ARTICLE IN PRESS

Human Movement Science xxx (2014) xxx–xxx

Contents lists available at ScienceDirect

Human Movement Science

journal homepage: www.elsevier.com/locate/humov

Effect of instructive visual stimuli on neurofeedback training for motor imagery-based brain–computer interface

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ARTICLE INFO

Article history:
Available online xxxx

PsycINFO classification:
2300

Keywords:
Brain–computer interface
Motor imagery
Event-related desynchronization
Neurofeedback training

ABSTRACT

Event-related desynchronization (ERD) of the electroencephalogram (EEG) from the motor cortex is associated with execution, observation, and mental imagery of motor tasks. Generation of ERD by motor imagery (MI) has been widely used for brain–computer interfaces (BCIs) linked to neuroprosthetics and other motor assistance devices. Control of MI-based BCIs can be acquired by neurofeedback training to reliably induce MI-associated ERD. To develop more effective training conditions, we investigated the effect of static and dynamic visual representations of target movements (a picture of forearms or a video clip of hand grasping movements) during the BCI neurofeedback training. After 4 consecutive training days, the group that performed MI while viewing the video showed significant improvement in generating MI-associated ERD compared with the group that viewed the static image. This result suggests that passively observing the target movement during MI would improve the associated mental imagery and enhance MI-based BCIs skills.

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http://dx.doi.org/10.1016/j.humov.2014.08.014
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Please cite this article in press as: Kondo, T., et al. Effect of instructive visual stimuli on neurofeedback training for motor imagery-based brain–computer interface. *Human Movement Science* (2014), http://dx.doi.org/10.1016/j.humov.2014.08.014

1. Introduction

The global incidence of stroke is increasing, along with the number of stroke patients living with significant physical impairments. To support and improve quality of life (QOL), various motor assistance devices have been developed, most of which aim to improve existing motor function rather than restore function to the paralyzed limbs. Brain Computer Interface (BCI) makes it possible to provide a communication channel from a human to a computer that directly translates brain activity into sequences of control commands. Such a device may give disabled people direct control over a neuroprosthesis or over computer applications as tools for communicating solely by their intentions that are reflected in their brain signals.

Recent work has shown that motor rehabilitation during the acute stages can decrease the effect of stroke (Cincotti et al., 2012), demonstrating that the rehabilitation exercise based on BCI neurofeedback enables a better engagement of motor areas with respect to motor imagery (MI) alone and thus it can promote neuroplasticity in brain regions affected by a cerebrovascular accident. It is important to consider motor learning in the context of brain plasticity. The signal flow in a motor control system can be described as: a motor command, generated in the motor area, that goes through the spinal cord and finally activates specific muscles. After muscle contraction, sensory feedback is transmitted to the somatosensory area in the cortex. This flow makes up the sensory-motor closed loop. However, stroke patients have difficulty learning specific motions because the loop is damaged. If a correlation between the motor command generation and the feedback signal to the somatosensory cortex can be achieved, this opens up the possibility for simulating the sensory-motor closed loop and thus enhance motor learning (Takahashi et al., 2012).

Therefore recent development of the BCI should be expected to activate sensorimotor regions and induce plasticity changes of the brain in neurorehabilitation (for review, see Pfurtscheller, Muller-Putz, Scherer, & Neuper (2008)). It has been postulated that the correlation of motor command generation and BCI may augment rehabilitation gains in stroke patients by activating corticomotor networks, providing sensory feedback to close the sensory motor loop.

One EEG feature that may be used to control BCIs is event-related desynchronization (ERD). Motor cortex ERD is defined as a relative decrease in EEG power within the alpha (8–13 Hz) and beta (14–26 Hz) bands that is correlated with both real movements and MI (Graimann, Allison, & Pfurtscheller, 2010; Pfurtscheller, 2001). An advantageous property of this ERD for BCI control is that it is somatotopic, e.g., right hand movement or MI of right hand movement may induce ERD in the EEG from the contralateral (left) sensorimotor cortex (Wolpaw, Birbaumer, Mcfarland, Pfurtscheller, & Vaughan, 2002). Therefore, the production of ERD from specific cortical regions may be used as a control cue for a range of movements. Furthermore, ERD can be internally generated, providing direct neural control over the BCI. In light of these characteristics, many have speculated that ERD can be used as the basis for an intuitive control interface for motor assistance (Leeb, Friedman, et al., 2007; Leeb, Lee, et al., 2007; Zhao et al., 2009) and neurorehabilitation methodology (Ono, Kimura, & Ushiba, 2013; Shindo et al., 2011; Takahashi et al., 2012).

To further facilitate the brain plasticity in clinical studies, it is crucial to detect the motor command generation in a single trial, Pfurtscheller, Brunner, Schlögl, and Lopes da Silva (2006) included event-related synchronization (ERS) as a neuronal marker to improve the classification of MI tasks on single trials. However, as described by Wolpaw et al. (2002), controlling ERD to reliably reflect appropriate mental images (like specific movements) is a difficult skill to master. Training programs for BCI control are further hampered by a lack of insight into the physiological mechanisms of ERD induction or control of ERD strength.

Neuper, Scherer, Reiner, and Pfurtscheller (2005) investigated the ERD during motor execution (ME), MI of own-movements (kinesthetic), motor observation (MO) and MI of someone else's movements (mental visualization), and they reported that the strongest ERD appeared when subjects imagined their own movements. In addition, Pfurtscheller, Scherer, Leeb, and Keinrath (2007) found that viewing a hand grasping movements on a head-mounted screen evoked a stronger ERD compared with that evoked by the image of a still cube, a moving cube or a still hand.

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Based on these previous studies, we speculated that the observation of dynamic hand motion that is correlated with the target MI could aid in ERD generation in the context of motor learning. The successful ERD generation will be a direct communication channel to control the computer interface or the robotic arm, enhancing MI-based BCI control. To test this assertion, we systematically examined improvements in ERD control during a 4-days neurofeedback training program in which participants were divided into two groups; during MI of hand grasping, one group observed a recording of hand grasping motion and the other group observed a still picture of forearms.

2. Methods

2.1. Participants

Twelve healthy participants (six females) aged 19–27 years (mean age: 22.7 years) participated in our MI-based BCI training experiments. All were right handed with no clinical history of neurological disorders according to self-reports. The study protocols followed the guideline of the Declaration of Helsinki on human experimentation, and were approved by the ethical committee of the Tokyo University of Agriculture and Technology. All participants provided written informed consent prior to participation.

2.2. Experimental system

During the experiment, participants were seated in a comfortable chair with their arms resting on the lower tier of a two-tiered table (Fig. 1). An LCD monitor was located on the upper tier on which participants were guided by visual instruction.

EEG signals were recorded using active dry electrode system (g.SAHARA, g.tec medical engineering, Austria), of which performance was validated with that of gel-type active electrodes (Guger, Krausz, Allison, & Edlinger, 2012). The 8 EEG channels were placed around the motor cortex; one electrode was placed at C3 with four electrodes around C3 (presumably the left primary motor area) and one more electrode was placed at C4 with two electrodes around C4 (the right primary motor area) according to the international 10–20 system (Fig. 2). For the C3 group, with respect to C3, two electrodes were placed in the anterior and posterior positions, and two in the right and left positions at the distance of 35 mm. For the C4 group, with respect to C4, two electrodes were placed at two equidistant in anterior and posterior positions. The reference and ground electrodes were attached to A2 (right ear lobe) and Fpz (forehead), respectively. EEG signals were amplified using a multi-telemeter system (WEB5000, NIHON KOHDEN, Japan) and digitized by an AD/DA converter at a fixed sampling frequency (256 Hz). The EEG data were bandpass filtered between 0.3 and 100 Hz by the amplifier.

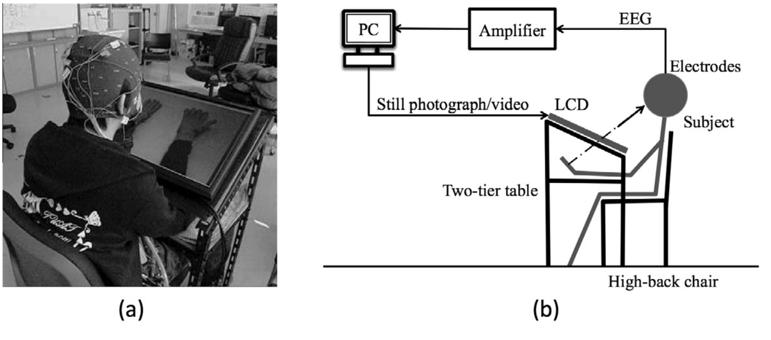

Fig. 1. Experimental system. (a) A participant performing the task. (b) Schematic diagram of the system. Participants were seated in a high-back chair with both arms on the lower tier of a two-tiered table. An instructive visual stimulus (a still photograph of forearms, a video clip of hand grasping movements, or a red/green cross on the black screen) was displayed on an LCD monitor located on the top tier of the table.

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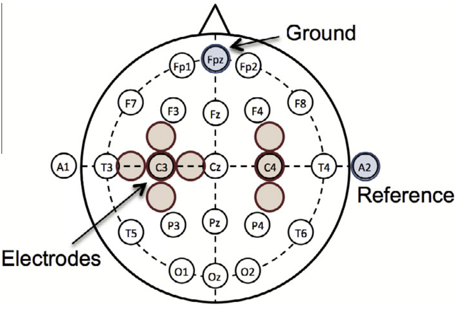

Fig. 2. Placement of eight active dry electrodes. Five electrodes were placed around C3 and three around C4 according to the international 10–20 system. The reference and ground electrodes were attached to A2 and Fpz, respectively.

2.3. Procedure

Participants were randomly assigned to one of two training groups. In Group P, MI training was performed while observing a still photograph of forearms, whereas in Group M, MI training was while watching a video clip of hand grasping movements. Their forearms were covered with gloves and a black shirt to generate the similar visual information to subject's hands shown in the display (Fig. 3), in order that the participants would feel the ownership of the hands displayed on the monitor. Moreover the speed of hand grasping movements in the video clip was slow (0.25 Hz) enough for participants to generate mental images of the target motion easily.

The experiment consisted of four types of sessions: motor execution (ME), motor observation (MO), training of MI (TR), and evaluation of MI (EV). As shown in Table 1, training experiment was scheduled

Fig. 3. Instructive visual stimulus for BCI training. A still photograph of forearms or a video clip of hand grasping movements was displayed on the monitor during the task period in the TR session. The participants' forearms were covered with gloves and a black shirt similar to subject's hands shown in the instructive visual stimulus, so that the participants would feel the ownership of the hands displayed on the monitor.

Table 1
Training schedule of 4 consecutive days. Abbreviations in the table: ME, EV, TR, and MO represent "motor execution", "evaluation", "training" and "motor observation" sessions, respectively.

Session #	Day 1	Day 2	Day 3	Day 4
1	ME	ME	ME	ME
2	EV	EV	EV	EV
3	TR	TR	TR	TR
4	TR	TR	TR	TR
5	TR	TR	TR	TR
6	TR	TR	TR	TR
7	TR	EV	TR	TR
8	EV	MO	EV	EV

over 4 consecutive days. Every day, participants started with an ME session, and then they executed a pre-EV, five TR, and a post-EV sessions. MO session was only executed as the last session on the second day, and the number of TR sessions on the day was reduced to four to prevent fatigue of participants.

In each session, participants repeated 40 experimental trials, and each of which consisted of rest and task periods to distinguish the change of EEG spectral power between the rest and task period. To avoid anticipatory response, the rest period had a random time duration from 3 to 5 s. During the rest period, participants were asked to relax while looking at a red fixation cross on the monitor. On the other hand, the task period lasted 4 s, and the instructions displayed during the period depended on the kind of groups and sessions. The detail information of each session in each group will be explained below.

The ME was an initial session of the day, and participants were asked to perform right hand grasping movements during the task period while watching a green fixation cross on the monitor. The session was meant to familiarize the participants with the experimental procedure and the proprioceptive sensation caused by real hand movements. The initial threshold value and specific frequency band for online ERD feedback training in the following TR sessions was determined based on the performance during this ME session.

The MO session was executed to evaluate the effect of a visual stimulus on passive generation of ERD. During the task period in this session, the participants observed the video of hand grasping movements without instruction to execute MI. The change in power spectrum of EEG between the rest and task period over the target frequency band was individually evaluated by a paired *t*-test to confirm the ERD.

In the TR session, participants were instructed to imagine hand grasping movement kinesthetically during the task period (Neuper et al., 2005). In our pilot study, we had confirmed that the surface EMG in the participants' forearms (flexor digitorum profundus muscles) was not activated during MI compared with the rest period ($p > .1$). Moreover experimenter visually checked participants' forearms during the MI period. To investigate the effect of visual stimuli on the MI-based BCI training, participants in Group P watched a still photograph of forearms Fig. 3), while participants in Group M watched a video clip of hand grasping movements during the task period.

In the paper we dubs these visual information as instructive visual stimuli. For online neurofeedback training, EEG signals were continuously processed to calculate an ERD value as a relative power decrease in the task period with respect to the one in the rest period, and a binary feedback (success or failure of ERD generation) was visualized on the monitor during the successive rest period with respect to the one in the rest periodFig. 4). The ERD threshold value for the online neurofeedback training was modified based on the performance in the previous session; namely it was increased at the rate of 10% if the success rate in the previous session was over the threshold of 75%, it was decreased at the rate of 10% if the success rate was less than 25%, otherwise it remained unchanged.the rate.

Finally, the EV session was set to evaluate the acquisition of MI-based BCI skill (spontaneous ERD production). For a sake of fair comparison, we evaluated the quantity of ERD production under an

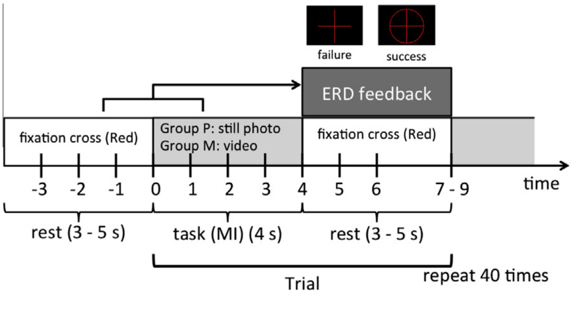

Fig. 4. Time course of a single trial in the TR session. Each trial consisted of rest and task periods. It started with the task period where participants tried to execute MI while watching an instructive visual stimulus differed depending on the group. For the online neurofeedback training, a binary feedback (success or failure of ERD generation) was visualized on the monitor during the successive rest period.

identical visual condition for both groups, i.e., participants of both groups were asked to execute hand MI during the task period while looking at a green fixation cross on the screen.

2.4. ERD detection

ERD was defined as a percentage of relative power decrease in a specific frequency band (Pfurtscheller, 2001). In this study we calculated the ERD value in both online and offline. As has been noted, the online ERD analysis was necessary for the neurofeedback training during the TR session, whereas the offline ERD analysis was required for evaluating the effects of the proposed neurofeedback training with instructive visual stimuli.

In the offline analysis, we calculated the ERD as follows. First, trials including the EEG amplitudes above a cut-off value (we used five-standard deviations) were discarded from the following analysis to eliminate artifacts. After the artifact reduction, EEG signals were filtered using a 4th order dual-pass Butterworth filter (pass-band was 3–35 Hz). The amplitude of each electrode was normalized and a bipolar montage was applied consisting of the four pairs with respect to EEG signals of C3. The bipolar montage signals were separated into epochs and transformed into time–frequency spectra by applying the short-time Fourier transform (STFT) with Hamming window of 1 second. Each epoch contained 256 samples (1000 ms) with 125 ms overlap of successive epochs. By squaring the absolute value of the time–frequency spectra, time-series of power spectrum was obtained. ERD was calculated by the following equations:

$$\overline{P}_{rest}(n,f) = \frac{1}{|T_{rest}|}\sum_{t\in T_{rest}} P(n,t,f), \tag{1}$$

$$\mathrm{ERD}(n,t,f) = \frac{P(n,t,f) - \overline{P}_{rest}(n,f)}{\overline{P}_{rest}(n,f)} \times 100, \tag{2}$$

where $P(n,t,f)$ is the signal power at each frequency f at time t in the nth trial. T_{rest} and $\overline{P}_{rest}(n,f)$ are the time duration and the averaged signal power of the rest period in the trial. In general, ERD caused by hand movements appears as mu-rhythm in contralateral sensorimotor area (Pfurtscheller, 2001). Accordingly we set the target frequency f_g to 7–11 Hz and we used a band power averaged within three consecutive frequency components (e.g., 7–9 or 11–13 Hz) by shifting the target frequency in 1-Hz steps. Moreover ERD for each bipolar channel was averaged across valid trials (N) in each session. Thus we obtained blurred ERD features $\overline{\mathrm{ERD}}(t,f_g)$ for five frequency bands and four derivation channels. The most significant channel with the largest power decrease within the target frequency band was selected for each session, and these ERD values were used as performance indexes of the BCI neurofeedback training experiment.

$$\overline{\mathrm{ERD}}(t,f_g) = \frac{1}{3|N|}\sum_{n\in N}\sum_{f=f_g}^{f_g+2}\mathrm{ERD}(n,t,f), \tag{3}$$
$$f_g \in F = \{7,8,9,10,11\}.$$

In the online ERD analysis we used the procedure described above without the artifact reduction process, and we used the most salient frequency band during the ME session of each day for the ERD feedback training.

3. Results

3.1. Effect of dynamic visual stimulus on ERD

Nine out of 12 participants showed significant ERD ($p < .05$, paired t-test) and two of the remaining three subjects showed clear trend ($p < .1$) on the second-day MO session. This result is consistent with the fact, in a number of previous studies, that observing movements automatically causes the ERD without execution of movements (e.g., Takata et al., 2012).

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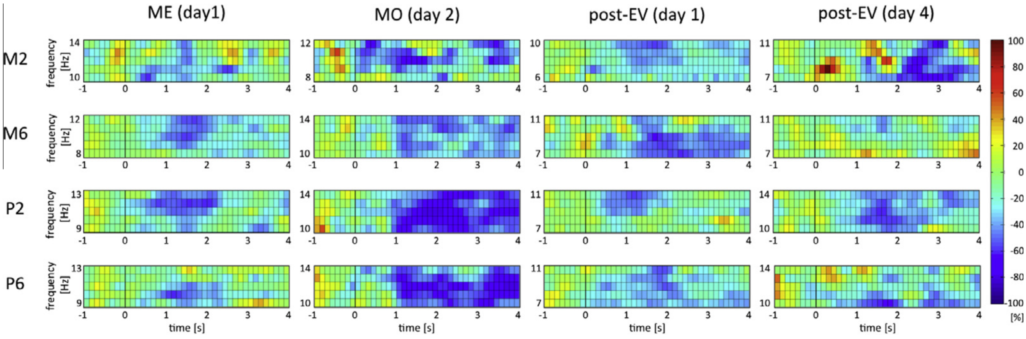

Fig. 5. Representative time–frequency maps of relative power change under ME (day 1), MO (day 2), and post-EV (day 1 and day 4) sessions for the best and worse subjects of each group. The spectrogram shows a significant power decrease (dark blue) in a specific frequency band during the task period. The unit is percentage calculated by Eq. (2). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 5 demonstrates representative time–frequency maps of relative power change under ME (day 1), MO (day 2), and post-EV (day 1 and day 4) sessions for the best and worse subjects of each group. We can confirm a significant power decrease (dark blue) in a specific frequency band during the task period under the MO session.

3.2. Effect of instructive visual stimuli on neurofeedback training

The mean ERD amplitude (% decrease in EEG spectral power) during the post-EV session on each training day is plotted for all participants (Fig. 6). Left graph is a result of Group P (i.e., trained with observing a still photograph of forearms), whereas right graph is a result of Group M trained with watching a video of hand grasping movements. Each line in the two graphs represents a linear regression of the mean ERD amplitude as a function of training day of each subject.

To investigate the effect of ERD training with instructive visual stimulation on the training of spontaneous ERD production ability, we performed statistical comparison between two groups. A two-way ANOVA with factors "group" and "day" showed a clear trend for a group × day interaction effect ($F(3,40) = 2.563$; $p = .0682$) and a small main effect of day ($F(3,40) = 2.277$; $p = .0944$), but no

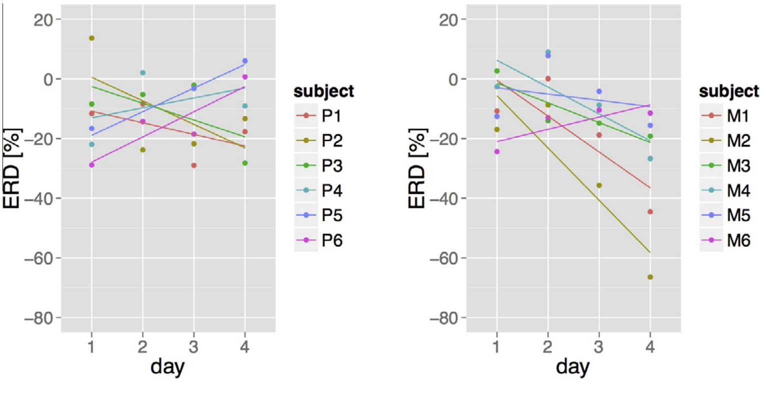

Fig. 6. Daily change of mean ERD amplitude during the post-EV session. Left graph presents the result of Group P participants who were trained with observing a still photograph, whereas right graph indicates the result of Group M participants trained while watching a video clip of hand grasping movements. Each line represents a linear regression of each subject.

main effect of group ($F(1,40) = 0.850; p = .3621$). A simple main effect of day was found for Group M subjects ($F(3,20) = 4.213; p = .0184$), and Tukey's HSD for multiple comparisons revealed significant improvement in ERD values between day 4 and day 2 ($p = .0127$) and increasing tendency among day 4 and day 1 ($p = .0925$).

It has become a trend in fMRI research to perform statistical analysis in individual subject basis to discuss individual response under a certain task. Thus, in addition to the group analysis above, individual subject analysis was performed to discuss the effect of training at the individual level.

Regarding the fact that the effect of ERD training was subject to individual variability, it was reasonable to perform Welch's *t*-test for the distribution of the ERD values of individual subjects in groups P and M between day 1 and day 4. We found that two subjects in group M showed statistically significant improvements ($p < .05$ and $p < .001$) and that no subjects showed statistical significance in group P.

In summary, the mean ERD amplitude improved significantly over the 4 training days in subjects who watched a video clip of hand grasping movements but not in subjects who viewed a still picture of forearms during MI. These results suggest that observing a target movement during MI may enhance the spontaneous ERD generation.

4. Discussion

The main focus of this study is to investigate whether observing an instructive visual stimulation of hand grasping movements during BCI neurofeedback training can enhance spontaneous production of ERD for motor imaginary since on-demand production of ERD facilitates a direct control over a BCI system. The experimental results can be summarized as follow; (1) simply watching a video clip of hand grasping movements induced ERD. (2) Watching the same video clip during MI-based BCI training significantly increased acquisition of spontaneous production of ERD, which leads to a useful skill in MI-based BCI, while (3) observing a still image had no effect on the spontaneous production of ERD. The first point is consistent with the previous report that the human primary motor cortex can be activated by not only ME but also MO (Hari et al., 1998). Moreover, the second point is related to the work in which an instructive visual stimulus that includes a moving object, particularly a biological movement, causes a stronger ERD (Pfurtscheller et al., 2007). Therefore, our results are consistent with these findings in the previous literature, as we observed a decrease in power within a specific waveband on EEG recordings at the left motor area while participants watched right hand grasping.

The signal flow in a motor control system can be described as follows. A motor command, generated in the motor area, that goes through the spinal cord and finally activates specific muscles to contract, and joints are rotated finally. The motor execution can be detected by ERD as has been previously discovered. After muscle contraction, proprioceptive feedback is transmitted to the somatosensory area in the cortex, and the visual feedback is also provided by observing the motion. These two flows make up the sensory-motor closed loop. The present study shows that the neurofeedback training is enhanced by closing the loop between motor command generation and the feedback information whereas the static image of the hand would contradict the sensory-motor anticipation after the generation of the motor command. Note here that simultaneity of the closed loop between the motor command generation and the visual feedback can be ensured within the time window of several seconds in order to enhance the drop of ERD.

In the case of stroke patients, they have difficulty performing specific motions because the closed loop is damaged. If a correlation between the motor command generation and the feedback signal to the somatosensory cortex can be achieved, this opens up the possibility for simulating the sensory-motor closed loop and thus enhance motor learning. The dynamic visual feedback training proposed in the present study indicates that the motor command generation can be trained in neuronal rehabilitation not only to control the electronic device, but also to reconstruct the closed loop due to brain plasticity.

The following points will be considered in the future study to further strengthen the finding in this study. First, we have not yet investigated the difference between the groups trained with and without instructive visual stimuli of corresponding hand image. Comparing the group performing MI while observing a still photograph of forearms (Group P) to a group performing MI without any instructive visual stimulus (e.g., only a green cross) may reveal an additional negative or positive effect on MI-based BCI skill acquisition. We speculate that discrepancy between motor imagery and a still image of forearms may actually produce an inhibitory effect (i.e., negatively impact skill acquisition). Second, unlike real movements, the hand grasping movements in the video used had a fixed timing and speed of hand motion. It is known that reafferent sensation, the sensory feedback in response to voluntary motor intention, is an important element to generate sense of agency. Online adjustment of the timing and speed of instructive visual stimulation could further improve BCI training on the ERD production. Third, the current study focused only on visual information, while somatic sensation is also known to evoke ERD even when limbs are moved passively by a human experimenter (Alegre et al., 2002), a robot (Formaggio et al., 2013), or by functional electrical stimulation (Müller et al., 2003). Therefore, combining visual and somatosensory stimulation for MI-based BCI training may be worth to investigate if multisensory integration is more effective, although concurrent presentation of multimodal sensory stimuli sometimes disturbs ERD production (Takata et al., 2012). Fourth, the performance of BCI systems would be higher by including frontally positioned electrodes as suggested by Leocani, Toro, Manganotti, Zhuang, and Hallett (1997). In association with this work, Daly, Nasuto, and Warwick (2012) recently reported that dynamics of inter-regional communication changes during real and imagined single finger taps compared to the rest state. The functional connectivity analysis incorporating the electrodes in frontal area should be possible to observe more carefully the time dependent phenomenon from motor intention, motor planning, and execution based on the dynamical networking of functional connectivity. Finally, both the quality of BCI feedback and subject motivation may be important factors for BCI training, particularly for BCI novices. However, these factors are often underestimated in most current BCI research (Lotte, Larrue, & Mühl, 2013). In spite of recent development of advanced signal processing and efficient machine learning techniques for optimizing a classifier, understanding the physiological mechanisms underlying ERD and the most reliable conditions for ERD-induction are crucial factors for developing a useful ERD-controlled BCI systems.

In the pioneer study of EEG-based BCI to support post-stroke motor rehabilitation of the upper limb, Cincotti et al. (2012) used the Fugl-Meyer (FM) physical performance scale to make a comprehensive assessment of physical function in stroke patients, including pain, balance, sensory and motor function, and showed that BCI-based group has better relative changes of clinical scales of FM assessment. Even though the training itself is such that the matched hand representation generates a visual illusion of hand movement in each trial and that the patients successfully controls the simple motion, grasping and opening of the virtual hand, patients showed high degrees of recover in more complex movements since FM assessment includes the coordination of arm wrist and hand movements (see, for example, Crow & Harmeling-van der Wel (2008)). There are a few works which incorporate the assessment for Activities of Daily Living (ADL) (Taub et al., 1993; Uswatte, Taub, Morris, Vignolo, & McCulloch, 2005). For example, they made a list of daily motion, categorizing most of the aspects of motion, that is, writing letters with pen, brushing teeth, tie shoe lace, etc. The important point here is that the subject measured by ADL assessment had a high correlation with the FM assessment.

These rehabilitation studies indicates that a simple task of MI, motion in single degrees of freedom, when correlated with effective feedback would promote the motor recovery of post-stroke patients in their daily life, and therefore, led us to anticipate that dynamic visual feedback training proposed in the present study would promote the motor recovery of post-stroke patients as complex as hand writing as it initiates the promotion of closing the loop between brain and body.

In the future study, we should be able to assess ADL with the ERD production in dynamic visual feedback training, and trajectories obtained in hand writing is a strong candidate for quantitative measure of ADL. What makes this line of enquiry interesting is to investigate a link between a simple experiment task in laboratory and quality of life represented by the assessment of hand writing. In our recent work (Nakayashiki, Saeki, Takata, Hayashi, & Kondo, 2014), it was found that the ERD reflected the motor planning (speed and trajectories) rather than motor command generation therefore, we anticipate that the assessment in handwriting task would be a comprehensive marker which is correlated with the strength of ERD production.

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Acknowledgments

The research was partially supported by JSPS KAKENHI, Grant-in-Aid for Scientific Research (B) (Grant No. 23300216) and for Scientific Research on Innovative Areas (Grant No. 26120005), and MEXT Fund for Smart Space Technology toward Sustainable Society.

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