2011 11th International Conference on Control, Automation and Systems
Oct. 26-29, 2011 in KINTEX, Gyeonggi-do, Korea

Analysis of Correlated EEG Activity during Motor Imagery for Brain-Computer Interfaces

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Abstract: Overall accuracy of noninvasive brain-computer interfaces (BCIs) based on motor imagery electroencephalography (EEG) is highly dependent on the extraction of features from the oscillation of sensorimotor rhythms (SMRs) during imagination of movements. In this study, we statistically evaluated whole-brain connectivity using the measurement of linear correlation coefficients (CCs) between EEG channel pairs instead of using conventional spectral analysis. We showed distinct patterns of temporal variations of CCs of all channel pairs and significant channel connections for four motor imageries, including left hand, right hand, both feet, and tongue, in two subjects. Contralateral connectivity was observed in the motor imagery of left and right hands, whereas central connectivity was observed in the motor imagery of both feet. Our results suggest to the implementation of the state-of-the-art BCIs based on whole-brain channel connectivity in motor imagery.

Keywords: Brain-computer interfaces (BCIs), electroencephalography (EEG), motor imagery, connectivity, correlation coefficients

1. INTRODUCTION

Brain-computer interfaces (BCIs) read brain activities in the form of various types of signals and translate them to control commands for external devices, such as a computer cursor and robot arms, realizing intended actions of those who have severe movement disability due to motor paralysis [1-2]. Noninvasive BCIs mainly rely on the recording of electroencephalography (EEG) from the scalp or magnetoencephalography (MEG) from magnetic fields surrounding the brain. As they do not require surgical procedures such as the implant of intracortical electrodes or the recording of electrocorticography (ECoG), they can be more practically applicable in a daily life with convenient measurement of brain signals [3-4]. In particular, EEG-based BCIs are the most prevalent noninvasive interfaces. EEG signals for BCIs are recorded from the scalp using multi-electrodes in response to specific stimuli such as unexpected auditory or visual cues and rhythmic visual stimuli, or during imagination of movements. Depending on stimulus type of imagery, EEG signals are characterized as event-related potentials (ERPs), stead-state visual evoked potentials (SSVEPs), sensorimotor rhythms (SMRs), or slow cortical potentials (SCPs) to name a few [5].

During the imagination of movements of body parts such as the hand or feet, known as motor imagery, SMRs generated from the somatosensory and motor cortices modulate their oscillations depending on which body part is being imagined [6-7]. Many studies reported that the power of SMRs at certain recording sites ranging from 8 to 12 Hz (mu rhythm) and from 12 to 30 Hz (beta rhythm) was significantly reduced, called event-related desynchronization (ERD), during the motor imagery. Also, the increase in the SMR power, particularly the beta power, called event-related synchronization (ERS), was simultaneously observed at surrounding recording sites. In particular, contralateral ERD has been observed during motor imagery of the left and right hands. Central ERD has been observed during the motor imagery of both feet [8-10].

Typical operating steps of EEG-based BCIs consist of recording, feature extraction, and classification. For BCIs with motor imagery, analysis of ERD/ERS is the main procedure for feature extraction. Overall accuracy of motor imagery EEG-based BCIs was highly dependent on the extraction of informative feature patterns in ERD/ERS corresponding to specific body parts. Spectral analysis using Fourier transform or wavelet transform has been mainly used to find features. Many recent studies showed noticeable ERD/ERS patterns during pre- and post-motor imagery in the time-frequency domain [11-14]. However, the feature extraction based on ERD/ERS patterns requires time-consuming and complex time-frequency analysis in every EEG channel. Also, it is spatially limited in EEG recording locations on the somatosensory and motor cortices.

To overcome these limitations, we explore connectivity between EEG channel pairs as an alternative feature for motor imagery. We investigate a linear correlation coefficient (CC) between two EEG signals, simplifying analysis within time domain. Our approach includes building connectivity maps over time by selecting significantly connected channel pairs using CCs and representing connectivity patterns for each of four different motor imageries, left hand, right hand, both feet, and tongue. Our goal is to find a spatio-temporal pattern of connectivity unique to each motor imagery without considering ERD/ERS. This may provide new information about whole-brain connectivity regarding motor imagery to help advance signal processing components of EEG-based BCIs.

978-89-93215-03-8 98560/11/$15 ©ICROS

2. METHODS

We used motor imagery EEG data from BCI Competition 2008 – Graz data set A [15]. The data set contained four different sets of motor imagery EEG signals, including left hand, right hand, both feet, and tongue, recorded from 22 scalp electrodes of nine subjects. All subjects participated in 6 runs each consisting of 48 trials of motor imagery. These trials were divided equally into four sets of 12 trials corresponding to the four motor imageries. In present study, we used the data set from two subjects. EEG signals were pre-processed with a 250Hz sampling frequency, a 100μV amplifier sensitivity, 50Hz notch filtering, and 0.5 Hz to 100 Hz bandpass filtering. Scalp electrodes based on the international 10-20 system were located at the following 22 positions from the frontal to occipital lobes: Fz, FC3, FC1, FCz, FC2, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CP1, CPz, CP2, CP4, P1, Pz, P2, and POz, denoted as channel 1 to channel 22 hereafter. We reorganized the EEG signals for each trial to obtain a total of 6-sec data that consisted of 2-sec pre-imagery and 4-sec peri-imagery segments. Finally, we filtered the reorganized EEG signals using a zero-phase bandpass filtering from 8 to 30Hz.

We grouped the filtered EEG signals based on the imagined body part into four where each group contained 72 trials. To evaluate temporal variation of connectivity, we used a short-time window and computed a CC in each window. Specifically, we moved a 1-sec time window over the pre-imagery and peri-imagery segments by step of 0.1-sec. This resulted in 11 and 31 windows from the pre-imagery and peri-imagery segments respectively. We showed four windows at 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds among the 31 windows over the peri-imagery segments in figure 1 and figure 2. In each window, the linear CC, which ranged from -1 to 1 was calculated for all possible 231 ($_{22}C_2$) channel pairs. All CCs in the pre-imagery segment were averaged and used as a baseline correlation level. CCs in the peri-imagery segment were subtracted by this baseline level. To statistically evaluate whether correlation between a given pair significantly increased or decreased during motor imagery at a given window, we performed t-test (0.01 significance level) with a null hypothesis that the mean of CCs is zero. Rejection to the null hypothesis indicated a significant change (either increase or decrease) of correlation.

We further investigated whether a connection between certain pair showed a change only for one of four imageries. To this end, we performed the Kruskal-Wallis (KW) test (0.01 significance level) for the CC values from the baseline and the entire 4-sec peri-imagery segment. This test resulted in a set of pairs that exhibited CCs uneven over motor imageries. Then, we categorized these pairs into one of four groups of motor imageries based on the mean-rank in the KW test. Finally, we constructed four connection maps for four motor imageries where each map showed the pair connections belonging to each of four imagery groups.

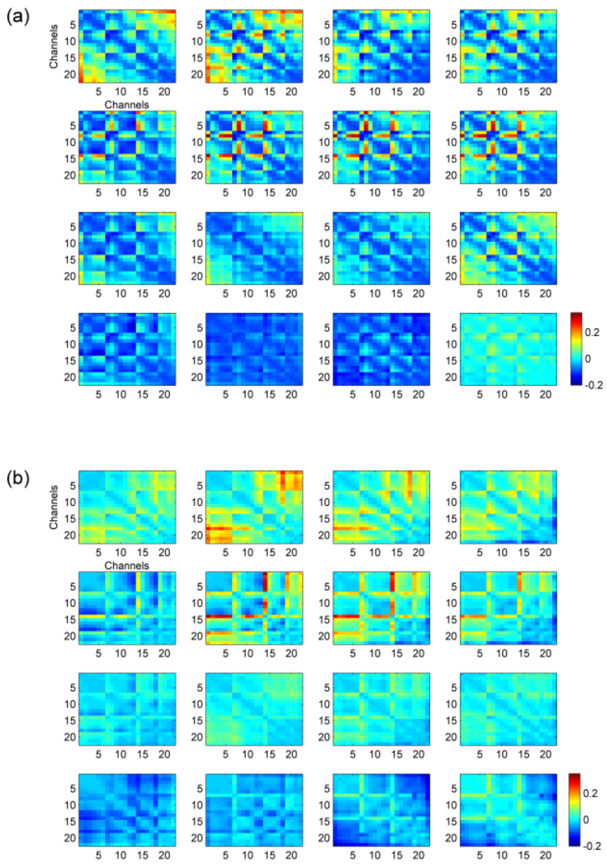

Fig. 1 Temporal variation of CCs for four motor imageries: left hand (the first row), right hand (the second row), both feet (the third row), and tongue (the fourth row), in two subjects (a, b). Four patterns of each row were corresponding to the time windows at 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds, from left to right.

3. RESULTS

Figure 1 shows the temporal variation of CCs of all channel pairs for four different motor imageries, including left hand, right hand, both feet, and tongue, in two subjects at the time windows of 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds over the peri-imagery segment. The temporal patterns of CCs exhibited clear differences among four motor imageries. The temporal patterns of the left and right hands showed more positive CCs than those of both feet and tongue. In particular, we observed distinct patterns between motor imageries of left and right hands in two subjects. CCs between channels 1-5 (frontal) and 18-22 (parietal) showed substantial difference between left and right hands at time windows of 0~1 second and 1~2 seconds in the first subject, similar to our previous study [16]. CCs between channels 4-6 (right hemisphere) and channels 8 and 14 (left hemisphere) showed substantial difference from time windows of 1~2 seconds in the first subject. CCs between channels 1-6 (frontal) and 17-22 (parietal) showed substantial difference at time windows of 1~2 seconds and 2~3 seconds in the second subject, similar to our previous study [16]. CCs between channels 1~6 (frontal) and a channel 14 (left hemisphere) showed substantial difference from time windows of 1~2 seconds in the second subject.

Figure 2 shows the temporal variation of statistically significant channel pairs (black-colored) for the four motor imageries in two subjects at the time windows of 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds. The temporal patterns of the occurrence of significant channel pairs were clearly different across four motor imageries. We observed the least number of significant channel pairs in the motor imagery of tongue in two subjects.

Figure 3 shows significant channel connections with respect to each of four motor imageries, determined by the KW test, in both subjects. We observed contralateral connectivity for motor imageries of left and right hands in two subjects. Channel connections were oriented towards the right hemisphere during imagery of the left hand and towards the left hemisphere during imagery of the right hand. We also observed the central connectivity for the motor imagery of both feet in the first subject. The first subject showed distinct contralateral connectivity for the motor imageries of left and right hands and central connectivity for the motor imagery of both feet. The second subject showed distinct contralateral connectivity for the motor imageries of left and right hands. The first subject showed 48, 46, and 18 significant channel connections in the motor imagery of the left hand, right hand, and both feet, respectively. The second subject showed 128 and 61 significant channel connections in the motor imagery of the left hand and right hand, respectively. Both subjects showed no significant channel connection in the motor imagery the tongue. The second subject also showed no significant channel connection in the motor imagery of the both feet.

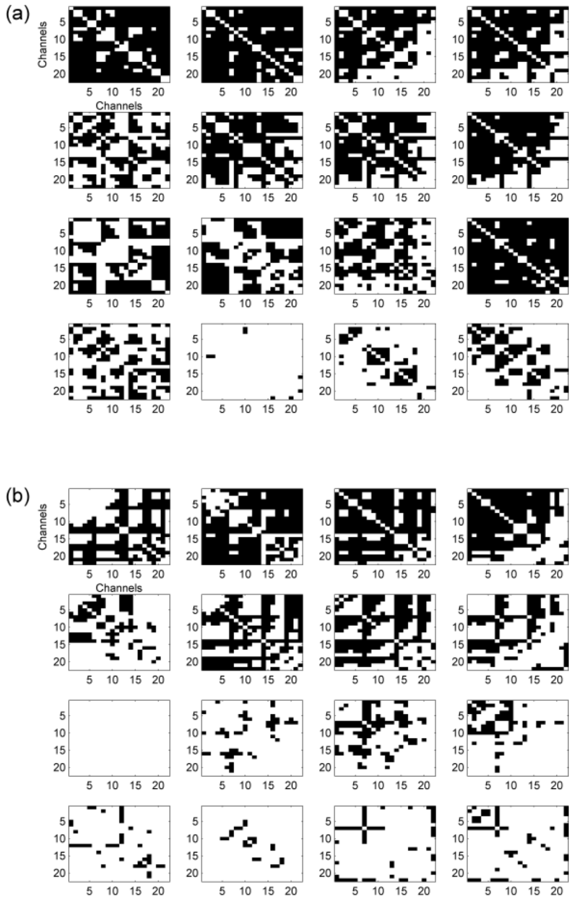

Fig. 2 Temporal variation of significant channel pairs (black-colored) for four motor imageries, left hand (the topmost row), right hand (the second row), both feet (the third row), and tongue (the bottom-most row), in two subjects (a, b). Four patterns of each row were corresponding to the time windows at 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds, from left to right.

4. DISCUSSIONS

In this study, we evaluated the temporal variation of CCs and the significantly correlated channel pairs during motor imageries of the left hand, right hand, both feet, and tongue in two human subjects. We observed distinct temporal patterns of CCs and channel connections with respect to each of the four motor imageries. In particular, we observed a clear difference in the patterns of the left and right hands based on the distribution of positive/negative CCs and the number of significant channel pairs. We also statistically evaluated significant channel connectivity for the four motor imageries. We observed contralateral connectivity for motor imageries of left and right hands in two subjects, and central connectivity for the motor imagery of both feet in one subject. The motor imagery of left hand showed channel connections oriented towards right hemisphere, the motor imagery of right hand showed channel connections oriented towards left hemisphere, and the motor imagery of both feet showed channel connections oriented toward central area.

The connectivity maps created from this study may provide a neural correlate of different types of motor imagery. Furthermore, it may lead to a novel design of noninvasive BCIs with a simplified feature extraction method based on the temporal patterns of connectivity.

Our method in this study adopted slightly different approaches compared with previous connectivity-related studies in terms of significant channel connectivity based on correlation coefficients in motor imagery. In previous researches, they used phase differences between phases and spectral coherences between two EEG signals in motor imagery mental tasks [17], topological organization of the cerebral connection network with a graph theory in auditive steady-state eveoked potentials [18], connectivity patterns of motor imagery EEG signals in gamma-band above 35Hz with beamforming and transfer entropy [19], and nonlinear regressive coefficients and phase coupling measures [20] to extract connectivity features. In the follow-up study, we are applying this connectivity feature set to BCI operations with motor imagery EEG such that classification of motor tasks is performed from the connectivity information. Also, we will investigate how to incorporate the polarity of connectivity in our

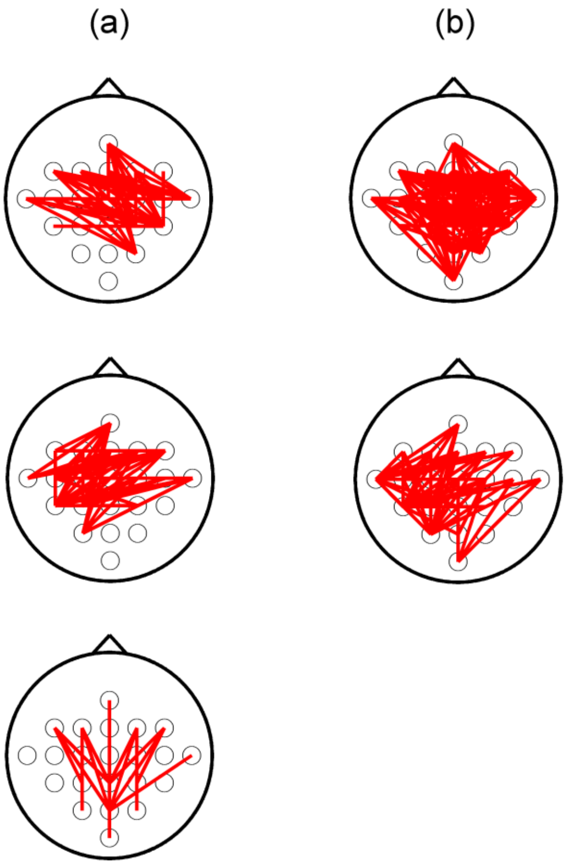

Fig. 3 Significant channel connectivity for the motor imageries of left hand (the topmost row), right hand (the second row), and both feet (the bottom-most row) in two subjects (a, b). The significant channels were statistically selected using the Kruskal-Wallis (KW) test.

features and how to quantify the connectivity patterns in more concise ways using network analysis.

ACKNOWLEDGEMENT

This research was supported by WCU (World Class University) program (R31-10008), Basic Science Research Program (R1009541) of the National Research Foundation (NRF) of Korea funded by the Ministry of Education, Science and Technology, and Hi Seoul Science/Humanities Fellowship from Seoul Scholarship Foundation.

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