Improving EEG-based Topographic Mapping by Combining Transfer Entropy with Effective Brain Network

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Abstract. In recent years there is an increasing interest in analyzing functional connectivity of the brain. In particular, EEG-based effective connectivity can provide directed interaction information of electrical activity between different brain regions. Based on this background, in this paper we proposed an improved EEG-based topographical mapping (iEEG-TM) technique by combining transfer entropy with the analysis method of effective brain network. To test the effectiveness of the proposed mapping strategy, we constructed iEEG-TM by using the data from the different patients with schizophrenia and normal controls. The results showed that the improved EEG-TM method may enhance the visibility of information interaction in different brain regions, and meanwhile has potential in diagnosing disorders in the brain.

Introduction

Electroencephalography(EEG), is generated by electrical activity in brain tissue and recorded as signals of time series[1]. The EEG signals reflect potential differences between different scalp electrodes. EEG-based topographical mapping (EEG-TM), which was first proposed by Duffy FH in 1979[2] and also known as brain electrical activity mapping(BEAM) or quantitative electroencephalogram (QEEG)[3], is a technique that can record and summarize time signals from multiple scalp electrodes and then transform the signals into visual images by computer-controlled topographic mapping software. After decades of development, EEG-TM technique has been verified that there are significant advantages in helping to understand the brain function and diagnosis of the brain diseases.

However, the traditional EEG-TM technique has remained some limitations. Firstly, the previous studies have been proved that the information flow of brain network not only has the difference in intensity, but also has the difference in flow direction[4]. Furthermore, the brain functional disorders are often caused by interactive abnormalities between distributive brain regions[5], and the most of traditional EEG-based analysis methods that could only show a reflection of an independent brain area, are insufficient to fully understand the mechanism and improve the diagnosis of the brain functional diseases. It would be very valuable to establish a novel analysis method which is convenient to characterize the intensity and direction of information interaction of the brain network.

It is known that the brain is a very complex and non-linear system, which produces the non-linear bioelectric signals. In order to measure and analyze the states of the complex system, especially by means of the bioelectrical signals, approximate entropy, mutual information were successively presented. The approximate entropy is defined as the conditional probability that the similar vectors may continuously maintain its similarity when increasing them from m dimension to m + 1 dimension[6]. The mutual information is used to calculate the sensitivity to the coupling strength of the two time series A and B[7]. However, according to the definition of mutual information, the relative effect of time series A to the time series B is consistent with the effect of the time series B to the time series A. This means that the mutual information is not suitable to analyze the asymmetric, directional
information transmission system. In this study, we employed the transfer entropy to explore the relationship between EEG electrodes.

The main purpose of this study is to propose an improved EEG-TM (iEEG-TM) method by combining transfer entropy with the analysis method of effective brain network. First, we recorded the 32 channel EEG time series and defined the 32 electrodes as network nodes. Then the functional brain network was built by transfer entropy and analyzed by graph-theoretical mode which has only recently been applied to neuroscience and provides a set of robust metrics for evaluating the properties of brain network. Finally, node degrees, including in-degree and out-degree, as graph theory metrics, were calculated. To test the effectiveness of the proposed mapping method, we drew the iEEG-TM by using the data from different patients with positive or negative schizophrenia (SZ) or normal controls, and the results showed that iEEG-TM method may enhance the visibility of information interaction between different brain regions, and is helpful to understand the complex brain, meanwhile has potential in diagnosing the different disorders in the brain.

Methods and Materials

Participants
The participants in this study were divided into three groups, 14 positive SZ (9 males, 5 females; mean age 31.71±13.2 years), 14 negative SZ (8 males, 6 females; mean age 29±11.84 years), and 14 normal controls (9 males, 5 females; mean age 27.8±4.24 years). The recruitment of the participants and the acquisition of the EEG data were implemented in the psychiatry department, Shaanxi Mental Health Center. All patient groups were recruited during an acute psychiatric episode and had been receiving atypical antipsychotic medication since admission. DSM-V is used to diagnose SZ, and PANSS is used to assess the severity of the condition. The number, age, and sex of the normal control group are matched with the patient groups. All participants in this study were right-handed and had no head trauma or abuse history. They were fully informed of the study and provided written informed consent before the experiment, and everyone was paid for the reward of the experiment. The study was endorsed by local authorities, which conform to the Helsinki Declaration.

Data Collection and Processing Procedures
In order to obtain as much high quality data as possible, all participants should sit quietly on a comfortable chair, close eyes and do not need special thinking activities, in the semi-dark, no noise interference and electromagnetic shielding room. The experimental process collected a total of five minutes of EEG data. EEG amplifier (NeuroTop NT9200) was offered by SYMTOP Instrument Co., Ltd., Beijing, China. The EEG signals were recorded at the 32 scalp loci (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz, Pz, FC3, FC4, CP3, CP4, FT7, FT8, TP7, TP8, FCz, CPz, Oz, PO9 and PO10, including two reference points on the left earlobe and right earlobe). A 0.5-50Hz band-pass filter and a 50Hz notch filter were employed and the collected EEG data were sampled at 250Hz, digitized to 16 bits, and preprocessed by using EEGLAB[8].

The implementation of the proposed iEEG-TM technique includes four different procedures. Firstly, EEG data were recorded and we used independent component analysis (ICA) strategy to remove the eye movements and other artifacts, and then the transfer entropy algorithm was employed to construct a 32×32 connection matrix. The matrix is regarded as quantitative characterization of the effective network in the brain, and the 32 electrodes were defined as the network nodes. In order to count the effective connections from information interaction between different network nodes, a simple method of feature scaling[9] was used to normalize the data, and a threshold was used to filter the too weak connection in the matrix. Finally, we calculated in-degree and out-degree[10] between the nodes and constructed the iEEG-TM based on those degree values. The work flow of the entire study is summarized in Figure 1.
Transfer Entropy

Assuming that the two interested time series $X=x_t$ and $Y=y_t$ can be approximate as Markov processes[11], according to the information entropy theory of Shannon[12], Schreiber[13] presented a definition of the transfer entropy from $Y$ to $X$ as:

$$T_{Y \rightarrow X} = \sum p(x_{t+1},x_t^{(k)},y_t^{(l)}) \log \frac{p(x_{t+1}|x_t^{(k)},y_t^{(l)})}{p(x_{t+1}|x_t^{(k)})}$$  \hspace{1cm} (3)

where $x_t^{(k)} = (x_t,\ldots,x_{t-k+1})$, $y_t^{(l)} = (y_t,\ldots,y_{t-l+1})$, here $k$ and $l$ represent the orders of the Markov processes $X$ and $Y$, respectively[16]. The transfer entropy is explicitly suitable to analyze the non-symmetric processes, since it measures the intensity and direction of information flow from $Y$ to $X$ and not vice versa[14].

In this study, $X$ and $Y$ are first-order Markov processes ($k=1=l=1$) and we used the above definition to calculate the transfer entropy. Each element in the $32 \times 32$ connection matrix represents a directional information transfer value from each node to the other 31 nodes respectively.

Normalized and Thresholding the Matrix

The first step in this procedure is data normalization. In our study, we used the rescaling method to normalize the raw data into a range of $[0, 1]$. The normalized formula is as follows[8]:

$$Q_{\text{norm}} = \frac{Q-Q_{\text{min}}}{Q_{\text{max}}-Q_{\text{min}}}$$  \hspace{1cm} (2)

where $Q_{\text{norm}}$ is the normalized data, $Q$ is the original data, $Q_{\text{max}}$ and $Q_{\text{min}}$ are the maximum and minimum values of the original data set, respectively.

In order to effectively quantify the relationship between different EEG channels, it is necessary to determine an appropriate threshold(TH) to create the thresholded matrices. The choice of TH directly affects the measure calculation of corresponding network based on graph theory, that is, the choice of threshold will result in different connection densities or sparsities in the network[15]. At present, there are several studies on the TH setting method, such as surrogate data(SD) method and significance level(SL) method[17], but there is no one to be thought optimal. Comprehensive consideration of all aspects, we used the SL-based method to determine the threshold TH and the TH was decided to 0.2.
Calculating the Measures Based on Graph Theory

According to the graph theory[18], the node degree of a network is one of the most important statistical features that describing the interconnection between nodes. The degree value $k_i$ of a node $i$ represents the number of edges directly connected to the node $i$.

In directional networks, the degree of node can be divided into in-degree and out-degree. The in-degree is the number of edges pointing from the other nodes to one node, and the out-degree is the number of edges pointing from that node to all other nodes. The in-degree of node $i$ is defined as[19]:

$$k_i^{in} = \sum_j a_{ij} \quad (3)$$

where $a_{ij}$ represents an element of row $i$ and column $j$ in the thresholder matrix. The out-degree of node $i$ is defined as[19]:

$$k_i^{out} = \sum_j a_{ij} \quad (4)$$

The greater the degree of the node, the more the edges that are connected to the node, the greater the role of the node in the network, and vice versa.

Results

To test the effectiveness of the proposed new mapping technique, we constructed iEEG-TM by using the data from different patients with positive or negative SZ and normal controls.

Relations of the Degrees and the Values of Threshold

In our study two different degrees, in-degree and out-degree, were computed over the thresholds from 0 to 1 with step 0.1 for this three groups.

Some interesting rules were found in Figure 2. For the two measures, in-degree and out-degree, the values were the smallest in the normal subjects over all the thresholds, while the values were larger in positive SZ, comparing with those in negative SZ. That is, both positive SZ and negative SZ should be stronger than the normal people refer to information interaction intensity. In addition, it can be clearly found in the figure that the three groups have the most significant difference in THs from 0.2 to 0.4, this fact also proved it is reasonable that we chose the TH = 0.2.

Maps Using the iEEG-TM Method

Figure 3 and Figure 4. show the typical in-degree and out-degree maps of the three groups respectively, based on the iEEG-TM method. In these figures, it can be found that, the information interaction intensity of functional brain network, for both input and output, is higher in the positive SZ than that in the negative SZ and normal controls. Furthermore, in terms of the intensity of information interaction, the iEEG-TM technique maybe supply an effective approach which can be helpful to identify the patients with brain disorders from normal subjects, and distinguish the different subtypes of the patients.
Discussion

In this study, we presented a novel technique about EEG-based topographic mapping. To test the effectiveness of the proposed mapping method, we collected the EEG data of the three groups named negative SZ, positive SZ and normal controls (NC), then we calculated the connection strength of each node and the other 31 nodes by using transfer entropy. Two measures, in-degree and out-degree of the effective brain network, derived from the thresher matrix. We finished the maps based on the proposed iEEG-TM technique.

Schizophrenia (SZ) is a clinically serious mental illness and often divided into positive SZ or negative SZ according to the symptoms. The positive symptoms include elation, delusions, visual or auditory hallucinations, disordered excitement and speech, etc.[20]. The negative symptoms are deficient in normal emotions and thinking reactions, including depression, lack of language, passion and emotional motivation, etc.[21]. The previous study[22] confirmed that EEG-TM method played an important role in distinguishing positive and negative types, although the traditional methods cannot reflect the interaction information between the EEG electrodes. Our research results, based on the iEEG-TM method, show that there are significant differences in the maps of the three groups, and comparing with the negative SZ, there are stronger information interactions in the brain of the positive SZ, which are in accordance with the previous conclusion of relative research[23].

There are still some limitations in this research. Firstly, due to the objective constraints of the experiment, the number of participants tested is some limited, which may have a bit of impacts on the results. We will increase the sample size in the further studies. Furthermore, in our study, only a simple choice was made for the network metrics, other commonly used metrics such as global efficiency and average path length were abandoned because of failing to meet the research requirements.

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References


