How Robust the Motor Imagery Induced EEG Sensorimotor Rhythm can be Extracted: A Test from a Cohort of Normal Subjects

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Abstract—**This study tested the robustness of the sensorimotor rhythm (SMR) features induced by motor imagery task and compared the result to those of other motor tasks, such as motor execution and observation. Thirteen subjects participated in the study and performed 5 runs of motor tasks with three different motor conditions (imagery, execution, and observation). Each run consisted of 15 motor task trials (5 for each motor condition), cued in a random sequence. 64-ch EEG was recorded while subjects performed the motor tasks. The separate runs of EEG data were concatenated and processed using independent component analysis (ICA) to separate the motor components from other brain or non-brain sources (including artifacts). Equivalent independent components from different subjects were selected using a K-means clustering method based on the features summarized from dipole location, time-frequency response, as well as scalp map. Finally, the average alpha (8-13 Hz) power changes were computed according to the motor conditions. The significance level of the event-related desynchronization (ERD) as compared to the baseline prior to the motor cue onset and the duration with significant ERD were compared across different motor conditions. Our result showed that no significant difference in terms of onset of motor induced ERD among the three motor conditions (around 370 ms after motor cue onset). However, the level of ERD was most pronounced for the motor execution condition (around -8 dB from the baseline). Both motor imagery and motor observation had similar level of the motor induced ERD. For the onset duration of the motor induced ERD, motor execution also showed the longest duration of alpha power decrease as compared to two other motor conditions. Both motor imagery and motor observation had much shorter duration of alpha power decrease; however, motor imagery elicited slightly longer ERD. As a result, the SMR-based BCI-controlled neurorehabilitation using a motor imagery should be quite challenging, if not impossible, for extracting SMR feature in real time given such a limited duration of the alpha ERD induced by the motor imagery.**

Keywords-sensorimotor rhythm (SMR); motor imagery; EEG; brain-computer interface (BCI); neurorehabilitation; event-related desynchronization (ERD); independent component analysis (ICA)

I. INTRODUCTION

BCI based neurorehabilitation process has been reported beneficial for the stroke patients in helping them to recover their motor control, which was damaged after stroke attack [1, 2]. Among the BCI neurorehabilitation protocol, sensorimotor rhythm (SMR) based BCI has been widely adopted in a variety of neurorehabilitation to restore the motor control function of stroke patients [3]. However, the effectiveness of the SMR-based BCI being used for controlling a rehabilitation device has yet been rigorously evaluated in the past. As a result, the outcomes of SMR-based neurorehabilitation seemed quite inconclusive in the literature [4, 5]. In this study, we empirically compared the SMR induced by motor imagery to those induced by real motor execution (grasping) as well as watching the video clip of someone grasping. The result should lend itself guidance for devising an SMR-based neurorehabilitation apparatus.

This article is organized as follows: The next section, Methods, gives the details regarding the subject population, experimental protocol, data acquisition, and data analysis. The third section presents the details of the result of the data analysis, including the ICA component selection as well as the grand average of the semsorimotor responses induced by motor imagery as compared to the other types of motor tasks. Finally, we project the future work based on our findings for devising an SMR-based BMC-controlled neurorehabilitation apparatus to improve the progress of rehabilitation for the patients after stroke attack and/or brain injury.

II. METHODS

A. Subjects

Thirteen normal healthy right-handed subjects (with mean age of 24±3 years old) participated in this study. All subjects were recruited on the campus of National Chiao Tung University, Hsinchu Taiwan and with neither history of neurological diseases nor central and peripheral nervous system injury prior to the experiment. None of them had experience with BCI neural feedback before. All subjects gave signed written consent before experiment. The

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Institutional Review Board (IRB) of China Medical University and Hospital, Taichung Taiwan, approved the experimental protocol.

B. Experimental Design

To compare the differences in the SMR induced by different motor tasks, an EEG experiment consisted of three types motor tasks, namely, motor execution, motor imagery, and motor observation was used. During motor execution trials, subjects were requested to physically grasp with their left (nondominant) hand slowly within a 3-sec window. During motor imagery trials, subjects were supposed to imagine they are grasping slowly with their left hand, without physical movement, in a 3-sec window. Likewise, during motor observation trials, a video clip of someone grasping slowly with his left hand in a 3-sec window was played and subjects were requested to watch carefully the video clip without any physical movement. The video showed only a left hand portion with no other body parts.

Each EEG bout consisted of 15 trials, five for each of the three motor conditions. Each trial started with 1 sec resting period as baseline and a white cross was displayed at the center of computer screen for subjects to fixate. Then, a visual cue with one of the three conditions (“grasp”, “imagine grasping”, and “watch grasping”) was displayed at the center of a computer screen for 3 sec for subject to perform the motor tasks (motor execution and imagery) accordingly, except for motor observation condition, in which a 3-sec grasping video was played instead and subjects were requested to watch the video clip attentively. Finally, 2-sec OFF-period followed by a 1-3 s interstimulus interval (ISI) was appended to form an 8-sec window for each trial. This resulted in a 120-sec long EEG bout. Four EEG bouts comprised an EEG session and 60 trials (15 trials x 4 bouts, 20 trials for each motor condition) were collected in total.

C. EEG Acquisition

The EEG data were acquired using a Neuroscan SynAmp2 (Compumedics Ltd., Victoria, Australia) with 64 channels, including two EOG channels. To monitor eye movements, the horizontal EOG was recorded from electrodes at the outer canthi of both eyes; the vertical EOG was recorded from the electrodes above and below the left eye. All electrodes were referenced to the linked mastoids and the ground electrode was placed at the location AFz. Electrode impedances were maintained below 5 KΩ before recordings. The EEG was recorded with a pass-band of 0.1 - 250 Hz and digitized at 1000 Hz sampling rate.

D. Data Preprocessing

An experienced EEG experimenter first inspected the acquired EEG signals from each individual subject and removed bad channels and the EEG portions that are highly contaminated. After being band-pass filtered with pass band of 0.1 – 50 Hz, data from the four EEG bouts were downsampled to 100 Hz and concatenated into one unified EEG data. The preprocessed EEG data were then segmented into 4-sec epochs, -1 sec prior to and 3 sec after motor cue onsets.

E. ICA and Clustering

For each of the individual subjects, all 60 motor event-related EEG epochs were concatenated and the two eye channels were excluded from the further independent component analysis (ICA). The ICA decomposition was conducted using an infomax ICA algorithm as implemented in EEGLAB (http://sccn.ucsd.edu/EEGLAB) [6]. It was to separate the independent brain EEG processes from those of artifactual components, such as eye artifacts (blinking and lateral eye movements), muscle activities, environmental noises, etc. The EEG data of 12 out of the 13 subjects were decomposed into 62 independent components (ICs) and one with 61 channels, due to one bad EEG channel having been removed prior to ICA decomposition.

After ICA decomposition, source localization process using the DIPFIT2 toolbox in the EEGLAB was used to select the SMR components [7]. Given that the independent EEG components are mostly dipolar, the ICs with residual variance larger than 15% using a single dipole fit were removed from the further data analysis [8]. This process removed 525 ICs from the original 805. The removed ICs were those with single-channel activation topography or EEG topography could not be accounted for by single dipoles. It should not affect the identification of right SMR components because, in general, the SMR component can be well explained by a single dipole.

The remaining 280 ICs from all 13 subjects were then clustered into equivalent component clusters to investigate the common EEG processes from the group of subjects. Here, we mainly used the feature of cluster analysis in EEGLAB study function. First, the feature variables (FVs), consisted of component topography, component event-related time-frequency (TF) plot (defined as event-related spectral perturbation, ERSP, in EEGLAB), and x-, y-, and z-coordinates of dipole location, were computed. Among the FVs, the component map was the inverse of the unmixing matrix obtained in ICA decomposition; the ERSP was computed by wavelet transformation with 3-cycle window lengths and 50% window overlap to convert the time-domain signals to a time-frequency plot. The FVs of component topography and ERSP were then summarized using principal component analysis (PCA) to reduce the dimension to 10 principal components for each FV. Finally, K-mean clustering algorithm was used to categorize, based on the 23-dimension feature space (10 each for component topography and ERSP and 3 for dipole location), the ICs into 15 clusters with an additional outlier cluster to put those ICs without being assigned into any of the 15 clusters [9].

The 15 clusters were visually inspected to find the cluster with average component topography mainly covering the right motor areas. Then, average component ERSPs across all the ICs within the same clusters were computed such that to determine the main frequency band for SMR components. As a result, one cluster best represented the right SMR activity was selected. In the selected right SMR cluster, some subjects may contribute more than one component. Thus, a final adjustment was performed by comparing the mean ERD profiles in the alpha band (8-13 Hz) derived from the component ERSP of each component. The purpose was to ensure each subject only contributed one equivalent IC to the selected cluster.

F. Statistical Analysis

After SMR component cluster had been identified, the conditional ERDs in the alpha frequency were computed according to the types of motor tasks for each individual subject. Then, the grand mean conditional ERDs were averaged across all 13 subjects. The level and duration of alpha power decrease from the baseline before the cue onset of the right SMR EEG components were compared across different motor conditions. Further, the onset timings of the alpha power decrease were computed for the conditional ERDs of each individual subject by finding the time (in ms) at which the ERD reach half of the amplitude of alpha power decrease from the baseline. The significance of the differences in onsets of alpha power decrease between any two of the motor conditions was estimated using a paired two-sample t-test.

III. RESULT

After ICA decomposition and component clustering, one of the 62 ICs (one of the 13 subjects came only with 61 components because one bad channel had been removed before ICA decomposition) was selected into the right SMR cluster from all 13 subjects. Finally, the average power changes of all three motor conditions within the alpha frequency band (8-13 Hz) were computed for each subject.

The results showed that all three motor conditions elicited significant alpha power decrease (event-related desynchronization, ERD) starting around 370 ms as compared to the baseline. The onset timings of alpha power ERD for all three motor conditions were comparable. However, motor execution condition elicited the largest ERD (around -8 dB from baseline) and the ERD lasted for up to few seconds. On the other hand, the ERD elicited by the motor imagery and motor observation conditions were quite comparable with the ERD induced by the motor imagery slightly larger and longer than that by the motor observation.

IV. DISCUSSION

To our knowledge, this is the first study rigorously testing the robustness of the ERD in alpha frequency band elicited by the motor imagery task as compared to the motor execution and motor observation. More importantly, it is also the first study using ICA to separate the sensorimotor rhythm (SMR) from other brain and non-brain sources/artifacts, so that we would be able to look into the pure SMR activity elicited by different motor conditions without interference from other unrelated components. As a result, this study lends itself a standard to test how robust the motor imagery induced alpha ERD as being used for BCI control.

In our preliminary result, it showed that all three motor conditions could successfully elicit ERD in the alpha frequency band with similar onset timings from the motor cue. At the first glance, the alpha ERD elicited by motor imagery was quite limited with much lower level of suppress (almost half the amplitude) as compared to the motor execution condition. In addition, the onset duration of alpha ERD induced by motor imagery was also much shorter than that of motor execution. This means that the translation module to extract the SMR features elicited by motor imagery process will need to be sensitive enough to find the small amplitude changes within the alpha frequency band, and fast enough to determine the presence of alpha ERD after motor imagery. This should raise some difficulties over devising an SMR-based BCI-controlled neurorehabilitation apparatus.

However, the result is currently yet conclusive, as we will still need to complete the data analysis on all 13 subjects. As we expected that the result of this study gives the best scenario of SMR changes elicited by motor imagery, which is the most commonly used brain signal features for neurological rehabilitation process currently. Therefore, the result presented here should be able to provide a guideline for devising an SMR-based BCI controlled neurorehabilitation apparatus.

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