Attention state analysis based on the improved k nearest neighbour network

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Abstract. In this paper, a method of analysis attention state based on the time series transformed by the improved k nearest neighbour network is proposed. In the proposed method, counting number state EEG signals and closing eyes state EEG signals are constructed into networks by the improved k nearest neighbour network respectively, and each networks are converted into time series, which are compared with original EEG time series by means of analysis of power spectrum. The results show that studying power spectrum of time series from network is more easily than original time series to distinguish between counting number state EEG signals and closing eyes state EEG signals. We confirmed that the proposed method could be of practical use.

Introduction

Complex networks are an important paradigm of modern complex systems sciences which allows quantitatively assessing the structural properties of systems composed of different interacting entities. Complex network theory that is used to study the EEG method has become a hot field. Usually, the EEG time series is constructed into the network, and then the network is studied by means of complex network theory [1,2]. The network constructed from EEG contains the inherent characteristics of the EEG time series, so studying on the complex network is equivalent to researching EEG time series. It has been becoming a popular method that nonlinear time series are transformed into network, but that network is transformed into time series conversely is neglected. There are some methods of transforming the network, such as eigenvalue [3, 4], the random walk method[5], and so on.

In this paper, both counting number state EEG signals and closing eyes state EEG signals were constructed into an undirected network by improved k nearest neighbour network[6], so an adjacent matrix can be created by the undirected network. Adjacent matrix is transformed into time series by computing eigenvalue and power spectrum of that time series were studied afterward.

The purpose of this paper is to study on time series that is from network. The results show that time series transformed by brain network can effectively distinguish between counting number state EEG signals and closing eyes state EEG signals by calculating power spectrum. This study can provide a great help for the research on different attention brain state.

Time Series to Network

K Nearest Neighbour Network. The approach to transform phase space vector to work is described in detail below

1. Compute a Euclidean distance matrix D_{ij} such that every ***i***-th row of the distance matrix contains distance from the ***i***-th point.

2. Select k near neighbours based on Euclidean distance for every *i*-th row. Let us denote the set of these k points as $M_i = \{x(j_2) \mathbf{L}\ x(j_k)\}$ such that $x(j_1)$ is the first nearest neighbour. $x(j_k)$ is known as k-th near neighbour.

3. Construct a binary matrix R such that $R_{ij} = 1$, if j belongs to set M_i else set $R_{ij} = 0$.

A bidirectional network will be constructed after above three steps. The degree distribution of the network is a fixed value, $P(k^{out}) \equiv d(k)$, where N is the number of points in phase space, k is the number of neighbour points.

Improved K Nearest Neighbor Network. K nearest neighbour network [6] is a bidirectional network and has advantage of fixed degree distribution. However, the network that can be transformed into time series by computing eigenvalues is un-directional network. It is necessary to convert bidirectional network into un-directional network so as to keep the excellent character of fixed degree distribution. The method of improved k nearest neighbour network is described in detail below.

1. Compute a Euclidean distance matrix D_{ij} such that every *i*-th row of the distance matrix contains distance from the i-th point.

2.sorting every *i*-th row. Let us denote the set of these k points as $M_i = \{x(j_2) \mathbf{L}\ x(j_k)\}$ such that $x(j_1)$ is the minimum value of the i-th row. $x(j_N)$ is the maximum value of the *i*-th row.

3.Statistics of the number of $R_{ij} = 1$ in the *i*-th row, $j = 1, \mathbf{L}\, i - 1, i + 1, \mathbf{L}\, N$.If the i node were connected with s points and k – s>0, k-s points should be chosen from M_i to connect with *i*-th node such that $R_{ij} = 1$ and $R_{ji} = 1$.If k – s<=0, change to the *i*+1 row.

Bidirectional network is converted into un-directional network by improved k nearest neighbour network. The network of which the degree distribution is almost 1 keeps the excellent character of directional network that is transformed by k nearest neighbour network.

From Network to Time Series

Let $A(=\{a_{ij}\})$ be an $N \times N$ adjacency matrix of a network .If vertices v_i and v_j are adjacent $a_{ij} = 1$,otherwise $a_{ij} = 0$ .In our method, we define the distance between vertices v_i and v_j ,d_{ij} as follows : if $a_{ij} = 0(i \neq j)$,$d_{ij} = w(>1)$,otherwise $d_{ij} = a_{ij}$ .First, A is transformed into a squared distance matrix $D = \{d_{ij}^2\}$ .Next, D is transformed by using the expression $G = -\frac{1}{2} J_N D J_N^T$,where $J_N = E - \frac{1}{N} 1_N 1_N^T$,E is $N \times N$ unit matrix ,and 1_N is a column vector with N ones. $G = P\Lambda P^T = (P\Lambda^{1/2}) \times (P\Lambda^{1/2}) \equiv XX^T$, where $\Lambda = diag(l_1, l_2, \mathbf{L}\ l_h)$, $\Lambda^{(1/2)} = diag(\sqrt{l_1}, \sqrt{l_2}, \mathbf{L}\ \sqrt{l_h})$,$P = (p_1, p_2, \mathbf{L}, p_h)$, $p_m = (p_{m1}, p_{m2}, \mathbf{L}, p_{mN})^T$, and h is the number of nonzero eigenvalues of G .The coordinate matrix X is described by $X = (x_1, x_2, \mathbf{L}, x_N)^T$, where $x_m = (x_{m1}, x_{m2}, \mathbf{L}, x_{mh})^T$. Finally, a time series is defined as $s_m(t) = \sqrt{l_m} p_{mt} (1 \le m \le h, 1 \le t \le N)$.In the paper, eigenvector corresponding to the maximum eigenvalue was selected.

Experimental Results and Analysis

Phase Space Reconstruction and Network Construction. The experimental data was from General Hospital of Nanjing Military Region, including two groups, counting number and closing eyes respectively. EEG data was recorded by 16 electrodes (FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6) and sampling frequency is 200 Hz. C4 is selected for this experiment. Power frequency interference was filtered by FIR. Delay time and embedding dimension was computed based on C-C algorithm[7] and the result were shown in Fig. 1.

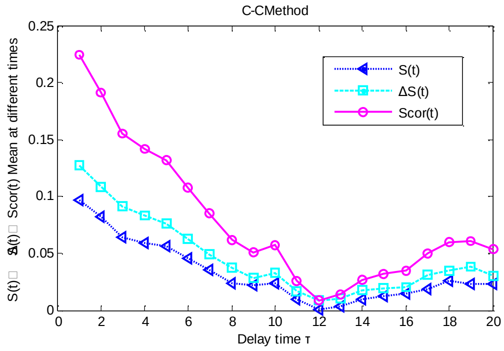

Fig. 1 The experimental result of the C-C algorithm (the vertical axis: The values of calculation formulas used in the C-C method corresponding time scale)

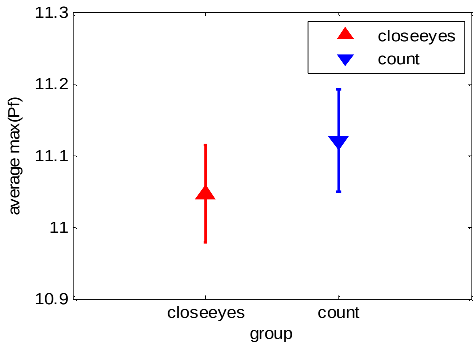

Fig. 2 The means of maximum power spectrum values were compared with eyes closed and counting number

As shown in the Fig. 1, $s(t)$、$\Delta s(t)$、and $\Delta s_{cor}(t)$ appeared minimal value when delay time is 12, so both optimal delay time and delay window are 12. Embedding dimension can be determined by m = $\frac{t}{t_w}$ +1, where m is Embedding dimension, t is optimal delay time, t_w is delay window. Phase space was reconstructed based on the delay time t and embedding dimension t_w.

Power Spectrum Analysis of Time Series. Let k = 20. An un-directional network is constructed by improved k nearest neighbor network.

The variable w is range from 1 to 2, and the interval is 0.2. Maximum value of power spectrum of time series is computed with the change of w, and then mean maximum value of power spectrum can be obtained with the change of w.

Both counting number state EEG signals and closing eyes state EEG signals are constructed into network of which size is 480×480. The results of mean maximum value of power spectrum are shown in Table 1 and Table 2.

Table 1 (close eyes) Mean values of maximum power spectrum under different time series versus w

subjects	1	2	3	4	5	6	7	8	9	10	Total mean	Total variance
mean	10.982	11.052	11.056	10.956	10.927	11.080	11.106	11.089	11.131	11.078	11.046	0.0677

Table 2 (counting number) Mean values of maximum power spectrum under different time series versus w

subjects	1	2	3	4	5	6	7	8	9	10	Total mean	Total variance
mean	11.159	11.216	11.209	11.171	11.140	11.073	11.084	11.011	11.026	11.110	11.120	0.0713

Independent sample T test was conducted in table 1 and table 2. Sig=0.029<0.05. Independent sample T test show that the average value of the maximum power spectrum of counting number EEG is greater than EEG of eyes closed, which can distinguish different attention brain state effectively. The means of table1 and table2 are shown in Fig. 2.

Time series above is from network transition and power spectrum of the time series was analyzed. The results of mean maximum value of power spectrum that is from original EEG of closing eyes and EEG of counting number are shown Table 3 and Table 4.

Table 3 the maximum value of the power spectrum of the original EEG signal from closing eyes state

subjects	1	2	3	4	5	6	7	8	9	10	Total mean	Total variance
mean	0.040	0.072	0.078	0.085	0.104	0.144	0.178	0.184	0.203	0.368	0.106	0.0999

Table 4 the maximum value of the power spectrum of the original EEG signal from counting number state

subjects	1	2	3	4	5	6	7	8	9	10	Total mean	Total variance
mean	0.034	0.046	0.053	0.053	0.055	0.057	0.058	0.129	0.272	0.306	0.146	0.0953

Independent sample T test was conducted in table 3 and table 4. Sig=0.382>0.05. Independent sample T test showed that the average value of the maximum power spectrum cannot distinguish different attention brain state effectively.

Conclusions

In this paper, attention EEG signal based on the improved k nearest neighbor network is analyzed. The improved k nearest network that has advantage of fixed degree distribution is an un-directional network. The probability of degree distribution of k is 1 in the improved k nearest network. In the experiments, eigenvector corresponding to the maximum eigenvalue is selected.

The results show that studying power spectrum of time series from network is more easily than studying time series from original time series to distinguish between counting number state EEG signals and closing eyes state EEG signals, which can be helpful for analysis of different attention brain state.

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