Abstract

OBJECTIVE: The purpose of this study was to investigate cortical lateralization of event-related (de)synchronization during left and right foot motor imagery tasks and to determine classification accuracy of the two imaginary movements in a brain-computer interface (BCI) paradigm.

METHODS: We recorded 31-channel scalp EEG from eight healthy subjects during brisk imagery tasks of left and right foot movements. EEG was analyzed with time-frequency maps and topographies, and the accuracy rate of classification between left and right foot movements was calculated.

RESULTS: Beta rebound at the end of imagination (increase of EEG beta rhythm amplitude) was identified from the two EEGs derived from the right-shift and left-shift bipolar pairs at the vertex. This process enabled discrimination between right or left foot imagery at a high accuracy rate (maximum 80% in single trial analysis).

CONCLUSIONS: These data suggest that foot motor imagery has potential to elicit left-right differences in EEG, while BCI using the unilateral foot imagery can achieve high classification accuracy, similar to ordinary BCI, based on hand motor imagery.

SIGNIFICANCE: By combining conventional discrimination techniques, the left-right discrimination of unilateral foot motor imagery provides a novel BCI system that could control a foot neuroprosthesis or a robotic foot.

EEG-based classification of imaginary left and right foot movements using beta rebound

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Financial Interests

The authors declare no financial interests or commercial considerations.

Highlights

• We confirmed the cortical lateralization of event-related (de)synchronization during left and right foot motor imagery tasks in human.

• Intensity of beta rebound recorded by bipolar electrodes at the end of imagination showed the left-right differences on the scalp.

• Beta rebound can provide high classification accuracy for brain-computer interface systems.

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1. Introduction

Brain-computer interface (BCI) classifies electroencephalographic (EEG) signals into several mental states using appropriate features of signals to translate user intent into useful commands for external devices. For example, BCIs that employ oscillatory EEG activity recorded over the sensorimotor cortex, an area reactive to hand-motor execution and motor imagery, allow subjects with tetraplegia to control a computer cursor (Wolpaw et al., 1991), a virtual environment (Hashimoto et al., 2010), a hand neuroprosthesis (Heasman et al., 2002; Pfurtscheller et al., 2003; Müller-Putz et al., 2005), and a hand orthosis (Pfurtscheller et al., 2000 a).

Brain electric oscillatory responses of different frequencies, which correlate to hand motor execution or imagery, can be studied using an event-related blocking response or an event-related amplitude enhancement of specific EEG frequency bands of mu (8–13 Hz) or beta rhythms (18–30 Hz) (Pfurtscheller and Lopes da Silva, 1999). The blocking response is termed “event-related desynchronization” (ERD), while the amplitude enhancement is termed “event-related synchronization” (ERS). The distribution of mu ERD during motor execution or imagery is restricted to the bilateral hand area of the sensorimotor cortex (Jurkiewicz et al., 2006), and is more prominent over the contralateral side than the ipsilateral side (Neuper et al., 2006). Using the left-right difference or laterality of mu ERD between contralateral and ipsilateral sides, BCI has been used to classify left- and right-hand motor imagery (Guger et al., 2003; Nam et al., 2011; Shindo et al., 2011). Even if a BCI user exhibits only a slight left-right difference, the user can nevertheless enhance differences and improve BCI control accuracy via visual feedback based on left-right differences (Pfurtscheller et al., 1997; Neuper et al., 2006; Hashimoto et al., 2010).

While a number of studies have shown left-right differences of ERD during hand motor imagery, as well as EEG-based discrimination between imagination of right and left hand movements or imagery, very little is known about EEG-based discrimination between right and left foot imagery. To date, there are two possible candidates of EEG features for discriminating left and right foot motor imagery tasks: mu ERD during motor imagery and beta ERS following termination of motor imagery. Kinesthetic foot motor imagery generates these two types of ERD/ERS at the vertex (Pfurtscheller et al., 2006). However, a previous study on unilateral foot movement reported no differences between left and right foot movement in topographic distribution of the beta rebound (Neuper and Pfurtscheller, 1996), while general foot motor imagery-based BCIs detect only feet motor imagery without discriminating the left- or right side (Pfurtscheller and Solis-Escalante, 2009; Müller-Putz et al., 2010). Thus, as yet there are no reports of beta-rebound based left-right classification of foot motor imagery. Nevertheless, mu ERD by foot motor imagery has been discussed in classifying left-right food motor imagery.

Anatomically, the foot representation area in the human sensorimotor cortex is located near the "mantelkante" (deep area within the interhemispheric fissure). In contrast to the hand areas, the left and right foot areas are closely situated each other. This somatotopic organization of the motor cortex, which has been confirmed by Penfield and Bordrey using invasive measures (1937), clearly explains why left and right foot movement produces nearly identical EEG patterns, whereas left and right hand motor imagery can be spatially discriminated with EEG. A recent study using functional magnetic resonance imaging suggested that the topographic distribution of imagery-related activities in the left foot and right foot areas were similar, with blood oxygenation level-dependent responses to both motor imagery tasks (Stippich et al., 2002). Nevertheless, classification of left and right foot motor imagery remains difficult. The establishment of a method for this discrimination, which improves analysis of mu ERD or beta rebound following foot motor imagery, would provide crucial information for the development of novel control channels for BCI. Further, this may provide a more natural control method for a computer or a virtual environment, and result in an EEG-controlled neuroprosthesis for a lower extremity or a robotic foot.

The aim of the present study was to: 1) analyze mu ERD and beta rebound following left and right foot motor imagery with EEG topography and time-frequency map using three EEG derivations – Laplacian derivation (Hjorth, 1975), which is generally used for detecting feet motor imagery (Pfurtscheller and Solis-Escalante, 2009; Müller-Putz et al., 2010), common average references (Thickbroom et al., 1984; Ludwig et al., 2009), and simple bipolar methods; 2) propose a novel BCI design for classifying imaginary left and right foot movements; and 3) evaluate the performance of the developed method with EEG data recorded from the healthy subjects.

2 Method and Materials

2.1 Subjects

Eight healthy, young subjects (1 female, 7 males: 22–28 years old) participated in the present study. Participants had no prior BCI experience and no history of neuromuscular disorders. The study protocol was approved by the ethics committee of Keio University, Kanagawa, Japan. Informed consent was obtained from all subjects prior to experimentation. The study was conducted in accordance with the Declaration of Helsinki.

Subjects were seated in a comfortable armchair and were asked to watch a 22 inch monitor from a distance of 2 m. Both legs were loosely fixed with the hip semi-flexed (110°), the knees flexed at 60° from full extension, and the ankles plantar-flexed at 10° from the neutral position. During all measurements, each foot was mounted to a plate that was connected to a torque meter for measuring flexion force.

2.2 Cortical activity recording

EEG was referenced to the right earlobe and recorded from 31 Ag/AgCl scalp electrodes with a 9 mm diameter. The electrodes were placed over the entire head (C1, C2, C3, C4, CP1, CP2, CP5, CP6, CPz, Cz, F3, F4, F7, F8, FC1, FC2, FC5, FC6, FCz, FP1, FP2, Fz, O1, O2, P3, P4, P7, P8, Pz, T7, and T8 of the international 10/20 electrode system; Fig. 1A). Monopolar EEG was amplified and band-pass filtered at a frequency range of 2–100 Hz, followed by digitization at 256 Hz using a biosignal acquisition system (g.USBamp; Guger Technologies, Graz, Austria). A ground electrode was positioned on each subjects' forehead.

During offline processing, the recorded EEG signals were converted into reference-free forms using three types of EEG derivation: Laplacian, common average references, and simple bipolar methods. For Laplacian and bipolar methods, the used monopolar electrodes were limited to those near the vertex (see Fig. 1B and C). The Laplacian method for five channels (C3, C4, CPz, Cz, FCz) used the mean voltage recorded from the four nearest neighbor monopolar channels (e.g., for Cz, the four nearest neighbor monopolar channels were FCz [anterior], C1 [left], C2 [right], and CPz [posterior]). The common average reference method used all electrodes as an identical reference electrode. In the bipolar method, voltage differences were transversely measured at two channels (e.g., subtracting Cz from C1) to emphasize left-right differences of beta rebound distribution. Eight bipolar channels (FC1-FCz, FCz-FC2, C3-C1, C1-Cz, Cz-C2, C2-C4, CP1-CPz, and CPz-CP2) were used for analysis.

2.3 Motor tasks

Five cue-based sessions were performed without feedback. Each session consisted of 40 trials, with 20 trials for the left foot and 20 trials for the right foot in a random order. In the first session, weak motor execution tasks, without imagery, were conducted to allow the subject to practice the motor tasks. During motor execution, the subject dorsi-flexed a foot and maintained 1 s movements (brisk movement). Following practice, 1 s imagery tasks of brisk movement were conducted from sessions 2–5, which led to 80 repetitions for each left and right foot imagery tasks. There were sufficient breaks between sessions to prevent fatigue.

The experimental paradigm of the cue-based session is shown in Figure 2. Each trial started with presentation of a fixation cross at the center of the computer screen for 3 s, and a short beep appeared 1 s before the motor task cue to allow the subject to pay attention. A visual cue of the left- or right-foot motor task was displayed for 1 s, randomly displaying a left or right arrow. The subject was asked to perform directed movement or imagery for 1 s (brisk movement). The duration of each trial was 10 s, with random intervals (0–0.5 s) at the end of the trials.

2.4 Muscle activity monitoring

During cue-based sessions, dorsal flexion force from both sides and surface electromyogram (EMG) were monitored. EMG recordings were performed from left and right TA muscles over the muscle belly using bipolar Ag/AgCl electrodes with a 10 mm diameter and a 20 mm inter-electrode distance. EMG was amplified and filtered (2–500 Hz), and then force and

EMG signals were digitized at 2000 Hz (12-bit AD converter; PCI-6071E, National Instruments Corporation, Austin, TX, US) and stored on a personal computer. During offline analysis, all motor imagery trials were eliminated as invalid data when subjects involuntarily contracted muscles. The ground for EMG recording was connected to the forehead electrode as for the EEG recording.

2.5 Individual time-frequency analysis and topography of ERD/ERS

ERD/ERS is defined as the percentage of power decrease (ERD) or power increase (ERS) in relation to a reference period (Pfurtscheller and Lopes da Silva, 1999). In the present study, the reference period was defined as a 2 s period before a short beep. Time-frequency maps (3–45 Hz) were calculated for each subject to evaluate changes caused by foot motor imagery. In addition, sinusoidal wavelets were used to assess changes in frequency domains by calculating the spectrum within a 1 s sliding window, followed by squaring and subsequent averaging over the trials (Makeig et al., 2004). The sliding window is shifted forward by 1/16 s in each step (i.e., 93.75% overlap). Statistical significance of the ERD/ERS values was determined by applying a t-percentile bootstrap algorithm (Davison and Hinkley, 1997) with a significance level of 1%.

Feature values from latency and frequency bands where beta rebounds were most reactive were used to construct topographic ERS maps on a simplified head (using “topoplot” command from EEGLAB software [http://www.sccn.ucsd.edu/eeglab/]). Significant beta rebounds, which were determined by time-frequency maps, were used for manual selection of the most reactive latency and frequency bands of visual inspection. The beta rebound duration was determined at 1.5 s after termination of the imagery process. A 1.5 s period for analysis of beta rebound was previously reported (Neuper and Pfurtscheller, 2001), and we confirmed that the selected periods almost covered significant beta rebounds caused by the motor imagery tasks. In addition, the ERD/ERS value on the edge of the head was set to 0.

To compare beta rebounds and mu ERD (around 10 Hz), EEG topographies for mu ERD were also computed. A frequency band was determined for each subject using the same time-frequency maps.

2.6 Feature extraction

To extract beta rebound features for online BCI procedures, spectral power in the most reactive frequency band, which was previously determined using time-frequency analysis ("band power [BP]"), was calculated. Two EEGs were selected, including bipolar derivation with the largest beta rebound during left foot motor imagery and during right foot motor imagery (Table 1). BPs were calculated for the two bipolar EEG signals every 250 ms (4 Hz) from -2 to 8 s (short beep appeared at 0 s), rather than sample-by-sample (256 Hz), to enable rapid analysis at these time points (Ron-Angevin and Díaz-Estrella, 2009), and were given to the classifier described below.

2.7 Evaluation of motor imagery classification

From the perspective of signal processing, BCI requires a synchronous (cued) or asynchronous (self-paced) design. In the present study, a traditional linear discriminant analysis (LDA; Bishop, 1995) was utilized to measure classification accuracy in synchronous mode, as previously reported (Pfurtscheller et al., 2000b; Guger et al., 2001), and the asynchronous BCI was then simulated. To evaluate the performance of the simulated asynchronous BCI, relative (or receiver) operating characteristic (ROC) curves were utilized (Townsend et al., 2004; Fatourechi et al., 2008; Hashimoto et al., 2010). We (Hashimoto et al., 2010) and others (Townsend et al., 2004) previously utilized this analysis method to measure classification accuracy of imaginary left and right hand movements with mu ERD. In asynchronous BCI with beta rebound, the same method may have induced classification errors in the present study. Details of our simulated asynchronous BCI are described below.

2.8 Asynchronous BCI design

The present study suggested an asynchronous BCI design for classifying imaginary left and right foot movements, termed “two-stage LDA”. This classification method combined a foot motor imagery detector and a simple left-right discriminator; first stage LDA detected beta rebounds following motor imagery using the two features (mu BP and beta BP) recorded from the Laplacian Cz channel. The weight vector and threshold were determined from the EEG data of each subject. A similar method using first stage LDA was previously described as the “Brain Switch” (Pfurtscheller and Solis-Escalante, 2009), which showed high accuracy during the simulated asynchronous mode. If foot motor imagery was detected by the first stage LDA, second stage LDA classified the imagery into left and right foot motor imagery using two beta BPs from two reactive bipolar channels (see Table 1). All BPs were subject-specific and were selected with EEG topographies for each subject (see Tables 1 and 2).

The second stage LDA used the weight vector that resulted in the best classification accuracy during synchronous analysis, which was performed sample-by-sample. In general asynchronous BCI operation, both the rate of errors during motor imagery periods (true positive rate: TPR) and the rate of errors during rest periods (false positive rate: FPR) are important factors for performance validation. Therefore, we calculated TPR and FPR to validate foot imagery detection using sample-by-sample analysis, using a previously described method (Townsend et al., 2004). In this analysis, the output signal of the first stage LDA was divided into control periods (events) and non-control periods (non-events). A latency of 1.5 s from the beta rebound (determined by time-frequency maps for each subject) was used for the control period, and the other periods served as the non-control periods.

The two axes of the ROC curves were TPR and FPR. TPR is a measure of sensitivity, while FPR is a measure of selectivity, both of which were calculated using the following equations:

$$R_{TP} = N_{TP} / (N_{TP} + N_{FN}) \qquad (1)$$

$$R_{FP} = N_{FP} / (N_{TN} + N_{FP}) \qquad (2),$$

where R_{TP} and R_{FP} represent TPR and FPR, respectively. N_{TP}, N_{FP}, N_{TN}, and N_{FP} are the numbers of true positives, false negatives, true negatives, and false positives, respectively. These numbers were determined by separately quantifying samples above or below a threshold during control or non-control periods. A total of 200 thresholds were tested, which varied from minimum to maximum values of output signal, and R_{TP} and R_{FP} were calculated for each threshold to generate smooth ROC curves.

When using a ROC curve as an evaluation tool, the area under the curve (AUC) determines the performance of the detector. For ideal detection, the TPR should be 100%, the FPR should be 0%, and the AUC should be 100%.

3 Results

All subjects successfully performed the tasks according to instructions. No subjects reported fatigue or anxiety during experimentation.

3.1 Time-frequency map

Figure 3 shows the time-frequency map for a representative subject (Subject 1). A Laplacian channel (Cz) and the two most reactive bipolar channels were selected for comparison. Time-frequency maps for the Laplacian method revealed a significant beta rebound (18–28 Hz, Onset time = 3.3 s, $P<0.01$), with equivalent characteristics between left and right foot motor imageries. However, the bipolar method clearly revealed strong left-right differences on the time-frequency maps, which demonstrated that right foot motor imagery generated a larger beta rebound at channel C1-Cz than left foot motor imagery. In addition, the time-frequency map at channel C2-Cz showed a larger beta rebound than at C1-Cz during the left foot motor imagery task.

To emphasize left-right differences of beta rebounds for each subject, two bipolar channels were manually selected: one was most reactive to left foot motor imagery and the other was most reactive to the right foot imagery. The time-frequency map for each subject was used for the subject-specific reactive band and onset time of beta rebound (Table 1). In most subjects, the bipolar channels of C1-Cz and C2-Cz were most reactive to right and left foot motor imagery, respectively. Beta rebound occurred in frequencies between 20–31 Hz and on average at 2.6 s after the beep. The channel FCz-FC2 was more reactive to left foot imagery than C2-Cz only in Subject 5, and Channel C1-C3 was more reactive to right foot imagery than C1-Cz in Subjects 3 and 6.

Figure 4 shows the average of beta rebounds of all subjects. The amplitude of beta rebounds exhibited differences depending on the types of derivation methods, although the original monopolar EEG signals were identical. In the Laplacian method, left-right amplitude differences were within 5%. By contrast, these differences were emphasized and exceeded 10% in the bipolar method.

3.2 EEG topographies of beta rebound

EEG topographies of beta rebounds from subject-specific reactive bands and occurrence times were displayed to show the distribution of beta rebounds (Fig. 5). Topographies were averaged from all subjects. The Laplacian (Fig. 5A–B) and common average reference (Fig. 5C–D) methods demonstrated that the beta rebounds were located around the vertex. By contrast, the bipolar method (Fig. 5E–F) revealed that the center-focused beta rebound and the lateralized distribution were contralateral to imagined foot movement.

3.3. EEG topographies of mu ERD

EEG topographies from subject-specific reactive frequencies of mu ERD (around 10 Hz) and occurrence latencies were displayed to compare the distributions of beta rebounds on the head (Fig. 5) with the case of the mu ERD (Fig. 6). As for beta rebounds, the frequency band and the latency of mu ERD were selected with time-frequency maps for each subject. Compared to beta rebounds, the EEG topographic distribution of mu ERD was not lateralized. The Laplacian (Fig. 6A–B) and common average reference (Fig. 6C–D) methods demonstrated that mu ERD was located around the occipital area. According to results from the bipolar method (Fig. 6E–F), the mu ERD map did not exhibit a lateralized distribution, as in the beta rebound.

The selection method for subject-specific reactive bands and onset times of mu ERD was identical to that used for beta rebound. The frequency band and onset time were 6–14 Hz and 1.5 s on average between all subjects, respectively. The average onset was 0.5 s after the visual cue that instructed the imagery side of both feet.

3.4. Classification accuracy in synchronous mode

The time-frequency map and EEG topographic analyses of beta rebound revealed left-right differences, which were particularly apparent in Subject 1. From the viewpoint of EEG classification, it is generally considered that the left-right difference is influenced by the classification accuracy. The present study demonstrated a time course of classification results during foot imagery tasks, as seen by representative Subject 1 in Figure 7A. Classification accuracy ranged from 50–80% for all classification time points and subjects. The greatest classification accuracy was observed in Subject 1 (80%). In addition, latency to achieve greatest accuracy was within 6 s from time of the beep. This classification was performed to discriminate between left and right foot imagery using the beta rebound. Therefore, classification accuracy under ideal conditions could achieve 100%, with a chance level of 50%.

Scatter plots in Figure 7B show the intensity of beta rebounds from channel Cz-C1 and its mirror site, channel Cz-C2, which illustrates the variance of feature values and LDA lines in the feature space from left and right foot motor imagery for Subject 1. The plots demonstrated the effect of contralateral preponderance of beta rebounds following the imagery, and results suggested that Subject 1 produced greater beta rebounds in the left hemisphere than the homologue of the right hemisphere following right foot imagery, and vice versa. The greatest classification accuracy for each subject in the synchronous mode is summarized in Table 3. Classification accuracy was 67.0% on average (61.5–80% for all subjects).

3.5. Classification accuracy in asynchronous mode

An ROC curve example, which was generated on a sample-by-sample basis using the simulated asynchronous output of LDA, is shown in Figure 8. Table 4 shows the TP rate at 10% FP rate for each subject, as well as the area under the ROC curve (AUC) for foot imagery from first-stage LDA. For ideal detection, the TP rate and AUC should be 100%. Subject 4 exhibited the greatest TP rate of all subjects at a 10% FP rate. In a total of four subjects, including Subject 4, AUC exceeded 70%, and the average AUC was 66.5% among all subjects.

In second-stage LDA, samples that correctly detected beta rebounds were simply classified as left and right foot data. This was determined using LDA and the LDA parameters from the synchronous mode analysis. Subject 1 and Subject 2 exhibited high accuracy (>64%), which was similar to the synchronous mode analysis.

4 Discussion

The present study analyzed beta rebounds following left and right foot motor imagery on EEG topography and time-frequency maps using the Laplacian method, common average references, and bipolar methods. Significant beta rebounds were observed following left or right foot motor imagery, which was consistent with previous studies (Doppelmayr et al., 1998; Pfurtscheller et al., 2005). Distribution of the beta rebound, which was localized at the vertex, was displayed in the EEG topography. In particular, beta rebound distribution was distinct following use of the common average reference method (Fig. 5C-D). The bipolar method clearly demonstrated left-right differences of beta rebounds, which were not observed by the Laplacian or common average methods. Compared to beta rebounds, distribution of mu ERD did not exhibit left-right differences in any EEG derivation. In addition, the bipolar method was able to more sensitively measure beta rebounds than the Laplacian method, which has been traditionally used to detect beta rebounds followed by foot imagery. To our knowledge, this work provides the first example of left-right differences in beta rebounds following unilateral foot motor imagery in EEG.

4.1. Bipolar method for detecting left-right differences of beta rebounds

A previous study of beta rebounds by foot motor imagery demonstrated no differences between topographical distribution of beta rebounds after left and right foot movement (Neuper and Pfurtscheller, 1996); we also confirmed this with EEG topography and time-frequency mapping using the Laplacian method. The results from the present study obtained through the use of the transverse bipolar method demonstrated left and right differences. However, it remains unclear why the bipolar method was more effective in detecting left-right differences of beta rebounds.

The Laplacian method is the second derivative of the instantaneous spatial voltage distribution, and thereby emphasizes activity in radial sources immediately below the recording location (Nunez et al., 1997). As described in the Materials and Methods, the

Laplacian method is computed by combining voltage at the location with voltages from surrounding electrodes (Hjorth, 1975). As the distance to surrounding electrodes decreases, the Laplacian method becomes more sensitive to voltage sources with higher spatial frequencies (i.e., more localized sources) and less sensitive to sources with lower spatial frequencies (i.e., more broadly distributed sources). By contrast, the bipolar method is the simplest spatial filter, which derives the first spatial derivative and thereby enhances differences in voltage gradient in one direction (Wolpaw et al. 2002). The main difference between these two methods is the reactive spatial frequency band. A previous EEG simulation study reported that the Laplacian method filters out EEG signals in low spatial frequencies, and that the bipolar method partly removes signals with near-zero spatial frequency (Nunez, 1997). Therefore, we speculate that the component with left-right differences of topographic distribution in beta rebounds likely includes lower spatial frequencies than the beta rebound itself.

4.2. Laplacian method for detecting left-right differences of beta rebounds

The Laplacian method has been used to detect beta rebounds following motor imagery of feet imagery in several BCI studies (Pfurtscheller and Solis-Escalante, 2009; Müller-Putz et al., 2010). These studies reported that the Laplacian method provides users highly accurate control of asynchronous BCI through the use of only one channel at Cz (at vertex). In addition, time-frequency maps obtained in the present study indicated that unilateral foot motor imagery generated beta rebounds, and that the Laplacian method detected significant beta rebounds ($P<0.01$) in most subjects (6/8 subjects) without BCI feedback training. These data suggest that the Laplacian method is suitable for detecting motor imagery from one or both feet. However, Subjects 4 and 6 did not exhibit significant beta rebounds in the Laplacian method, but did exhibit beta rebounds in the bipolar method, suggesting that the Laplacian method is not necessarily the ideal method for all subjects. We speculate that it may be necessary to combine the Laplacian and bipolar methods to cover all subjects.

Considering the merits of each derivation method, our proposed design of asynchronous BCI utilized a two-stage LDA. The first LDA detected foot motor imagery, while the second LDA classified left and right foot imagery. Although the LDA is a very simple method, and the true positive rate was low compared to other asynchronous BCI studies (Galán et al. 2008), the present BCI design had two technical advantages. First, as it used a simple classifier LDA, calculations were fast compared to other more complex algorithms (e.g., Gaussian classifier [Galán et al. 2008] or SVM classifier [Fatourechi et al. 2008]), which validated the classifier parameters. In addition, this BCI design utilized only one Laplacian and two bipolar channels, which were produced from 5–7 monopolar channels. Secondly, our BCI design was able to prevent false positives. Beta rebounds sometimes follow beta ERD, as seen in Subject 1, 3, 6, and 8. To classify left and right hand (or foot) motor imagery, it is generally difficult for a BCI system to distinguish between the beta rebound following left foot motor imagery and the beta ERD during right foot motor imagery, as such a BCI system often monitors only the balance of EEG powers on the left and right sides of the head. The BCI system we propose avoids this type of error by separating the processes of beta rebound detection and classification of left and right motor imagery. Thus, the asynchronous BCI design utilized in the present study provides a solution for preventing these errors.

4.3. Comparison of hand motor imagery-based BCIs

As previously described, there are multiple BCI studies of hand motor imagery. Guger et al. (2003) used similar methods to the present study, and showed classification accuracy of left and hand motor imagery with band powers as EEG features in 99 healthy subjects. Their results clearly showed a high classification accuracy during each subjects' first attempt at BCI operation. Approximately 93% of subjects were able to achieve classification accuracy >60%, and 20% of the subjects achieved >80%.

The foot motor imagery results from the present study also showed similar classification accuracy. All subjects achieved classification accuracy >60%, and one subject achieved 80%, as shown in the synchronous analysis. These data suggest that foot motor imagery has the potential to elicit left-right differences in EEG, similar to hand motor imagery.

In present study, we could not monitor the effect of repetitive use of BCI or neurofeedback training for brain activities. Nevertheless, other studies of hand motor imagery have reported that the training is the key to improved classification accuracy (Dobkin, 2007; Hashimoto et al., 2010; Shindo et al., 2011). As for hand motor imagery-based BCI, repeating our use of foot imagery-based BCI should increase the classification accuracy. Our next goal is to study the effect of neurofeedback training to establish a foot motor imagery-based BCI control technique.

In conclusion, the results of this study revealed imagery-related lateralization of beta rebound in association with foot imagery tasks, and showed that the bipolar method can emphasize the ERD/ERS lateralization. In synchronous mode, our BCI achieved the same accuracy level as hand motor imagery-based BCI, using only two EEG signals recorded via bipolar electrodes on the vertex. By adding one Laplacian EEG signal, the BCI can be converted into asynchronous mode. Further studies are required to determine the effect of neurofeedback training on classification accuracy.

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Figure Legends

Figure 1. Electrode locations and EEG derivation. Monopolar EEG signals were recorded from 31 Ag/AgCl scalp electrodes. The monopolar EEG in the black- and gray-framed areas were used in the Laplacian and bipolar methods for offline analysis, respectively (A). "G" and "Ref" indicate positions of ground and reference electrodes, respectively. Topography data were plotted at five positions in the Laplacian method (B) and at eight positions in the bipolar method (C).

Figure 2. Timing of cue and motor task during one trial. The visual cue of a left- or right-foot motor task is displayed for 1 s, showing a left or right arrow at 1 s after the beep.

Figure 3. Time-frequency maps (Subject 1). A Laplacian channel Cz (A and B) and two bipolar channels, Cz-C1 (C and D) and C2-Cz (E and F), were utilized. Panels in the left column are for left foot imagery tasks (A, C, and E), and the right column panels are for right foot imagery tasks (B, D, and F). Only significant (P<0.01) band power changes are shown during the trial period of -2 to 8 s in the frequency range of 3–45 Hz. The reference period for ERD/ERS calculation is -2 to 0 s. The window area in the panels indicates subject-specific reactive bands and occurrence times of beta rebounds (around 20 Hz) and mu ERD (around 10 Hz). Red indicates significant power increases (ERS), and blue represents significant power decreases (ERD).

Figure 4. Average amplitude of beta rebounds from all subjects. Blue and red bars show the average amplitude of beta rebounds after left and right foot motor imageries, respectively. The error bars represent standard deviations.

Figure 5. Average EEG topographies of beta rebounds following foot motor imagery from all subjects. The panels indicate results using five Laplacian channels (A and B), 31 common average reference channels (C and D), and eight bipolar channels (E and F). The left column shows left foot motor imagery and the right column shows right foot motor imagery. In the bipolar methods, channel locations were set to the center of each electrode pair (e.g., value at C1-Cz was plotted at the center between channels C1 and Cz). Red indicates power increases (ERS). The value on the edge of the head was set to 0 (green).

Figure 6. Average EEG topographies of mu ERD (around 10 Hz) during foot motor imagery from all subjects. Panel layout is identical to Figure 5. Blue represents power decrease of mu rhythms (ERD). The value on the edge of the head was set to 0 % (green).

Figure 7. Time course of classification accuracy during cue-based sessions (A) and logarithm to base ten of power of beta rhythms in Subject 1 (B). Cz-C1 and C2-Cz channels were used for left (cross) and right (triangle) foot imagery. The filled star shows time at best classification accuracy.

Figure 8. ROC curves generated on a sample-by-sample comparison of the classifier against foot motor imagery for Subject 1. The Laplacian channel at vertex (Cz) was used.

Figure 1
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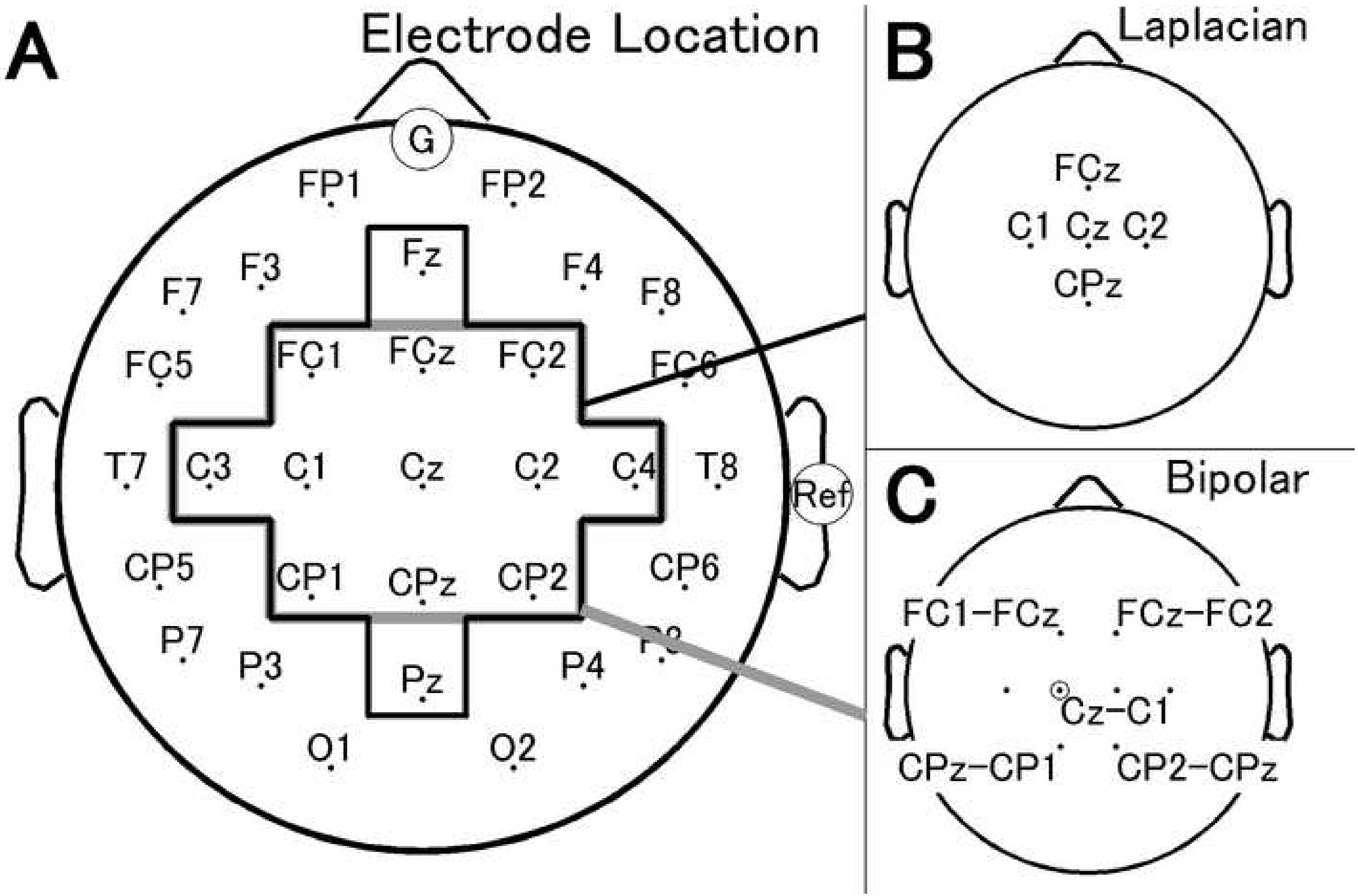

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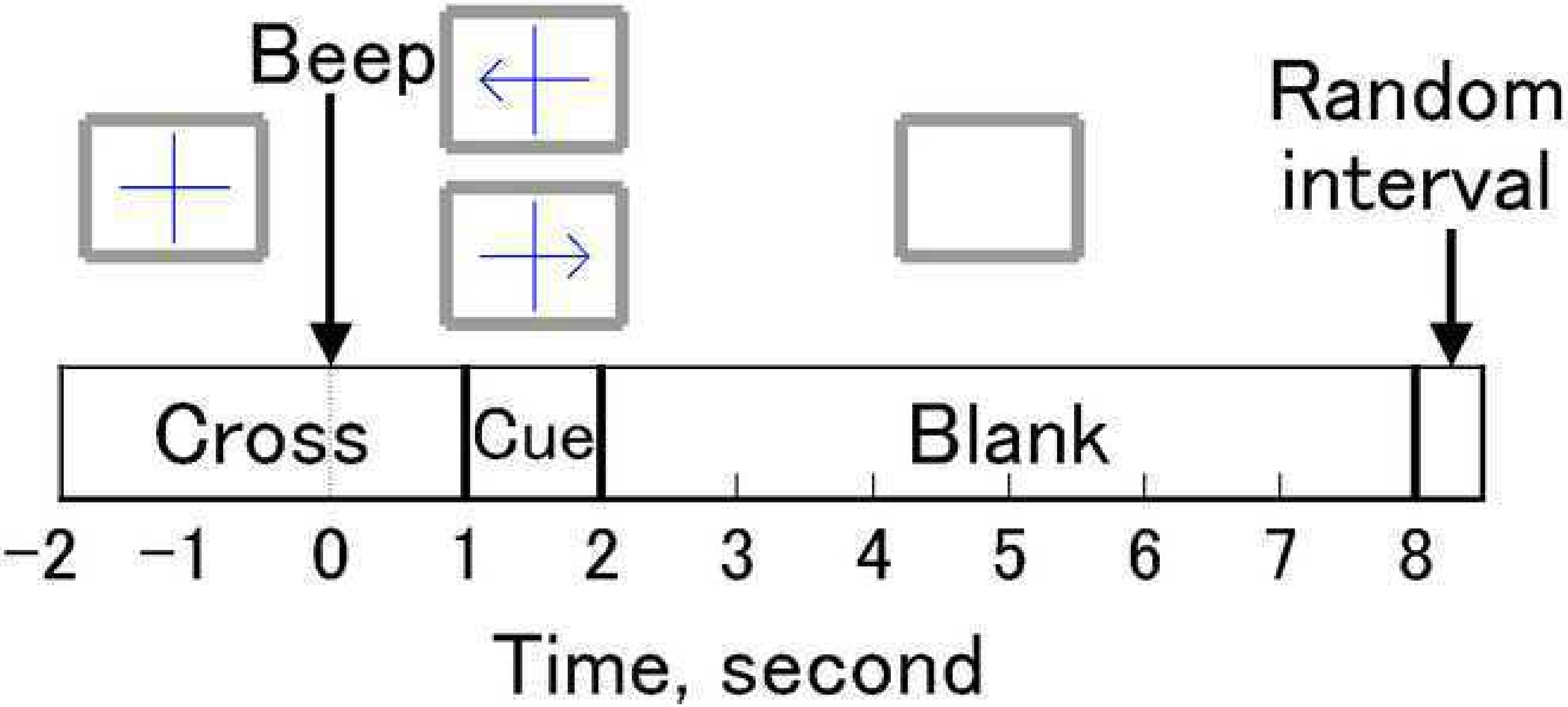

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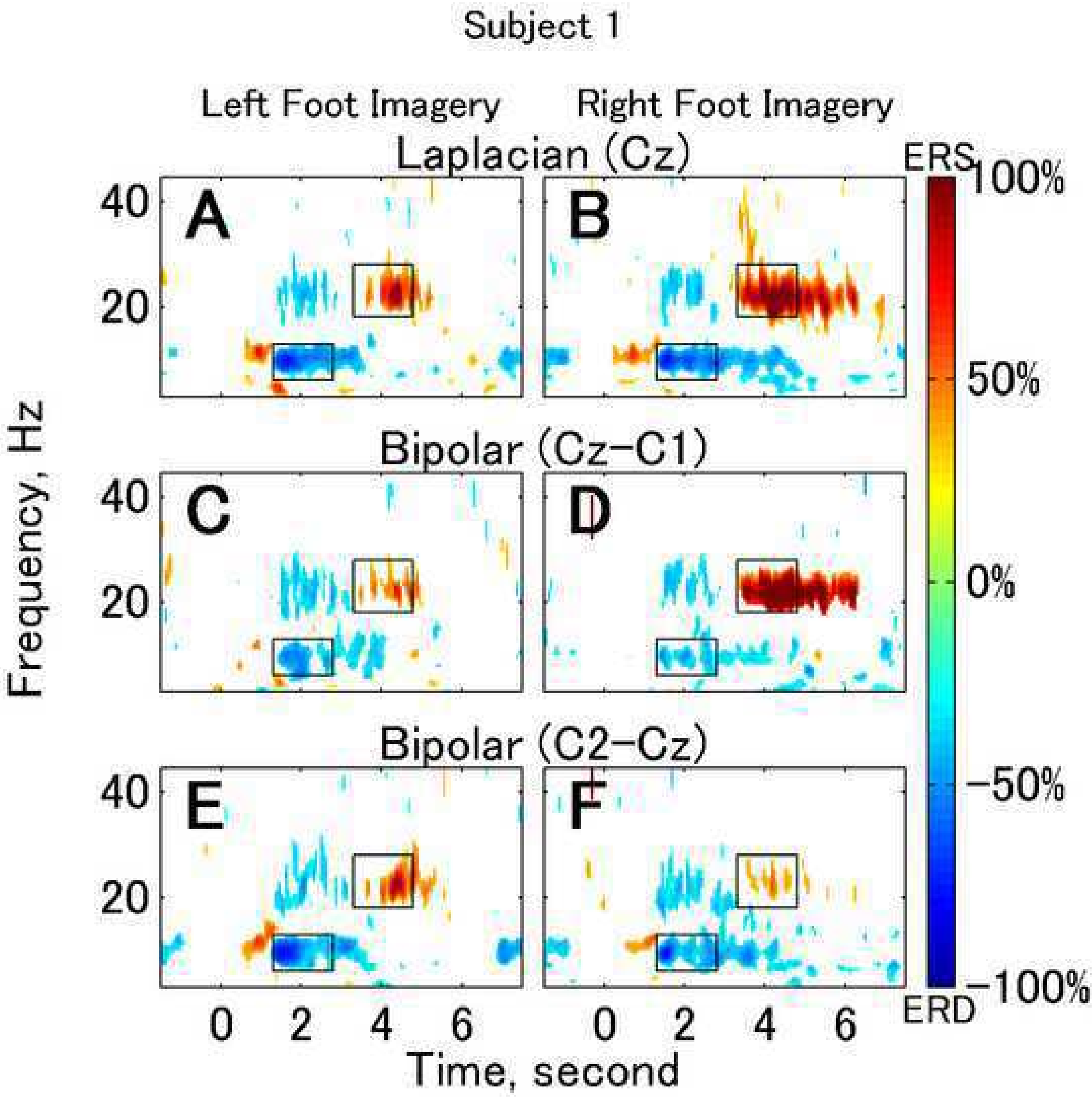

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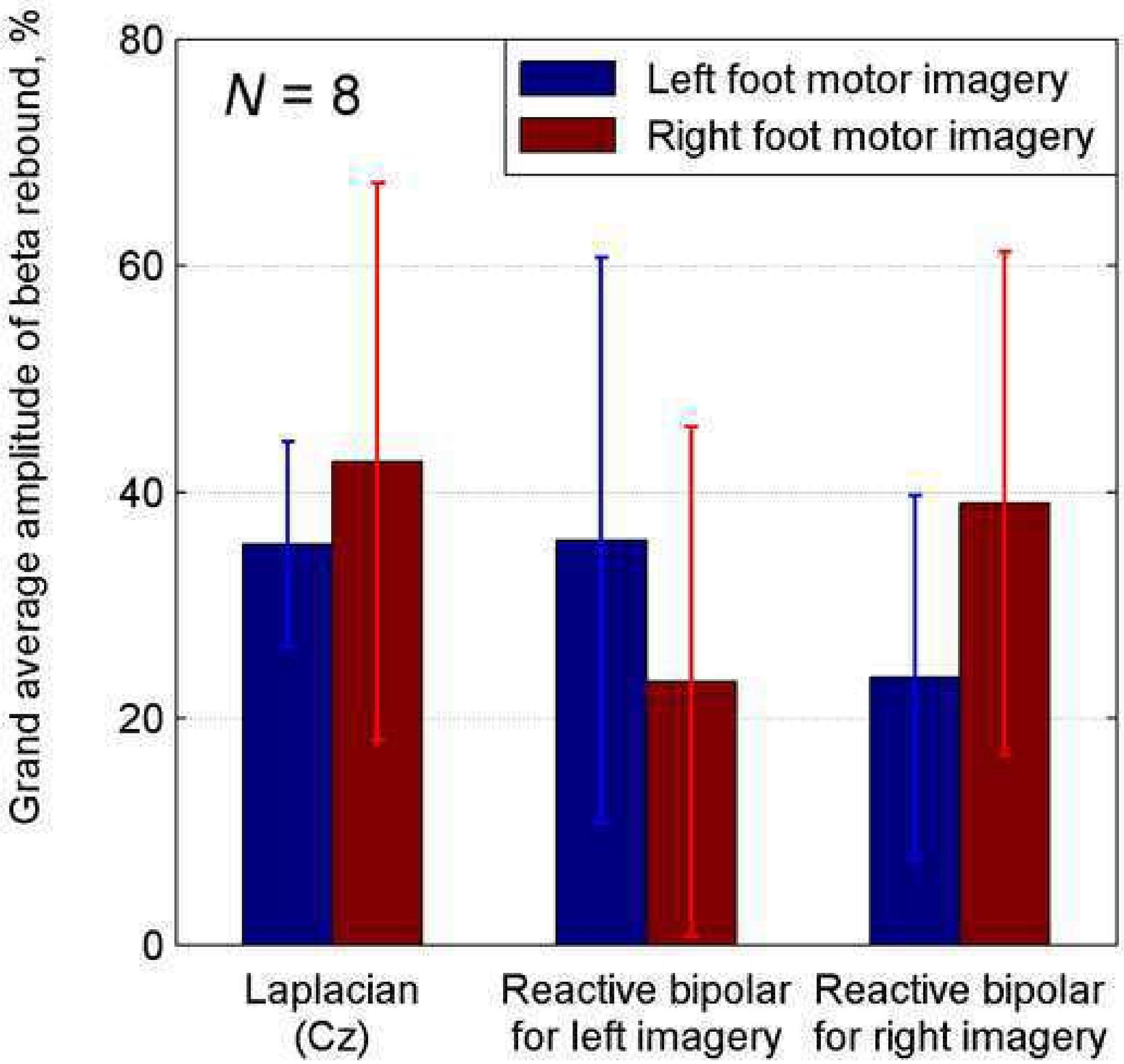

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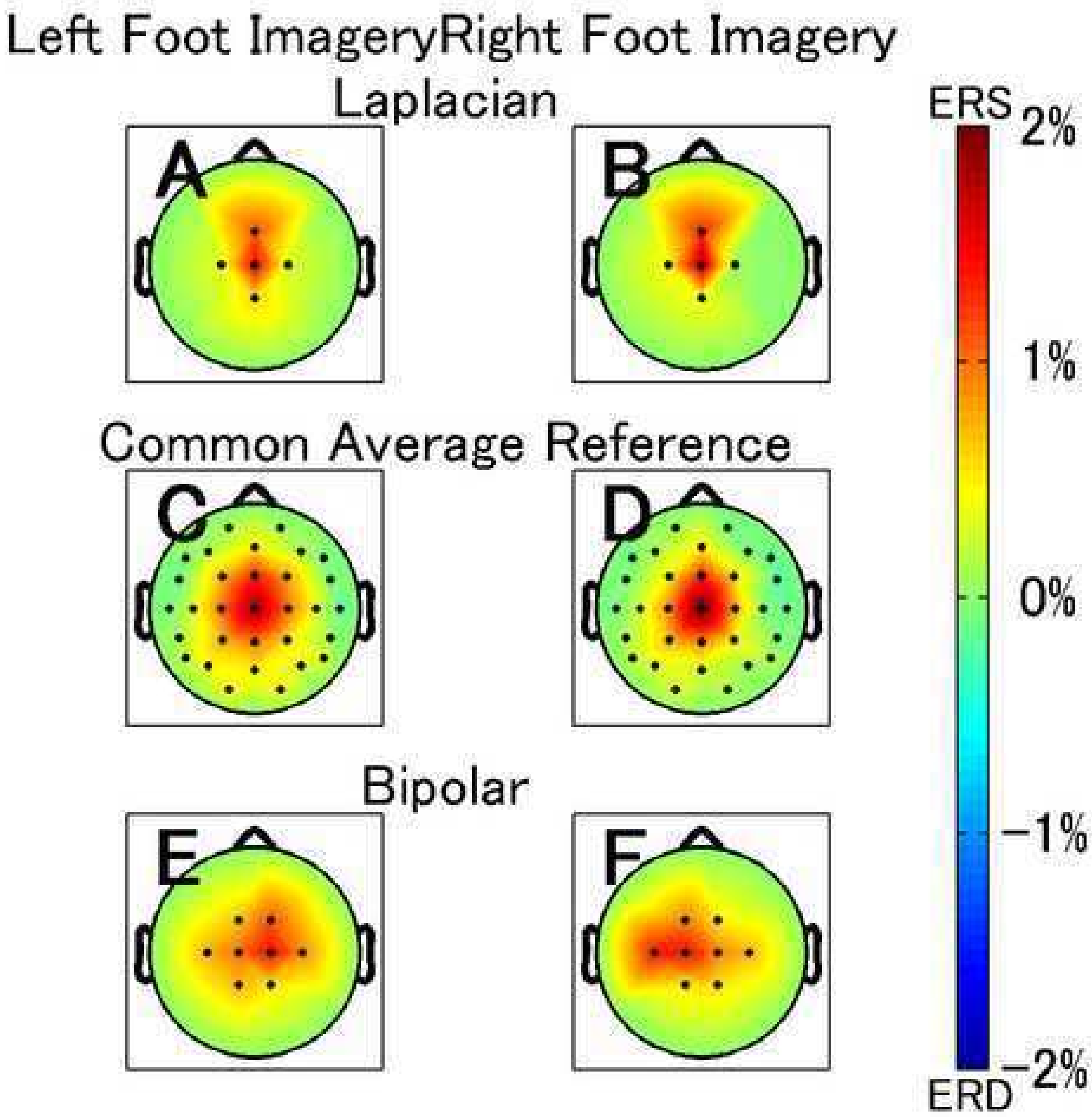

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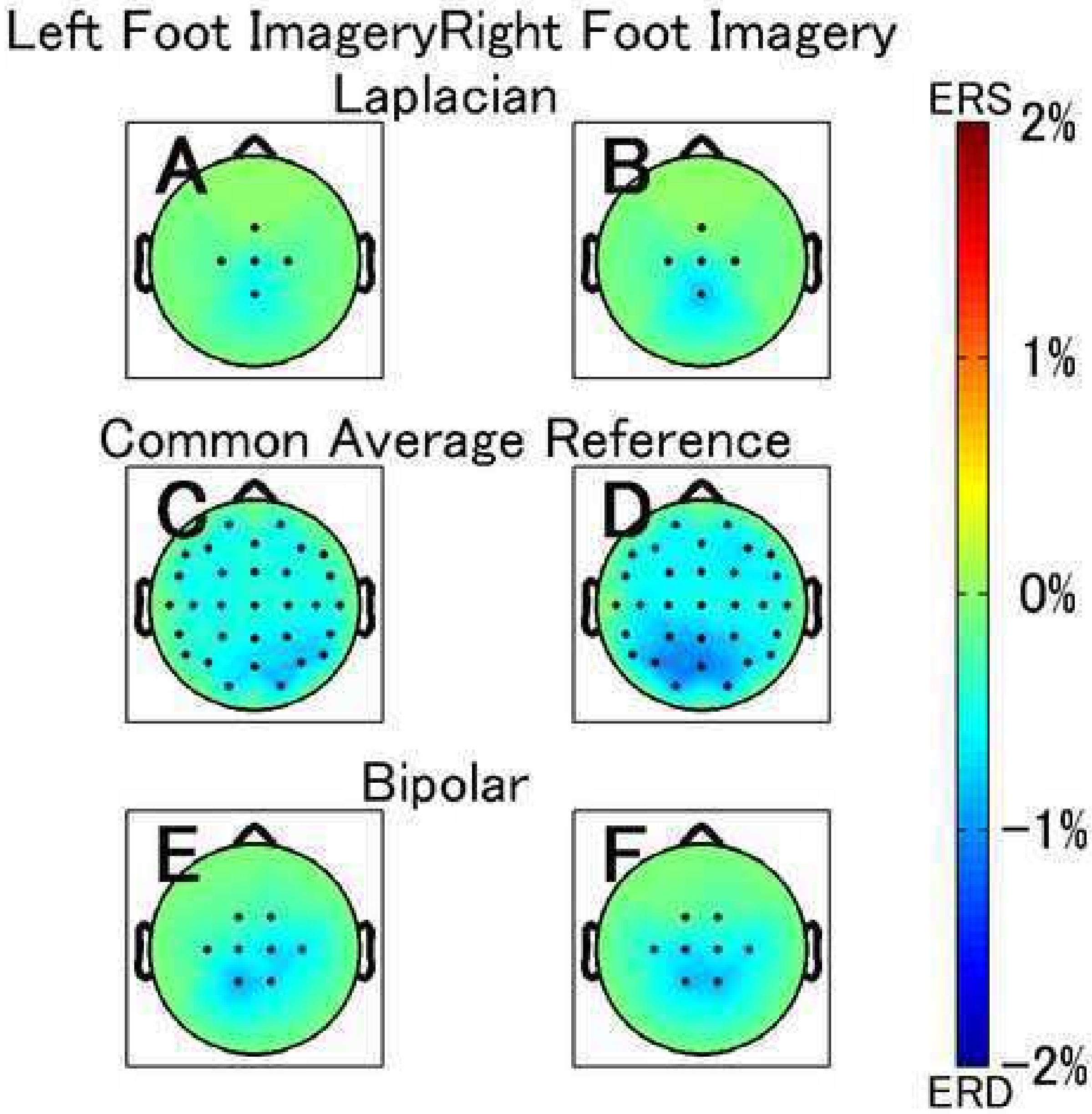

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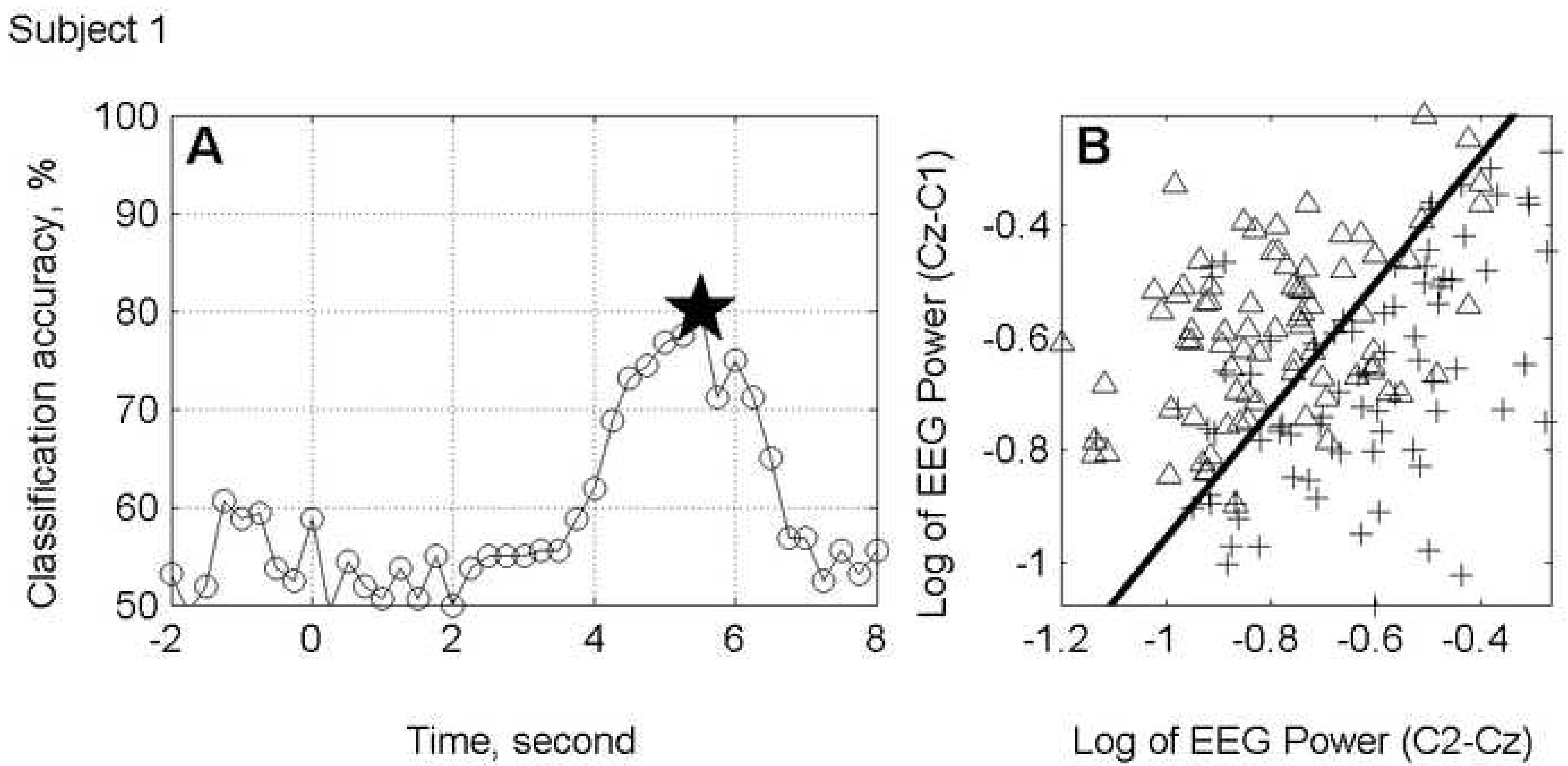

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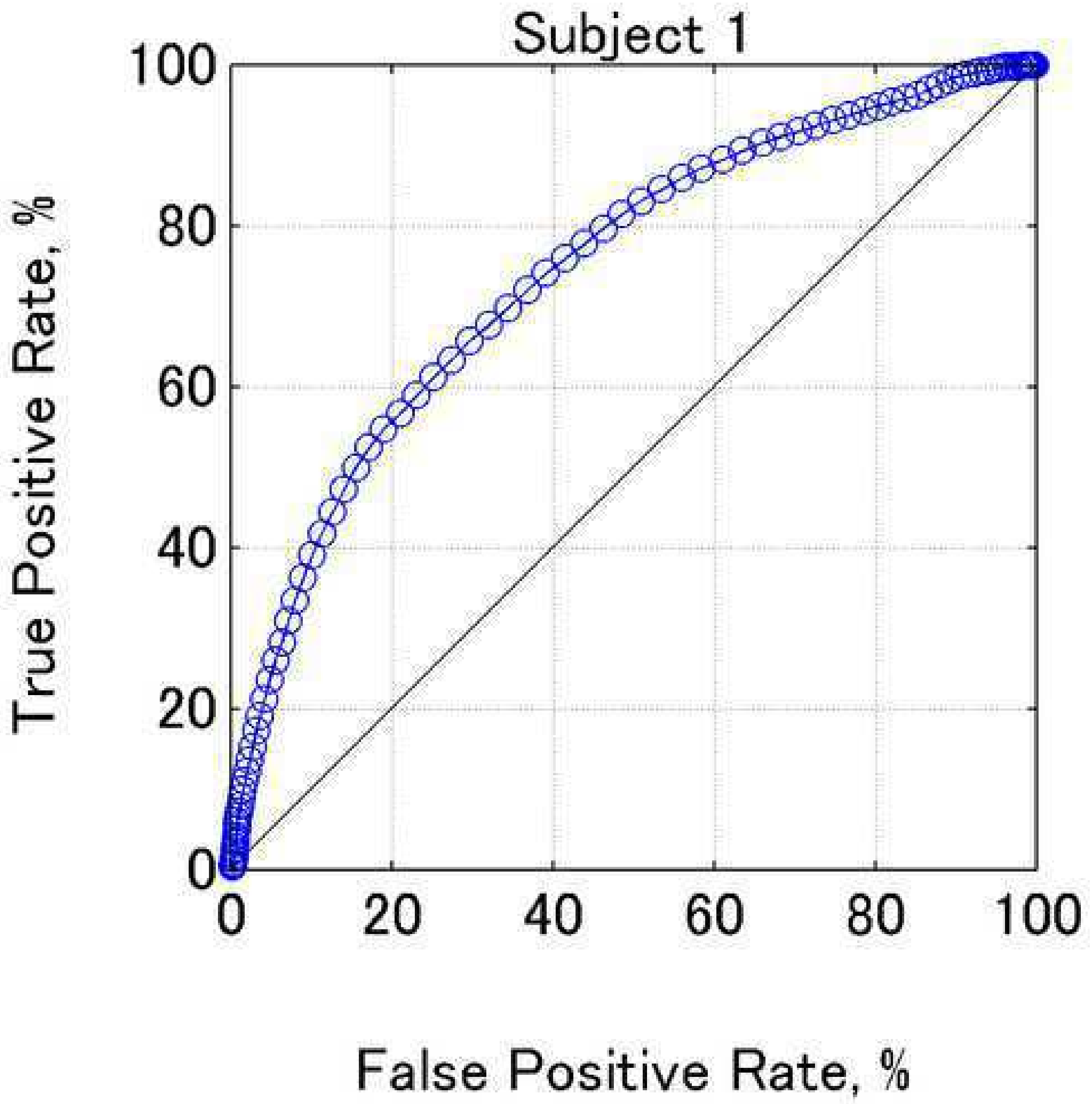

Table 1

Table 1. Summary of beta rebound property and most reactive bipolar channels for left and rig

	Beta rebound		Most reactive bipolar channel	
Subjects	Frequency	Onset	Channel R	Channel L
1	18 – 28 Hz	3.3 s	Cz-C1	C2-Cz
2	13 – 26 Hz	2.4 s	Cz-C1	C2-Cz
3	24 – 36 Hz	2.4 s	C1-C3	C2-Cz
4	22 – 33 Hz	3.8 s	Cz-C1	C2-Cz
5	23 – 33 Hz	2.4 s	Cz-C1	FCz-FC2
6	14 – 24 Hz	2.4 s	C1-C3	C2-Cz
7	24 – 33 Hz	1.8 s	Cz-C1	C2-Cz
8	22 – 34 Hz	2.8 s	Cz-C1	C2-Cz
Mean	20 – 31 Hz	2.7 s		
SD	4 4	0.6		

Channel R represents a bipolar electrode pair that records largest beta rebound by right foot motor imagery; Channel L represents the left foot.

Table 2

Table 2. Summary of mu ERD property and most reactive bipolar channels for left and right foot

Subjects	mu ERD Frequency	Onset
1	6 – 13 Hz	1.3 s
2	6 – 12 Hz	1.3 s
3	7 – 15 Hz	1.5 s
4	6 – 14 Hz	2.3 s
5	6 – 14 Hz	1.3 s
6	7 – 12 Hz	1.5 s
7	6 – 14 Hz	1.3 s
8	6 – 14 Hz	1.3 s
Mean	6 – 14 Hz	1.5 s
SD	0 1	0.3

Table 3

Table 3. Summary of classification accuracy in synchronous mode.

Subjects	Accuracy
1	80.0 %
2	67.5 %
3	67.5 %
4	67.5 %
5	65.6 %
6	63.7 %
7	62.5 %
8	61.3 %
Mean	67.0 %
SD	5.8

Table 4

Table 4. Summary of performance in asynchronous mode.

	First-stage LDA		Second-stage LDA
Subjects	TPR (FPR=10%)	AUC	Accuracy
1	33.9%	71.3%	67.6%
2	28.5%	64.1%	64.5%
3	40.3%	70.3%	55.7%
4	13.3%	52.5%	62.6%
5	28.1%	67.6%	61.6%
6	32.3%	70.7%	57.0%
7	28.9%	64.1%	54.8%
8	39.8%	71.7%	52.9%
Mean	30.6%	66.5%	59.6%
SD	8.5%	6.5%	5.2%