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Epileptic brain network analysis based on Kendall’s improved synchronization algorithm

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Abstract. In this paper, we use a new algorithm, the IRC algorithm, to improve the Kendall algorithm. Research on complex networks has gradually deepened into all areas of social science. The study of brain networks has become a hot topic in the study of brain function. The method of wavelet filtering is used to filter the EEG data to obtain the required α-band (8-16 Hz). Using the improved IRC algorithm, the brain functional network is constructed based on the EEG data, and the related characteristics of the brain network constructed are analyzed. The experimental results show that the method is suitable for distinguishing the network degree indicators of epilepsy and normal brain tissue, and further deepening the study of the neurokinetic behavior of the brain.

1. Introduction
Epilepsy, commonly known as claw typhoon (or epilepsy), is a chronic neurological disease and a high-incidence rate that is second only to cerebrovascular disease. Seizures are characterized by excessive discharge of neurons in the brain. Clinical symptoms include seizures, autonomic disorders, and transient loss of consciousness. Due to the long-term recurrent epilepsy, it not only brings physical pain to the patient, but also leads to mental and psychological disorders to a certain extent. It has some harm to the patient and the society. [1, 2] At present, epilepsy is diagnosed and diagnosed clinically mainly through electroencephalogram (ESG or EEG) pathological wave examination. As a non-invasive detection method, EEG can effectively reflect the physiological and pathological conditions of the brain, and has become an indispensable method for clinical detection and diagnosis of various brain dysfunction diseases. The frequency of α-waves is 8~13Hz (the average is 10Hz) and the amplitude is 20~100 μV. It is the basic rhythm of normal human brain waves. If there is no additional stimulus, the frequency is fairly constant. The rhythm is most noticeable when people are awake, quiet and closed their eyes. Therefore, the analysis of α-waves is used to distinguish the brain power between epilepsy and normal people.

The brain is a complex physiological system. The interactions between different brain regions form a comprehensive complex network. The brain itself is a network of nerve cells connected by axons.
The use of complex network theory for the analysis of brain function associations can abstractly describe the physiological structure of the brain and deepen the understanding of the mechanisms of brain function disorder. Neural network research of epilepsy has found that the functional connection of brain neural networks has the characteristics of small-world networks, and the interaction between neural networks in different brain regions is the main factor that induces, spreads and maintains epilepsy. The use of complex network research methods [3-5] to analyze brain function coupling [6-8] and the mechanism of occurrence is the current research hotspot.

Kendall rank correlation coefficient is a common non-parametric measure. It uses the rank of the variable observation value to calculate the correlation coefficient between variables, which can effectively measure the nonlinear relationship between variables. Kendall’s measure of the correlation between variables is insufficient. We have enhanced the measure of nonlinear correlation between variables by improving the count of concordant pairs in Kendall’s rank correlation algorithm and the division of nodes in binary random variables. Using a modified IRC algorithm constructs brain function networks in 8-16 HZ in epileptic patients and normal subjects. By studying the topological structure of the brain network of epilepsy patients and the interaction between different brain regions, the understanding of seizures can be further deepened.

2. IRC algorithm

2.1. Kendall rank correlation coefficient

$X_1, X_2, \cdots, X_n$ and $Y_1, Y_2, \cdots, Y_n$ are samples from $X$ and $Y$ respectively. They form a two-dimensional random sample $(X_i, Y_j), i, j = 1, 2, \cdots, n.$ with a capacity of $n$. If the product $(X_j - X_i)(Y_j + Y_i) > 0$, $(X_i, Y_j)$ and $(X_j, Y_i)$ are concordant. On the contrary, if the product is less than zero, we call it disconcordant. To test whether the binary variables $X$ and $Y$ they represent are related to. Record $N_c$ for the number of coordination pairs,

$$N_c = \sum_{1 \leq i < j < n} \Psi[(X_j - X_i)(Y_j - Y_i)]$$

where $\Psi[xy] = \begin{cases} 1, xy > 0 \\ 0, others \end{cases}$. $N_d$ is the number of uncoordinated pairs. When there is no knot in the two sets of variables, That is, there is no case where $(X_j - X_i)(Y_j + Y_i) = 0$. the Kendall rank correlation coefficient (Kendall’s $\tau$) is calculated as:

$$\tau = \frac{2(N_c - N_d)}{n(n-1)} = \frac{4N_c}{n(n-1)} - 1$$

The range of Kendall’s correlation coefficient is $[-1, 1]$. A positive value indicates a positive correlation and a negative value indicates a negative correlation. The greater the absolute value, the stronger the correlation. When the order of the size of sample $X$ and sample $Y$ is completely the same, $\tau = 1$, when the order of the size of sample $X$ and sample $Y$ is completely opposite, $\tau = -1$.

2.2. IRC principle

Our algorithm is different from the count of Kendall’s concordant pairs, and the division of knots in binary random variables. First, sample sequences $X$ and $Y$ for $X_1, X_2, \cdots, X_n$ and $Y_1, Y_2, \cdots, Y_n$. We sort the sequence $X_i, i, j = 1, 2, \cdots, n$ in non-decreasing order to get the new sequence $X'_i$. Remember that $\tau_{xi}$ is the length of each knot in sequence $X'_i$. Another time series $Y_i, i, j = 1, 2, \cdots, n$ corresponds to $X'_i$ to get $Y'_i$, and let $Y'_i$ in the length $\tau_{yi} = \tau_{xi}$. We redefine $N_c$:

$$N_c = \sum_{1 \leq i < j < n} \Psi[(y'_j - y'_i)(x'_j - x'_i)] \Psi[(y'_{j+1} - y'_i)(x'_j - x'_i)], y'_j \notin \tau_{yi}$$

Indicate the relevance of variable $Y$ to variable $X$:

$$IRC_{Y \rightarrow X} = 1 - \frac{4N_c}{n(n-1)}$$

Obviously, if the sequence $Y_i, i, j = 1, 2, \cdots, n$ is non-decreasingly arranged and $X_i$ corresponds to rearrangement, the new concordant logarithm $N_c$ and the correlation $IRC_{Y \rightarrow X}$ of the variable $X$ to the variable $Y$ are obtained.
2.3. Network topology features
Average degree is a simple and important concept used to describe the attributes of a single node. The clustering coefficient is described in the language of graph theory as the average probability of the connection between two nodes connected to the same node in the network. This coefficient is usually used to reflect the local structural characteristics of the network (also called clustering).

3. Data processing
The experimental data were from the clinical sample of the General Hospital of Nanjing Military Region. The patient group and normal group signals were used to compare the correlation between EEG and ECG. For the patient group and the normal person group, there were 22 subjects in each group. The epilepsy data were taken from the interictal period, and most of them were patients with frontal lobe epilepsy and temporal lobe epilepsy. The data for each subject included a 16-lead brain electrical signal and a lead ECG signal with a record length of more than one minute and a sampling period of 512 Hz.

Because of its ability to characterize the local characteristics of signals in the time-frequency domain and the characteristics of multi-resolution analysis, wavelet transform is widely used in the field of artifact removal of non-stationary random signals (such as brain waves). This paper uses db5 wavelet basis functions. The EEG signal is decomposed by 5 layers, and d5 coefficients are used for wavelet reconstruction to obtain the filtered signal [9].

When constructing the brain network, first define the network nodes. In this paper, these nodes are defined as 16-electrode array electrodes. Then calculate the IRC coefficients of all pairs between the 16 electrodes to generate a $16 \times 16$ association matrix. Select an appropriate threshold to generate an adjacency matrix that defines the connections between the nodes. For the connectivity of EEG signals [10], this paper selects the mean value of the coefficient matrix multiplied by the coefficient 0.8 as a threshold by several experiments. Since our algorithm is asymmetric, the corresponding directions of the two leads represented by the elements in the upper triangular matrix and the lower triangular matrix are opposite. We calculated the average of non-zero elements of the matrix as the threshold. Each element in the matrix is compared with a threshold. Elements greater than the threshold consider that the two nodes are linked. If they are less than the threshold, they are considered to be unrelated.

4. Result analysis
In this experiment, we used wavelet filtering to filter the EEG data to obtain the required band. Each lead of the EEG acquisition device is regarded as a node of a brain network, and the calculation between any two nodes The IRC coefficients form a $16 \times 16$ matrix of coefficients. The average degree is calculated for the upper triangular matrix and the lower triangular matrix of the matrix (LTM indicates the brain function network constructed by the lower triangular IRC coefficient matrix. UTM represents the upper triangular IRC. A network constructed by a coefficient matrix) and subjected to analysis of variance (t-test) for this set of data. The results are shown in table 1.

| IRC | LTM | IRC | UTM | Kendall |
|-----|-----|-----|-----|---------|
| Nor | Abn | Nor | Abn | Nor | Abn |
| Mean | 5.0256 | 5.5369 | 5.0284 | 5.5256 | 4.4659 | 4.4688 |
| variance | 0.1293 | 0.1357 | 0.1301 | 0.1502 | 0.1506 | 0.14168 |

For a more intuitive comparison of the IRC network and the Kendall network, the data in the above table is plotted as a graph (Nor represents a normal population and Abn represents a patient with epilepsy).
It can be seen intuitively from figure 1 that the brain network constructed based on Kendall’s correlation coefficient can’t clearly distinguish the brain network of normal population and epilepsy patients, and the brain network constructed by the improved IRC algorithm can clearly distinguish epilepsy patients from normal patients; T test was performed and table 2 was obtained.

**Table 2.** Significant differences in brain function network mean scores between epileptic and normal subjects.

| The network | IRC UTM | IRC LTM | Kendall |
|-------------|---------|---------|---------|
| P value     | 7.16E-05| 3.19E-05| 0.980451|

If P>0.05, we cannot distinguish between normal and epileptic patients, and P <0.05, we can distinguish between normal and epileptic patients. The analysis of the average degree of variance of the upper triangular wavelet gives a P value of 0.005991, and the P value of the variance analysis of the clustering coefficient is 0.076322. The following conclusions are obtained by analyzing the upper triangular and lower triangular of the band data matrix: There is a significant difference in the average degree of epileptic brain waves and normal brain waves, but there is no significant difference in the clustering coefficient. That is to say, the 8-16Hz frequency band obtained by wavelet filtering can be used as the brain-electricity signal to construct the brain function network. The average degree of the network can distinguish between normal people and epilepsy patients.

5. Conclusions
In this paper, the wavelet filtering method is used to filter the EEG data to get the α-band we need. The experimental data has a frequency range of about 8-16 Hz. Then we use the Kendall coefficient and IRC algorithm improved by Kendall algorithm to construct the brain functional network, and calculate the network average degree and clustering coefficient. The experimental results show that the improved algorithm IRC can clearly distinguish the average degree and clustering coefficient of the brain network between normal people and epilepsy patients, and the average degree of epilepsy patients in the α-band brain network is greater than the normal population. However, the brain function network constructed by the Kendall coefficient cannot effectively distinguish between epilepsy and normal people. Analyzing the average IRC network will help the clinical diagnosis of epilepsy. It is of great significance for the prediction and judgment of epilepsy diseases.
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References
[1] Witte H, Iasemidis L D and Litt B 2003 IEEE T. Biomed. Eng. 50 537
[2] Mormann F, Andrzejak R G, Elger C E and Lehnertz K 2007 Brain 130 314
[3] Varela F, Lachaux J P, Rodriguez E and Martinerie J 2001 Nat. Rev. Neurosci. 2 229
[4] Sporns O, Chialvo D R, Kaiser M and Hilgetag C C 2004 Trends Cogn. Sci. 8 418
[5] Hou F Z, Dai J F, Liu X F and Huang X L 2014 Acta Phys. Sin. 63 040506 (in Chinese)
[6] Wang J and Yu Z F 2012 Chin. Phys. B21 018702
[7] Wang J and Zhao D Q 2012 Chin. Phys. B21 028703
[8] Zhang M, Cui C, Ma Q L, Gan Z L and Wang J 2013 Acta Phys. Sin. 62 068704 (in Chinese)
[9] X.Xu, Y.Zhou and Q.L.Ma. 2011 Matlab Filtering Simulation Design and Analysis of EEG Data Signals Journal of Nanjing University of Posts and Telecommunications: Natural Science Edition 31 37-43
[10] Breakspear M and Terry J R. 2002 Topographic organization of nonlinear interdependence in multichannel human EEG Neuroimage COM-16 (no.3) 822-835