Evaluation and comparison of effective connectivity during simple and compound limb motor imagery

Weibo Yi, Lixin Zhang*, Kun Wang, Xiaolin Xiao, Feng He, Xin Zhao, Hongzhi Qi, Peng Zhou, Baikun Wan, Dong Ming*

Abstract—**Motor imagery (MI) has been demonstrated beneficial in motor rehabilitation in patients with movement disorders. In contrast with simple limb motor imagery, less work was reported about the effective connectivity networks of compound limb motor imagery which involves several parts of limbs. This work aimed to investigate the differences of information flow patterns between simple limb motor imagery and compound limb motor imagery. Ten subjects participated in the experiment involving three tasks of simple limb motor imagery (left hand, right hand, feet) and three tasks of compound limb motor imagery (both hands, left hand combined with right foot, right hand combined with left foot). The causal interactions among different neural regions were evaluated by Short-time Directed Transfer Function (SDTF). Quite different from the networks of simple limb motor imagery, more effective interactions overlying larger brain regions were observed during compound limb motor imagery. These results imply that there exist significant differences in the patterns of EEG activity flow between simple limb motor imagery and compound limb motor imagery, which present more complex networks and could be utilized in motor rehabilitation for more benefit in patients with movement disorders.**

I. Introduction

Motor imagery (MI), defined as mental rehearsal of a motor act without any overt motor output, can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with a real executed movement [1-2]. Different from steady-state visual evoked potential (SSVEP) or event-related potential (ERP), motor imagery could be interpreted as particular control signals to build a brain computer interface system which could reflect subjective movement-related mental state of the user directly without any inducing factors outside. In addition, motor imagery has also been demonstrated beneficial in motor rehabilitation in patients with movement disorders.

The causality dependence between time series is a topic of interest not only in econometrics, but also in biology and other natural sciences [3]. Recently, there is a growing concern for interactions of the activated brain regions, typically in terms of 'effective connectivity' [4]. Effective connectivity is a powerful method to analyze causal interaction among multiple neural regions in brain studies based on brain imaging techniques such as electroencephalogram (EEG), functional magnetic resonance imaging (fMRI).

Weibo Yi, Lixin Zhang, Kun Wang, Xiaolin Xiao, Feng He, Xin Zhao, Hongzhi Qi, Peng Zhou, Baikun Wan, Dong Ming are with the Department of Biomedical Engineering, College of Precision Instruments and Optoelectronics Engineering, Tianjin University, Tianjin 300072, China (corresponding author to provide e-mail: richardming@tju.edu.cn and lxzhang@tju.edu.cn).

Therefore, the mutual interactions between different channels overlying core regions during MI tasks could be revealed by effective connectivity networks. In recent years, electrical brain activity propagation in sensorimotor areas during right/left hand movement imagery was determined, where 10-channel Multivariate Autoregressive model (MVAR) was fitted to EEG signals recorded from subsets of electrodes overlying central and related brain areas [5]. In addition, the patterns of EEG activity propagation in the beta and gamma band during imagination and execution of a finger movement were investigated using Short-time Directed Transfer Function (SDTF), which revealed the similarities of propagations and the differences concerning time course of communication between structures in both tasks [6]. On the other hand, phase synchronization analysis has also been employed for the study of functional connectivity in multiple cortical areas [7], while conditional Granger causality was applied for effective connectivity based on functional magnetic resonance imaging (fMRI) data during actual and imagined finger tapping [8].

However, most researches have been concentrated on simple limb motor imagery involving single part of the limbs such as, e.g., left-hand, right-hand. The effective connectivity networks of compound limb motor imagery have not been studied before. With respect to motor imagery of simple limb movement, several parts of limbs like hand (forearm, postbrachium) and foot (shank, thigh) are involved in compound limb movement imagination, which may activate the neurons oscillation in multiple functional areas of cerebral cortex simultaneously.

In this paper, the effective connectivity networks of six kinds of movement imagination have been constructed, including three tasks of simple limb motor imagery and three tasks of compound limb motor imagery combining hand with hand/foot. Simple limb motor imagery include left hand, right hand, feet (flexion of forearm, stretch of lower leg). And, we tended to design compound limb movements being closer to the normal behavior of most human such as simulating walking posture. Compound limb motor imagery include both hands (twist off the bottle cap with both hands), left hand combined with right foot, right hand combined with left foot (flexion of forearm combined with stretch of contralateral lower leg). The goal of this paper is to investigate the difference of the information processing between simple limb motor imagery and compound limb motor imagery by the means of effective connectivity network. The underlying causal interaction between brain structures during MI tasks was approached by means of the Short-time Directed transfer Function (SDTF).

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II. MATERIAL AND METHODS

A. experiment procedure

Ten right-handed healthy subjects (7 females and 3 males, 23-25 years old) participated in this experiment [9]. All of the subjects have no prior experience with motor imagery before. Before EEG recording, they were asked to train for one week to learn all MI tasks well. The subjects sat on a chair at one-meter distance from a computer screen. At the beginning of each trial (8 seconds), a white circle appeared at the center of the monitor. After 2 seconds, a red circle (preparation cue) appeared for 1 second to remind the subjects of paying attention to the coming character indication. After disappearance of red circle, character indication ('Left Hand', 'Left Hand & Right Foot', et al) was presented on the screen for 4 seconds, during which the participants were required to perform MI tasks kinesthetically rather than visually while avoiding any muscle movement. After 7 seconds, 'Rest' was presented for 1 second before next trial (Fig. 1). The experiments were divided into 9 sections, involving 8 sections consisting of 60 trials each for six kinds of MI tasks (10 trials for each MI task in one section) and one section consisting of 80 trials for rest state. The sequence of six MI tasks was randomized. Intersection break was about 5 to 10 minutes.

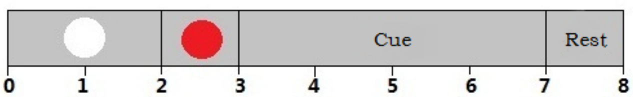

Figure 1. Experimental paradigm of one trial.

EEG data were recorded from 64 Ag/AgCl scalp electrodes placed according to the International 10/20 System referenced to nose and grounded prefrontal lobe (Fig. 2). The EEG signals were acquired by a Neuroscan SynAmps2 amplifier whose sampling rate is 1000Hz and band-pass filtering range is 0.5-100 Hz. In addition, a 50Hz notch filter was applied during data acquisition. Thereafter, the original EEG signals were band-pass filtered between 0.5 and 50Hz, then downsampled at 200Hz for the following analysis.

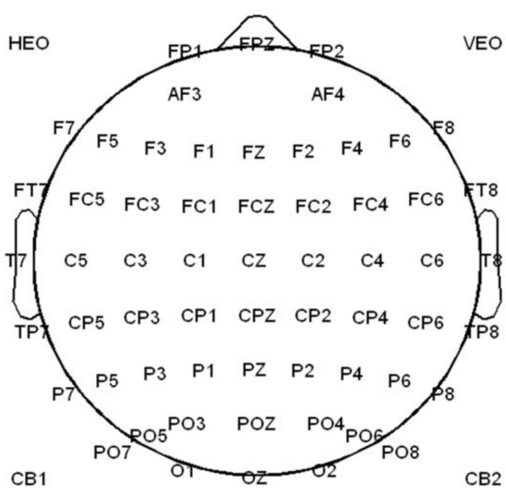

Figure 2. 64-electrode positions.

B. Short-time Directed transfer Function

Directed transfer function (DTF), allowing for calculation of the causal interactions for arbitrary number of channels, was introduced by Kamiński and Blinowska [10]. The approach is based on a Multivariate Autoregressive model (MVAR) [11], through which the k-channel EEG signals $X(t) = (X_1(t), X_2(t), \cdots, X_k(t))^T$ can be represented as

$$X(t) = \sum_{i=1}^{p} A(i)X(t-i) + E(t) \tag{1}$$

where $A(i)$ are the model coefficients, $E(t)$ is a the vector of white noise values, p is the model order. Transforming the model coefficients into the frequency domain yields

$$A(f) = I - \sum_{j=1}^{p} A(i)e^{-i2\pi j} \tag{2}$$

Directed Transfer Function (DTF) which describes causal influence of channel j on channel i at frequency f is defined as

$$DTF_{ij}(f) = \frac{H_{ij}(f)}{\sum_{m=1}^{k} H_{im}(f)} \tag{3}$$

where $H(f) = A^{-1}(f)$. Equation (3) produces a ratio between the inflow from channel j to channel i and the join inflows from all other channels to channel i, ranging from 0 to 1.

The Short-time DTF (SDTF) method depends on dividing the entire data epoch into short overlapping time intervals and to compute the DTF value for each interval [12]. In addition, zero-mean time series are required for MVAR model fitting. As a result, appropriate reprocessing is necessary to guarantee the stationary in short time intervals before the calculation of DTF [13].The first step is to subtract the best-fitting line from each time series. The second step is to remove the temporal mean from each observation of the time series and divide the data by the temporal standard deviation over all channels. For multi-realization data, ensemble mean should be subtracted from every data point which also should be divided by ensemble standard deviation across trials. The MVAR model coefficient was estimated by the method of Levinson, Wiggins, Robinson (LWR) algorithm [12]. The common optimal model order p was estimated by Bayesian Information Criterion (BIC). Statistical significance of the results could be obtained through the bootstrap technique which can be applied to evaluate the error of the estimated functions.

III. RESULTS

In the present study, EEG signals, recorded from 21 electrodes that were chose from 64 electrodes, were used to calculate the effective connectivity network. These 21 electrodes are overlying central and related brain areas, involving Fc3, Fc1, Fcz, Fc2, Fc4, C5, C3, C1, Cz, C2, C4,

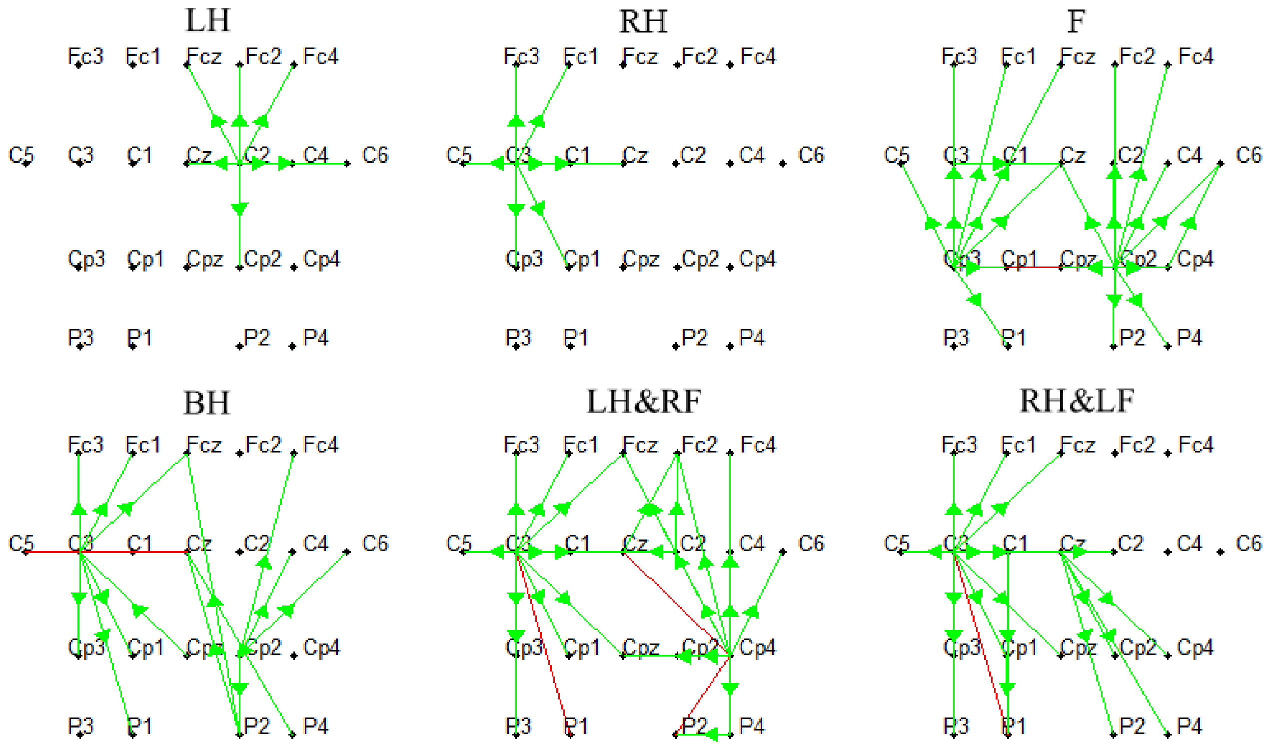

Figure 3. The networks of six different types of mental tasks. left-hand, right-hand, feet, both hands, left hand combined with right foot, right hand combined with left foot are represented by LH, RH, F, BH, LH&RF, RH&LF. Green line represents the unidirectional connectivity whereas the red line represents the bi-directional connectivity.

C6, Cp3, Cp1, Cpz, Cp2, Cp4, P3, P1, P2, P4. Considering the lack of bilateral coherence between both hemispheres [6], therefore the channels from different hemispheres could be evaluated separately and the following MVAR model was fitted simultaneously to 12 channels including electrodes from right/left hemisphere plus midline electrodes Fcz, Cz, Cpz. SDTF was evaluated for each mental task by sliding a short window in steps of 20% overlap, in which DTF was calculated for 100 samples long interval shifted by 20 samples. Therefore, we can obtain the time-frequency maps of SDTF for each combination of selected channels during simple and compound limb motor imagery.

In order to calculate the information flow between each selected channels, we averaged DTF value in the fixed frequency band and time interval during the performance of MI tasks within beta band. Fig. 3 shows the effective connectivity networks of six different types of mental tasks for one subject. Here, left-hand, right-hand, feet, both hands, left hand combined with right foot, right hand combined with left foot are represented by LH, RH, F, BH, LH&RF, RH&LF. In order to make the causal interaction between channels more clear, the amount of connectivity was limited by setting a threshold which was set at 60% of the maximum SDTF value. The outflows are showed by green arrows with their bases at 'source electrodes' and the tips pointing toward electrodes to which the flows are directed, whereas the red line represents the bi-directional connectivity. As revealed by Fig. 3, the effective connections can be found above the contralateral hemisphere for the single hand motor imagery. It can be observed that the outflows originate from electrode C2 and C3 respectively during left and right hand motor imagery. For the imagination of feet movement, the main outflows come from Cp3 and Cp2 overlying the somatosensory areas. Moreover, the obvious feature is the larger effective connectivity seen from the networks of compound limb motor imagery as compared to that of simple limb motor imagery. In particular, differing from the EEG flow patterns of left/right hand imagery, both hemispheres are involved and the outflows can be observed from left and right brain regions (C3 and Cp2) with the addition of few outflows from P2 and P4 during both hands imagery. Furthermore, as showed in the network of left/right hand combined with contralateral foot imagery, the outflows can be found not only from the central electrodes overlying sensorimotor areas (C3, C2, Cz, Cp4), but also from the electrodes from posterior parietal regions (P1, P2, P4). At the same time, similar effective connectivity networks can also be observed in the rest of the subjects.

IV. Discussion

The direction of information flow has been studied with both Partial Directed Coherence (PDC) [14] and Directed Transfer Function. However, PDC emphasizes more on sinks rather than sources because of different normalization [13], which means DTF is more effective to obtain a clear description of the EEG information flow. Therefore, DTF was adopted here to evaluate effective connectivity networks for six MI tasks, at the same time, investigate the distinction between simple limb motor imagery and compound limb motor imagery.

From the results, contralateral hand representation is involved during left/right hand motor imagery, whose EEG flow patterns correspond with the existing knowledge about single hand imagery [15]. Moreover, the pattern of information flow observed for the imagination of feet movement may result from the special location of feet area in the mesial wall [16]. At the same time, the most important finding is the new patterns of EEG flow concerning the dynamics of the information processing during compound limb motor imagery, whose patterns of interactions among brain regions are totally different from that of simple limb motor imagery. The observed phenomenon is the increasingly more effective interactions overlying larger brain regions. The fact of bigger involvement of sensorimotor regions with the addition of posterior parietal regions may be the result of the involvement of a larger neural network or more cell assemblies in information processing during compound limb motor imagery. Simultaneous imagination of both hands contributes to the simultaneous activation of bilateral hand areas. As a result, both hemispheres are involved and the effective connections appear on both left and right hand areas simultaneously for movement imagination of both hands, while only contralateral hand areas is involved during single hand motor imagery. Due to the involvement of upper limb and contralateral lower limbs together, larger regions overlying the sensorimotor areas are activated. Besides the sensorimotor areas, posterior parietal regions are involved at some extent during compound limb motor imagery. The activations within the posterior parietal cortex are likely to reflect such higher cognitive functions as preparing the simulated movement and updating its postural representations while imagining a movement [17]. Therefore, the patterns of EEG flow are probably not the simple linear superposition of information flow generated by different limbs during compound limb motor imagery, whose effective connectivity networks may imply the information exchange between sensorimotor areas and posterior parietal areas. Such phenomenon also indicates the feasibility and benefit of compound limb motor imagery in motor rehabilitation for patients with movement disorders, at the same time, may imply a more complex cognitive process occurring during compound limb motor imagery.

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