A wavelet time-frequency representation based complex network method for characterizing brain activities underlying motor imagery signals

ZHONGKE GAO\(^1\), ZIBO WANG\(^1\), CHAO MA\(^1\), WEIDONG DANG\(^1\), AND KAILI ZHANG\(^1\)

\(^1\)School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China.

Corresponding author: Zhongke Gao (e-mail: zhongkegao@tju.edu.cn).

This work was supported by National Natural Science Foundation of China under Grant Nos. 61473203, 61873181 and the Natural Science Foundation of Tianjin, China under Grant No. 16JCYBJC18200.

ABSTRACT Brain is the most complex organ of human which serves as the center of controlling most activities. A novel methodology called complex network is capable of characterizing the functional connectivity of human brain by means of graph theoretical measures. We designed and conducted experiments to record EEG signals during left and right hand movement imagery tasks, and then probed into brain activities by analyzing multichannel motor imagery signals from perspective of complex networks. More specifically, we firstly utilized wavelet time-frequency analysis to calculate energy sequence of each channel, then modeled human brain as a graph by treating the channels of scalp EEG as nodes and determining interconnections according to the distance between energy sequences of each channel. The functional connectivity of derived brain networks could be interpreted with characteristics of nodes and edges. Results demonstrated that when subjects imagined left hand movements, the node betweenness centrality (BC) of right sensorimotor area was greater than that of left sensorimotor area. The node BC distribution was roughly opposite when imagine right hand movements. It could be concluded that nodes of contralateral sensorimotor regions were more likely to be activated to control information flows during motor imagery tasks.

INDEX TERMS Brain network, Complex network, Motor imagery, Time series analysis, Wavelet transforms.

I. INTRODUCTION

THE quantum leap of brain science promotes the development of a multidisciplinary technology called Brain-Computer Interface (BCI). BCI establishes communication pathways between human brain and external environment without relying on neurons and muscles [1], [2]. For electroencephalograph (EEG) based BCI systems, the commonly used experimental paradigms are Steady-State Visual Evoked Potentials (SSVEP), P300 and motor imagery (MI). SSVEP and P300 are elicited by external stimuli whereas MI signals are originated voluntarily by subjects. MI based BCI systems can greatly facilitate the life of disabled patients in various aspects, such as controlling external devices like wheelchair [3]-[6], a cursor on the screen [7] or a keyboard [8], helping with motor recovery in rehabilitation [9].

Imagination of left hand movement results in Event-Related Desynchronization (ERD) in right hemisphere while imagination of right hand movement in left hemisphere. The ERD phenomenon which occurs in contralateral sensorimotor area is reflected as the amplitude reduction, acknowledged as the estimator of brain activity associated with an event. ERD patterns are usually defined by percentage values according to the amplitude in time domain after bandpass filtering, then ERD distribution is further analyzed by spatial mapping methods [10]. Common spatial patterns method is a linear spatial filtering technique used to extract ERD patterns by projecting origin signals into low-dimensional subspace [11]. However, traditional linear analytical methods are awkward to quantitatively describe the interactive dynamics among brain regions due to the nonlinear dynamical
characteristics of human brain.

Recent years, an emerging methodology called complex network establishes new avenues towards analyzing complex nonlinear system by describing statistical patterns of dynamical interactions among components of the system [12]-[14]. The successful application of complex network method in various field has aroused extensively attention, such as meteorology [15], sociology [16], multiphase flows analysis [17], [18] and physiological systems [19-21]. Especially, in neuroscience field, the thought that the nervous system is a network comprised by a set of linked neurons and circuits has a notable history [22], [23]. The development of modern brain mapping techniques like EEG, functional magnetic resonance imaging (fMRI) open up opportunities for modeling human brain from perspective of complex network underlying large physiological signal dataset [24]. Complex network approaches serve as efficient tools to analyze topological structure and further reveal brain patterns via various neurobiological meaningful measures [25], [26]. For examples, brain network was constructed to efficiently analyze the mental fatigue symptoms during SSVEP experiment [27]; the change of brain network associated with sleep deprivation could be estimated via brain network inferred from multichannel EEG signals [28]; visibility graph method was adopted to classify epileptiform EEG signals with a high accuracy [29]. Such researches indicated the effectiveness of complex network method as a tool to characterize brain functional activity.

In this paper propose wavelet time-frequency representation (TFR) based complex network method to investigate the interrelation and connectivity between brain regions. As the schematic diagram shown in Fig. 1, we firstly extracted energy series of each channel via wavelet time-frequency representation. The features of signals could be captured by scaled and translated wavelets. Next, we constructed functional brain network by defining channels of scalp EEG as nodes and determining the edges according to the 2-norm distance between the energy series of each channel (shorter distance indicated stronger correlations). The functional connectivity could be revealed through exploring the properties of nodes and edges within the derived networks. Our method combined time-frequency localization feature of wavelet with complex network analysis, aiming at decoding underlying brain mechanisms during left and right hand movement imagery tasks. The results indicated that our approach gained novel insights into the brain functional network mechanisms underlying motor imagery EEG signals.

II. EXPERIMENTAL DESIGN

A. DATA ACQUISITION

The experimental process was approved by the ethics committee of General Hospital Affiliated to Tianjin Medical University in China. EEG signals were acquired by Neuroscan NuAmps amplifier and sampled at 1000 Hz through 40 electrodes arranged according to the international 10-20 system. Electro-oculogram (EOG) signals were recorded by two electrodes placed medially above and below the left eye, and two electrodes placed horizontally next to both eyes.

B. SUBJECTS AND EXPERIMENTAL PARADIGM

Eight subjects (mean age 24 years) participated in the motor imagery experiment. All participants’ eye sight were normal or corrected-to-normal. Subjects were instructed about the experimental procedure and trained before the experiment. Subjects were required to refrain from caffeine, alcohol or tea approximately one day before the experiment.

In the experiment, subjects sat on a comfortable chair placed approximately 70 cm away from the display screen. Subjects’ eyes were at the same height with the center of the display screen. The experiment began with a warning tone ‘beep’ followed by an arrow pointing to left or right. The subjects were asked to imagine left or right hand movement for four seconds according to the direction of the arrow. The interval between each two imagery tasks was three seconds. Each subject accomplished ten times left hand movement imagery and ten times right hand movement imagery in one trial. There was a two minutes short break between each trial. An experiment contained five trials.

C. DATA PREPROCESSING

EEG signals were filtered by 1-40 Hz frequency band and referenced with common average reference. Eye blink and eye movement artifact were removed through Independent Component Analysis (ICA). We obtained 30 channels EEG signals after eliminating EOG components. Signals were then down-sampled to 250Hz. Data of each channel were linear normalized. Data of left hand and right hand movement were extracted respectively for further analysis.

III. WAVELET BASED COMPLEX NETWORK INFERENCE FROM MI SIGNALS

A. WAVELET TIME-FREQUENCY REPRESENTATION

Wavelet analysis is acknowledged as a valid tool in the fields of signal processing and time series analysis due to its ability to capture the characteristics of signal in joint time-frequency domain [30]-[33]. Continuous wavelet transform (CWT) is a TFR method allows wavelet transforms at every scale with continuous translation, mathematically defined as [34]:

\[
WT = \langle s(t), \psi_{a,b}(t) \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t) \psi^*(\frac{t-b}{a}) dt, (a > 0, s, \psi \in L^2(R)).
\]

(1)

Equation (1) in frequency domain can be interpreted as:

\[
WT = \sqrt{a} \int_{-\infty}^{+\infty} S(\omega) \psi^*(a\omega) e^{j\omega b} d\omega,
\]

(2)

where \(W{T}\) is the two-dimensional time-frequency representation (wavelet coefficient) matrix, \(s(t)\) is the signal, \(a\) is the scale, \(b\) is the translation, \(\psi(t)\) is the basis wavelet function,
ψ_{a,b}(t) is the scaled and translated wavelet, ψ^{*}(t) is the complex conjugate of ψ(t). S(ω) and ψ(ω) are the Fourier transforms of s(t) and ψ(t) respectively. And ψ(ω) should satisfy the admissible condition as follow:

\[ \int_{-\infty}^{+\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty. \quad (3) \]

Wavelet coefficient WT represents the pattern matching between signal and wavelets. Higher coefficients indicates better matching [35]. The characteristics of the signal at various frequency could be measured by scaled and translated wavelets.

Let s(t) = s(kΔt), t ∈ (k, k + 1) then the computation process can be achieved by:

\[ WT = \sum_{k} \int_{k}^{k+1} s(t) |a|^{-1/2} \psi^*(\frac{t - b}{a}) dt \]
\[ = \sum_{k} \int_{k}^{k+1} s(k) |a|^{-1/2} \psi^*(\frac{t - b}{a}) dt. \quad (4) \]

In wavelet analysis, frequency is related to scale a by the following relationship:

\[ F_a = \frac{F_c}{a}, \quad (5) \]

where \( F_c \) is the center frequency of a specified wavelet, \( F_a \) is the pseudo-frequency corresponding to the scale \( a \). Therefore, the change of scale \( a \) leads to the squash and stretch of wavelet, which allows capturing the characteristics of signal over different frequencies.

**B. NETWORK INFEERENCE BASED ON WAVELET TFR**

In order to construct complex network, we in this paper considered channels of scalp EEG as nodes and estimated the relevance among nodes in terms of the 2-norm distance between energy series extracted via wavelet TFR technique. For EEG signal \{x_{ch}(n)\}, \( ch = 1...30, n = 1...L \) with 30 channels of length \( L \), we obtained the wavelet TFR of each channel based on Daubechies4 wavelet, denoted as \{WT_{j,ch}f(n)\}, \( ch = 1...30 \). The two-dimensional time-frequency wavelet representation of channel C4 was shown in Fig. 2. In this study, the Nyquist frequency was 250/2=125 Hz. Thus frequency \( f \) between 0 and 125 Hz was considered. We obtained energy matrix of each channel by calculating the absolute value of each element in \{WT_{j,ch}f(n)\}:

\[ \{ E_{j,ch}^{f}(n) \} = \text{abs} ( \{ WT_{j,ch}f(n) \} ). \quad (6) \]

Due to the fact that motor imagery signals are mostly concentrated in frequency band of 8-30 Hz [36], the energy series of specified frequency band were averaged as \( \{ E_{avg}^{ch}(n) \} \).

Each channel of scalp EEG was regarded as a node, the channel locations was shown in Fig. 3. The relationship between node p and q was determined in terms of the 2-norm distance between energy series as follows:

\[ d_{pq} = \left\| E_{avg}^{p} - E_{avg}^{q} \right\| = \sqrt{\sum_{n=1}^{L} (E_{avg}^{p}(n) - E_{avg}^{q}(n))^2}. \quad (7) \]

Thus, we obtained a distance matrix \( R \) of size \( 30 \times 30 \) in which element located at column \( p \), row \( q \) represented the distance between node \( p \) and \( q \). Shorter distance indicated
stronger correlation. In order to acquire sparse matrix, we preserved a proportion $p$ (defined as edge density, $0 < p < 1$) of the strongest correlations (smallest distances). A small edge density $p$ led to a matrix where nodes were nearly isolated whereas a large $p$ resulted in an almost fully connected matrix. We obtained binary adjacency matrix $A$ from sparse distance matrix $R$ by setting the preserved elements to 1 and the other elements to 0. The topological structure of the derived functional brain network was entirely determined by binary adjacency matrix $A$.

C. CHARACTERIZATION OF BRAIN NETWORK DURING MI TASKS

After obtaining the structure of brain network, prominent features of the derived networks were calculated in order to characterize brain activities during motor imagery tasks. According to graph theory, important nodes act as the “hub” of mutual information exchange and tend to interact more with the others. Node betweenness centrality (BC) estimates the significance of each single node properly based on the above criteria, expressed as the fraction of all shortest paths that travel through a specified node [37]:

$$bc_i = \sum_{h,j \in N \atop h \neq j, h \neq i, i \neq j} \frac{\rho_{hj}(i)}{\rho_{hj}}, \tag{8}$$

where $bc_i$ is the node betweenness centrality of node $i$, $N$ is the set of all the nodes in the network, $\rho_{hj}$ is the number of shortest paths between node $h$ and $j$ (shortest path between two nodes in binary network is the minimum number of edges connecting two nodes), $\rho_{hj}(i)$ is the number of shortest paths between $h$ and $j$ that go through node $i$. Researchers had found that, nodal BC could identify hub regions in brain networks of different species [38], and the core of human cerebral cortex in Alzheimer’s Disease was recognized by exploring the distribution of node BC [39].

In this paper, we firstly implemented our wavelet TFR method to construct brain network from motor imagery signals, then calculated node BC at different edge density levels. As the line graph shown in Fig. 4, for subject 4, the BC value of node C4 (located at right sensorimotor area) was greater than that of C3 (located at left sensorimotor area) during left hand movement imagery. Whereas the BC value of node FC3 at left sensorimotor area was greater when
imaging right hand movements. Such results implied that hub nodes might appear at contralateral sensorimotor area in process of hand movement imagery.

In order to assess the average effect over edge densities, we also calculated the Area Under Curve (AUC) of BC by integrating BC value with edge density ranging from 10% to 30%. Sensorimotor rhythms originated in primary sensorimotor area located at central region of the cortex [40]. Thus the properties of nodes overlying primary sensorimotor area were worthy exploring in order to discover brain patterns under different imagery tasks. As shown in Fig. 5(a), during left hand movement imagery task, the AUC of BC at right sensorimotor area was greater than that at left sensorimotor area as a result of paired-sample t-test (p<0.002). The opposite situation could be discovered during right hand movement imagery tasks as illustrated in Fig. 5(b), that is, the AUC of BC at left sensorimotor area was higher (p<0.002). It could be seen from Fig. 6 that the brain patterns varied slightly among subjects because of the individual differences, but the AUC distribution was rather clear, that is, the AUC of BC value was higher at contralateral sensorimotor area. Such phenomenon further elaborated ERD patterns during motor imagery tasks from the viewpoint of complex network.

Nodes with high BC values were more associated with interactions and thus played the role of connecting and integrating brain regions. The results indicated that, to some extent, the nodes of contralateral sensorimotor area were more likely to be activated and served as the pivotal agent of information flow during motor imagery tasks.

IV. CONCLUSIONS
Characterizing brain functional activities from multichannel EEG signals is a challenging problem eliciting considerable attention in research fields. Our innovative wavelet time-frequency based complex network method is capable of transforming complex system like human brain into a set of nodes and edges and gaining insights into brain behaviors by analyzing the topological structure of derived networks. In summary, we firstly extracted energy sequences via wavelet time-frequency representation of 30-channel EEG signals, and then constructed complex brain network by treating each channel as a node and determining the functional connections between nodes in terms of the 2-norm distance. The properties of brain network during motor imagery task could be efficiently revealed by complex network measures. That is, the node betweenness centrality of contralateral sensorimotor area was greater than that of ipsilateral sensorimotor area. As we all know, body movement of each side is accomplished under contralateral brain motor area’s control, but whether the connectivities between brain regions are altered during movement or motor imagery remains to be further explored. Our results indicated that nodes of contralateral sensorimotor area were more likely to be activated compared with nodes from ipsilateral sensorimotor area and consequently served as hubs of processing signal transfer during MI tasks. Our approach is able to characterize brain activities underlying MI signals from the perspective of complex network and efficiently reveals the key nodes during the execution of MI tasks. Our method establishes an effective way for multivariate information analysis which is a challenging problem in science and engineering.

REFERENCES


ZHONGKE GAO received the M.Sc. and Ph.D. degrees from Tianjin University, Tianjin, in 2007 and 2010, respectively. He has been a Full Professor at Tianjin University since 2016. His research interests include brain-computer interface, complex networks, measurement science and technology, multi-source information fusion and deep learning.

ZIBO WANG received the B.Sc. degree from Civil Aviation University Of China, Tianjin, China, in 2016. He is currently working toward the M.Sc. degree at the School of Electrical Engineering and Automation, Tianjin University, Tianjin, China. His research interests include brain-computer interface, EEG signals analysis and complex networks.

CHAO MA received the B.Sc. and Ph.D. degrees from Nankai University, Tianjin and Beijing Normal University, Beijing in 2010 and 2018, respectively. He is currently working at the School of Electrical Engineering and Automation, Tianjin University, Tianjin China. His research interests include cognitive neuroscience, brain imaging analysis and complex networks.

WEIDONG DANG is currently pursuing the Ph.D. degree with The School of Electrical and Information Engineering, Tianjin University, Tianjin, China. His current research interests include multi-source information fusion, brain-computer interface, measurement science and technology, and complex networks.

ZHONGKE GAO received the M.Sc. and Ph.D. degrees from Tianjin University, Tianjin, in 2007 and 2010, respectively. He has been a Full Professor at Tianjin University since 2016. His research interests include brain-computer interface, complex networks, measurement science and technology, multi-source information fusion and deep learning.

KAI LI ZHANG received the B.Sc. degree in automation from Civil Aviation University Of China, Tianjin, China, in 2016. She is currently working toward the M.Sc. degree at the School of Electrical Engineering and Automation, Tianjin University, Tianjin, China. Her research interests include brain-computer interface and complex networks.

VOLUME 4, 2016