Inter-channel connectivity of motor imagery EEG signals for a noninvasive BCI application

Yoon Gi Chung
Department of Brain and Cognitive Engineering
Korea University
Seoul, Republic of Korea
e-mail: uskeywest@korea.ac.kr

Min-Ki Kim
Department of Brain and Cognitive Engineering
Korea University
Seoul, Republic of Korea
e-mail: mkworks@korea.ac.kr

Sung-Phil Kim
Department of Brain and Cognitive Engineering
Korea University
Seoul, Republic of Korea
e-mail: spkim@korea.ac.kr

Abstract—**Noninvasive brain-computer interfaces (BCIs) based on motor imagery translate brain activity into motor execution commands to control external devices. They have largely relied on the measurement of the sensorimotor rhythms (SMR) and the beta rhythms in electroencephalography (EEG). However, most BCIs of this type have exploited SMR and beta rhythms observed from a few EEG channels over the sensorimotor area. They also extracted movement-related information from each channel independently, without considering connectivity between channels. In this study, we aim to investigate whether we can obtain useful information of movements from the connectivity measures across a wide range of EEG channels, over the whole brain. To address this question, we evaluated a simple connectivity measure - cross-correlation coefficients (CCs) - for twenty-two EEG channels distributed over different brain regions to differentiate four different motor imagery states, including left hand, right hand, both feet, and tongue. The temporal variations of CCs across twenty-two channels exhibited distinct patterns as to four motor imagery states. It suggests that we may use connectivity as a useful source to derive noninvasive BCIs.**

Keywords-component; brain-computer interfaces; motor imagery; connectivity; correlation coefficients

I. Introduction

Brain-computer interfaces (BCIs) convert brain activity into specific commands or messages to manipulate external devices [1-2]. Measurement of brain activity can be performed using invasive or noninvasive modalities. Invasive methods record neural spikes in the cellular level or electrocorticography (ECoG) in the epidural level. Noninvasive methods record electroencephalography (EEG), magnetoencephalography (MEG), or functional magnetic resonance imaging (fMRI) outside the brain. Due to the problems in surgical implantation for invasive recording, noninvasive measurement methods have been preferred to implement BCIs. Noninvasive BCIs have high applicability for a rehabilitation therapy in patients who have neurodegenerative disorders and motor paralysis. People with motor disabilities, in many cases, have unimpaired brain functions to generate motor commands to handle their limbs. Yet, they have a critical failure in the transmission tracks of the motor commands [3-6]. Thus, BCIs have aimed to bridge the failed gaps between the brain function and the body parts.

EEG-based noninvasive BCIs are one of the most prevalent BCIs due to their simple recording and low cost. EEG is the recording of electrical brain activity with multiple scalp electrodes. It measures the outcome of synchronous activity of multiple cortical cells related to specific events such as an intention of motor execution and visual or auditory perception [2, 6]. It has been reported that EEG signals varied with the imagination of movements in specific body parts such as hands and feet [7-9]. The change of EEG signals in response to motor imagery was specified by the oscillation of a sensorimotor rhythm (SMR) ranging from 8 to 12 Hz and a beta rhythm ranging from 12 to 30 Hz. From this fact, various EEG-based BCIs were built on a basis of temporal changes of SMR and beta rhythms, which are called event-related desynchronization (ERD) and event-related synchronization (ERS). ERD refers to the significant reduction of the power of the SMR and beta rhythms in response to imagined contralateral hand movement. On the other hand, ERS refers to the significant increase of the power of the SMR and beta rhythms after imagined contralateral movement [10-13]. The performance of EEG-based BCIs depends on the detection of the ERD and ERS [14-15]. EEG-based BCIs using the analysis of ERD and ERS are spatially restricted to the recordings from the sensorimotor area.

To overcome these restrictions, a number of studies have attempted to find movement-related information in the patterns of connectivity between different brain regions [16-19]. In this study, we investigate the inter-channel connectivity using a simplest measure - a linear correlation coefficient (CC) – and how its variations are related to the

movement information during four motor imageries: left hand, right hand, both feet, and tongue. We used the EEG signals within the band related to SMR and beta rhythms to evaluate CCs between EEG channels. Our method did not explore the variation of ERD and ERS but extract features for motor imagery from the inter-channel connectivity. Furthermore, we considered not only sensorimotor areas but also other areas to extract connectivity patterns corresponding to the four different motor imagery states. By constructing connectivity maps for each state, we provide a different aspect of EEG properties that can add useful information to current design of a BCI.

II. METHODS

Motor imagery EEG data in this paper were obtained from the data sets of BCI Competition 2008 - Graz data set A [20]. All EEG data in the Graz data set A were originally recorded from nine subjects. All subjects were instructed to imagine moving one of four body parts - left hand, right hand, both feet and tongue - after a visual cue. The subjects participated in 6 runs. Each run included 48 trials that were divided into four sets of 12 trials corresponding to four motor imageries. Here, we used the EEG data from the first subject. In each trial, a 2-sec fixation was followed by 4-sec motor imagery after a visual cue. The parameters of EEG data preprocessing were as follows: a 250 Hz sampling frequency, a 100 µV amplifier sensitivity, notch filtering at 50 Hz, 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. After this preprocessing, we filtered the signal in each trial using a specific bandpass filter based on zero-phase filtering from 8 to 24Hz using EEGLab toolbox (sccn.ucsd.edu/eeglab) [21], which included the SMR and beta rhythms.

The filtered EEG signals were then grouped by the type of motor imagery. Each group contained 72 trials. A single trial consisted of a 1-sec resting period before a motor imagery cue and a 4-sec imagery period after the cue. For each channel, we segmented a single-trial EEG using a 1-sec time window that started from the onset of cue. The window moved towards the end of trial by the step size of 0.1 second. The resting period was regarded as a windowed segment (reflecting baseline activity). In doing so, there were 31 segments from the imagery period and one from the resting period. In each segment, linear correlation coefficients (CCs) were calculated for all possible pairs of channels. The total number of pairs from 22 channels was $_{22}C_2 = 231$. Note that a CC ranges from -1 to 1. For each trial, CCs from the motor imagery period were subtracted by CCs from the resting period.

These baseline-corrected CCs were analyzed in the following ways. First, we evaluated inter-channel connectivity using a channel-to-channel correlation. We examined how the temporal patterns of CCs over all channel pairs varied across different motor imageries. We used the Kruskal-Wallis (KW) test (p < 0.01) to statistically evaluate if there was a significant difference of CCs across four groups (corresponding to four motor imageries) for a given channel pair. We used the 4-sec motor imagery period without segmentation and obtained the difference of CCs from the period. If the p-value was below 0.01, we regarded that correlation between given two channels provided meaningful movement-related information. Second, we computed the sum of CCs per channel for each segment. To obtain the sum of CCs for a given channel, all CCs for every pair connecting to the channel were summated and divided by the number of pairs (in fact, there were 21 pairs including a particular channel). All procedures in this study were performed using the signal processing toolbox of Matlab (The MathWorks, Natick, USA). Topological maps were constructed using the EEGLab toolbox (sccn.ucsd.edu/eeglab) [21].

III. RESULTS

The channel-to-channel CCs showed distinct temporal patterns for each of four motor imagery states. Fig. 1 shows time-varying patterns of channel-to-channel CCs for each imagery state. All of the channel-to-channel CC patterns were obtained from the four different time windows at 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds during the motor imagery period. Overall, the temporal CC patterns for the motor imagery of both left and right hands were clearly different from those of feet and tongue. The CC patterns of the left and right hands mainly exhibited positive values, whereas those of the both feet and tongue did negative values. Furthermore, the CC patterns of the left hand were slightly different from those of the right hand. Positive CC values were observed over a wider range of connections for the right hand than the left hand in the first 1-sec period. CCs on the connections between channels 7-13 (central) and channels 18-22 (parietal) showed a substantial difference between the left and right hands. The CC patterns of the both feet were also slightly different from those of the tongue, especially on the connections between channels 1-6 (frontal) and channels 18-22 (parietal). The difference of CCs was maximally observed in the first segment (0~1 second after the cue). This result may suggest that we can rapidly predict which type of motor imagery is being imagined right after the first 1-sec period, without waiting until motor imagery is fully completed.

The temporal patterns of the average CCs per channel were shown for each motor imagery state in Fig. 2. The average CCs over all channels showed distinct patterns for each motor imagery. The average CC patterns of the left hand were different from those of the right hand in that it exhibited lower CCs overall and the channels with high CCs sustained their values for a shorter period. Also, the average CC patterns of the both feet were different from those of the tongue in that the CCs of the tongue exhibited relatively lower values.

Fig. 3 shows the topological maps of the average CCs for each of four motor imagery states. Four topological maps in each motor imagery state were obtained from four different time windows at 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds during the motor imagery period. Again, the
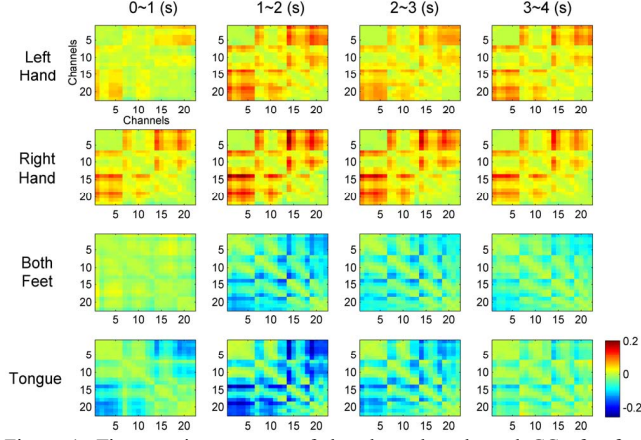
Figure 1. Time-varying patterns of the channel-to-channel CCs for four different motor imagery states: left hand (the topmost row), right hand (the second row), both feet (the third row) and tongue (the bottom-most row) were shown. Four patterns per each row were obtained from the time windows at 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds, from left to right.
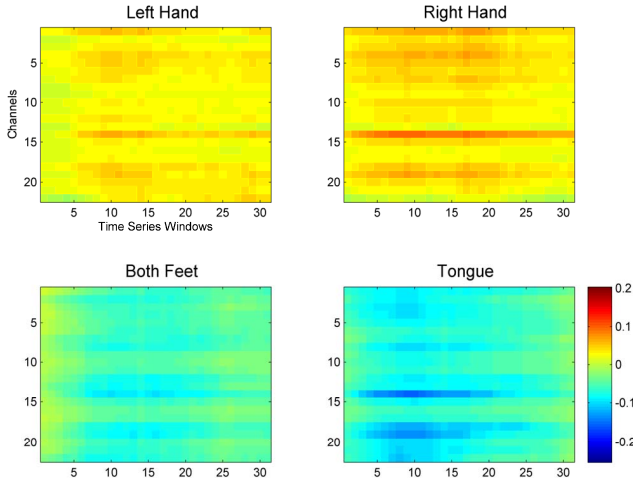

Figure 2. Time-varying patterns of the average CCs per channel for four different motor imagery states, left hand (top left), right hand (top right), both feet (bottom left) and tongue (bottom right) were shown. Each pattern was shown over the 31 consecutive time series windows covering 0~4 seconds of motor imagery.

average CC patterns were maximally different at the first window covering 0~1 second.

The Kruskal-Wallis test showed the significant channel-to-channel connectivity that contributed to the difference between the four motor imagery states. Inter-channel connectivity was evaluated by the statistical evaluation of the channel-to-channel connections and mean ranking of the four motor imagery groups. For each channel-to-channel connection, one motor imagery state showing the highest mean ranking was found. Then, the channel-to-channel connections showing the p-values higher than the defined significant level were rejected. Fig. 4 shows the significant channel-to-channel connectivity for the four different motor imagery states. Motor imagery of the left hand showed right-sided inter-channel connectivity. Motor imagery of the right
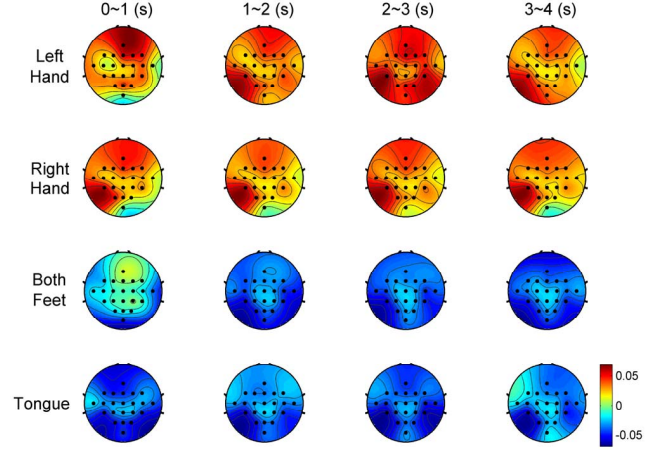

Figure 3. Topological maps for the time-varying patterns of the average CCs per channel for four different motor imagery states, left hand (the topmost row), right hand (the second row), both feet (the third row) and tongue (the bottom-most row) were shown. Four topological maps in each row were obtained from the time series windows at 0~1 second, 1~2 seconds, 2~3 seconds, and 3~4 seconds, from left to right.

hand showed large-scale inter-channel connectivity over the brain. On the other hand, inter-channel connectivity of the both feet and tongue showed no significant correlations.

IV. CONCLUSION

In this study, we evaluated the temporal patterns of connectivity between EEG channels by the time-varying patterns of the channel-to-channel CCs and the average CC per channel. We compared these time-varying connectivity measures among the four motor imagery states, including left hand, right hand, both feet, and tongue. It was observed that the temporal connectivity patterns of the left and right hands were obviously different from those of the both feet and tongue. The temporal connectivity patterns for the left and right hands, also for the both feet and tongue, were slightly different from each other. The difference of the connectivity patterns between imageries was maximized at the early period (0~1 second) of motor imagery. When the connectivity measure was statistically evaluated, motor imagery of the left hand showed right-sided significant connectivity, whereas motor imagery of the right hand showed a broader range of significant connectivity. However, motor imagery of the both feet and tongue did not show any significant connectivity.

This study may provide specific motor imagery EEG patterns based on inter-channel connectivity. It leads to new approaches for the implementation of novel BCIs with simple feature extraction and whole-brain connectivity. Although we have not tried to apply our method to actual BCI operations, we showed new analytical results in terms of four-class motor imagery tasks with twenty-two EEG channels. Our approach is different from the previous connectivity studies for mental tasks [16-17], gamma-band EEG [18], and two-channel motor imagery EEG recording [19]. For future work, we will apply our method to multiple subjects to evaluate its feasibility for BCI applications. Also, we will perform an in-depth study of positive and negative
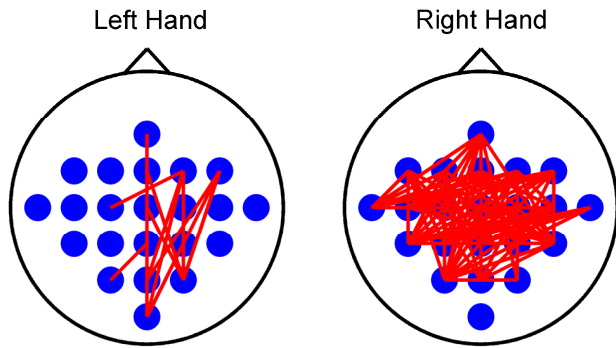
Figure 4. Patterns of the inter-channel connectivity for the motor imagery states of left hand (left) and right hand (right). Patterns of the inter-channel connectivity for the motor imagery states of both feet and tongue were not shown here. Channel-to-channel connections showing p-values higher than the defined significant level, 0.01, were rejected.

inter-channel connectivity with help from neurophysiologic interpretation.

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