time slice (Im et al., 2007).

2.4. EEG data acquisition

Fig. 2 shows the experimental paradigm used for the EEG recordings. First, we used gray (RGB: 132, 132, 132) background and after presenting a blank screen for 3s, a circle with a black and white checkerboard pattern appeared randomly on either the left or right side of the screen for the next 0.25s, indicating which hand movement the participant was to imagine. After 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 (90 each for right and left hand motor imagery).

Figure 2. Experimental Paradigm.

To confirm if the participants physically moved their hands, we also recorded an electromyogram (EMG) form electrodes attached on their both forearms [Wolpaw and McFarland, 2004] during the EEG recording sessions. Facial EMG and EOG were also recorded during the EEG recordings and used as references in the artifact rejection process.

2.5. EEG data analysis

We used the 3.0 s time segment marked in Fig. 2 for the data analysis. After the data acquisition, raw EEG signals were converted to a common average reference (CAR) to compensate for common noise components [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 eye-ball 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, which is 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. We then obtained a time-frequency pattern maps 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, two time-frequency combinations that had the smallest p-value in the time-frequency 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 two average feature vectors computed on the reference data sets (45 right and 45 left hand motor imagery trials each) were compared and the trials 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. 3 shows the time-frequency pattern maps for a participant (GS) of the trained group, 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, 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 the first and second EEG data sets.

Table 2. Changes in classification accuracy before and after motor imagery training (or first and second EEG recordings in the control group).

![Figure 3. Distribution of time-frequency patterns showing significant difference (p < 0.05, black rectangles) between left and right hand motor imagery.](image-url)
4. Conclusions

In this study, 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.

References


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Participant Before (%) After (%) Participant First (%) Second (%)