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A new method for automatically modelling brain functional networks

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ABSTRACT

Traditional methods for constructing brain functional network often need to artificially set a certain threshold, which requires professional and technical personnel to do this work. In order to overcome this deficiency, this study proposed a new method that can automatically construct brain functional network from electroencephalogram (EEG) data, based on positional relations among the vertices and network motif theories. To verify this method, resting state and task state EEG data were converted into brain functional networks with both the new method and traditional methods to explore the discrepancies of network features. The results showed that the mean physical distance increased with the increasing of network edges, evidently suggesting that higher weights of the edges have shorter physical distances, which is the direct model foundation. Besides, consistent results of network features were obtained among these methods, especially in weighted networks, indicating that this new method had the same capacity in accurately characterizing network features compared with the traditional methods. Moreover, this new method can efficiently distinguish the networks that have big differences in the weights, if the network has higher weights, the corresponding network would have more edges, which is in line with one of the traditional methods that using a threshold of weight. We also applied this model in mental fatigue detection, and the results of network characteristics, which obtained from the model and traditional method, have the same variation tendency, approximate values, and similar statistical differences, demonstrating that the proposed model can replace the traditional methods in differentiating similar brain functional states. The new method have potential applications in real-time brain functional networks construction.

1. Introduction

Brain is one of the most complex systems in the real word. Since Hans Berger firstly recorded human brain electroencephalogram (EEG) signals in 1924, EEG has been widely applied to study the human brain [1]. For deeply exploiting the human brain, brain functional network analysis has been developed, and become a popular research field over the past 20 years. Brain functional network is often used to demonstrate the temporal function correlations between remote brain regions in the processes of neural physiological events. After *small word* character of most real networks [2] and *scale free* character of large scale networks [3] were discovered, brain functional network has come into a high speed development time, and been widely applied to study brain science in different brain functions and dysfunctions. Commonly neuroimaging modalities for brain functional networks generally base on the data of EEG [4–7], magnetoencephalogram (MEG) [8], positron emission tomography (PET) [9], functional magnetic resonance imaging (fMRI) [10], near infrared reflectance spectroscopy (NIRS) [11]. Among the mapping techniques mentioned above, EEG is the best choice for engineering applications because of its lower costs, higher temporal resolution and more convenient operation, except its limitation in spatial resolution. For the formation of adjacency matrix, some measurements could be applied to evaluate the functional connectivity between any two brain regions, such as correlation [11], coherence [12], mutual information (MI) [8], synchronization likelihood [5], etc. Among the various measurements for functional connectivity, we chose MI in this study, which quantifies the comprehensive information of the signal amplitude and phase between two time series based on information theory.

In order to convert an adjacency matrix into a brain functional network, two popular methods have been developed by previous

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researchers. These two methods were named as traditional method A and B for convenient description. Traditional method A: use a constant threshold (the weight of the functional connectivity) or a series of continuously changing thresholds [5,6]. This approach can sufficiently take the weights of functional connectivities into consideration. If the whole weights in one adjacency matrix is higher than that in another one, the corresponding network would contain more edges, which would simply result in higher clustering coefficient, and shorter characteristic path length. Then the differences of the network features between these two networks can be obviously distinguished. Traditional method B: keep the number of edges fixed in a network [4,5]. By fixing the number of edges (the weights of the edges selected from high to low), all networks have the same numbers of vertices and edges; the only difference is in the spatial arrangement [5]. Therefore, we can compare the topological structures between different networks without bias from differences in numbers of edges. However, both of these two traditional methods need to artificially set a certain threshold: a threshold of weight or a fixed degree, which might be too complex to be applied in real-time engineering. Thus, a new method that can automatically construct brain functional networks is an urgent need in this area.

Complex network theories are widely exploited for studying properties of brain functional networks and comparing the differences in internal and external functional conditions. Generally explored network theoretical metrics include the degree (distribution), betweenness and closeness centrality, clustering coefficient, characteristic path length, and global and local efficiency [2,13–15]. The applications of these evaluation metrics to study the dissimilarities of brain functions pervade various aspects, such as the normal participants that in eyes-closed and eyes-open states [16], that with lower and higher education levels [6], and that at different sleep stages [4], as well as the participants that suffering from brain diseases and dysfunctions [5,17]. But fewer studies explore the differences of the network features between resting state (RS) and task state (TS) with complex network theories. In functional brain mapping, TS can be compared to RS [18]. The functional changes of the spontaneous brain activity from RS to TS still remain unclear. Several researchers have investigated the topological organizations of brain functional networks in eyes-closed and eyes-open states [8,10,19]. Compared to eyes-closed state, the increased attentional load and raised level of arousal are sustained in eyes-open state [20]. Therefore, distinct topological features are revealed between these two states [16]. We can boldly address the following hypothesis that the topological characters and structures of brain functional network would have significant changes from RS to TS.

In the present study, we attempted to propose a new method for automatically modelling brain functional network, and verify this method by comparing with the traditional methods in studying the dissimilarities of the network features (clustering coefficient and characteristic path length) between RS and TS. Then this method is applied in mental fatigue detection to testify its validity and practicability. Functional connectivity between all pairs of EEG channels was determined by MI in the following five EEG frequency bands: delta, theta, alpha1, alpha2, and beta. These connectivities were used to form the adjacency matrices, which were then converted into brain functional networks. The traditional methods were also used to compare with this new method.

2. Methods

2.1. Participants

Eighteen healthy male participants of engineering graduate students were recruited in this study. They are all right-handed, and between the ages of 23 and 26 (24.5 ± 1.5, mean $\pm$ SD). The body mass index (BMI) of them are $20.7 \pm 1.8\,\mathrm{kg/m^2}$. All enrolled volunteers were required to have a regular life routine, have a normal eyesight or rectified normal eyesight, and have no history of brain diseases, such as epilepsy, schizophrenia, brain trauma, etc. All evaluated individuals were asked to do not stay up late and take any alcohol drink and drugs in a week preceding the experiment, have no smoking, no coffee, and no strong tea in eight hours before tests, and to wash their hair in two hours before EEG data recording. All the requirements were reported by themselves. All procedures performed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study. All participants can get some monetary reimbursements for the incentives of their better cooperation in the tests.

2.2. EEG data acquisition and preprocessing

EEG data were recorded by a digital EEG apparatus (SYMTOP NT9200) at the following 19 positions of the 10–20 systems: Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz, and Pz (Fpz was chosen as the grounding electrode), referred to linked A1 + A2 electrodes. Electrode impedance was below 5000 Ω. Two states were considered in EEG data acquisition: RS and TS. RS refers to be awake, closing the eyes and relaxed, and participants were requested to concentrate their attention on the breath for avoiding thinking other things. Meanwhile, TS means that participants were required to keep the body still and do a mental arithmetic math problem, a three-digit number subtracts a single digit continuously (keep the same for all participants and showed on a computer screen). Two minutes of the EEG data were recorded for each condition. The tests were conducted in a sound attenuated, and temperature, humidity and light controlled room while participants sat on a chair with a comfortable posture during the data collections.

For the present analysis, 10 pieces of 5 s of artifact-free contiguous data (containing no eye blinks, slow eye movements, electrocardiogram artifacts, baseline drift, etc.) were selected offline from each condition by EEGLAB. Then, the EEG data were down sampled to 256 Hz, resulting in time series of 1280 data points for further analysis. The MI between all pairs of electrodes was calculated after digital, FFT filtering to distinguish EEG frequency bands (delta, 2–4 Hz; theta, 4–8 Hz; alpha1, 8–10 Hz; alpha2, 10–13 Hz; beta, 13–30 Hz), resulting in an undirected 19 by 19 (the number of EEG channels) adjacency matrix. The MI (see Ref. [8]. for detailed description and definition) is calculated by a software written by Moddemeijer [21].

2.3. Brain functional network modelling

In this study, we constructed brain functional network model with network motifs theories based on the physical distances and weights of the functional connectivities. Network motifs were firstly put forward by Milo et al. [22] and defined as patterns of interconnections that recur in a network at frequencies much higher than those found in corresponding random networks. Network motifs are identified as the basic building blocks of complex networks [22]. Most networks are composed of repeated appearances of network motifs [23]. In undirected networks, 3 nodes motifs only have two patterns. One pattern is with triangular connectivity structure among 3 vertices: triangle motif. The other pattern is with two edges among 3 vertices. Here, we only consider