A Novel Feature Extraction Method for Epileptic EEG Based on Degree Distribution of Complex Network

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Abstract: - Automatic seizure detection is significant in relieving the heavy workload of inspecting prolonged electroencephalograph (EEG). Feature extraction method for automatic epileptic seizure detection has important research significance because the extracted feature seriously affects the detection algorithm performance. Recently complex network theory shows its advantages to analyze the nonlinear and non-stationary signals. In this paper, we propose a novel feature extraction method for epileptic EEG based on a statistical property of complex network. The EEG signal is first converted to complex network and the degree of every node in the network is computed. By analyzing the degree distribution, the weighted mean value of degree distribution is extracted as classification feature. A public dataset was utilized for evaluating the classifying performance of the extracted feature. Experimental results show that the extracted feature achieves not only higher classification accuracy up to 96.50% but also a very fast computation speed, which indicate the extracted feature can clearly distinguish the ictal EEG from interictal EEG and has great potentiality of real-time epileptic seizures detection.

Key-Words: - Feature Extraction Method, Epileptic Seizure Detection, Electroencephalograph (EEG), Degree Distribution, Complex Network, Nonlinear Time Series Analysis

1 Introduction

Epilepsy, the second most common serious neurological disorder in human beings after stroke, has a significantly adverse impact on patient daily life and work. Symptom of epilepsy attack is that a person has repeated seizures or convulsions. In spite of available dietary, drug and surgical treatment options, nearly one out of three epilepsy patients cannot be treated because the epilepsy attacks are completely sudden and unforeseen [1]. Electroencephalograph (EEG), which is a graphical record of electrical activity of the brain, is a low-cost but safe and effective technique for examining electrical activity of the brain and diagnosing brain diseases in clinical setting. However, traditional epileptic seizure detection, which needs time-consuming observation and analysis of the entire length of EEG by a neurologist, is a tedious and subjective diagnostic process. Recently, automated seizure detection system, which can considerably reduce the analysis time, has been proposed. Automated seizure detection system liberates the neurologist from the tedious work and allows them treat more patients in a given time, but it still has important clinical research significance.

Feature extraction method, which is primary part of epileptic EEG detection algorithm, extracts several objective quantitative features. An ideal classification feature should contain only intrinsic information of the research objects and can clearly characterize the fundamental difference between them. Brain is composed of a huge amount of nerve cells and each nerve cell connects to other nerve cells, making brain a complex non-linear system. Therefore, non-linear analysis methods could better facilitate opening out the characteristics and mechanisms of EEG. Andrzejak et al. [2] concluded that the EEG segments from epileptogenic zones possessed strong indications of non-linear determinism, while EEG segments from other regions demonstrated linear stochastic dynamics, which indicated that non-linear analysis of epileptic EEG signal might provide helpful seizure detection information. Numerous nonlinear methods have been applied into the analysis of the EEG signals. Yao et al [3] the third order cumulant, which highlights the nonlinear behaviour, were used to analyze epileptic EEG signals and extracted several useful features, which could be used to detect epileptic seizures. In [4,5] higher order spectral analysis, which is a powerful tool for the nonlinear dynamical analysis of nonlinear, non-stationary and non-Gaussian physiological signals, was used for analyzing epileptic EEG signals. Jing et al. [6] analyzed the correlation dimensions of epileptic EEGs and concluded that the correlation dimension of the epileptic EEG is larger than the normal EEG's. Based on largest Lyapunov exponent, Osowski et al. [7] discussed the detection and prediction of epileptic seizure. The Hurst exponent of the epileptic EEG was discussed in [8] and the results shown that the normal EEG is uncorrelated whereas the epileptic EEG is long range anti-correlated. Spectral entropy and embedding entropy, which can be used to measure the system complexities, were introduced to epilepsy detection in [9,10]. Acharya et al. [11] applied the recurrence plot and recurrence quantification analysis in the three-class classification of epileptic EEG signals. These literatures show that the main research direction for EEG feature extraction is nonlinear feature extraction in the future. Combined with the well-performance nonlinear feature, the classifiers, such as artificial neural network (ANN) and support vector machine (SVM), have also been widely applied into the epilepsy detection algorithm [12-17]. However, we can conclude that feature extraction method is still important, since an excellent classification feature not only achieves better classification performance but also spends less computational complexity, since it can reduce the burden of the classifier or even does not need combined with classifier. These advantages are significant for the clinical application.

Recently, complex networks theory shows its advantages in analysis of nonlinear time series. In 2006, Zhang and Small [18] proposed the pioneering conversion algorithm that converted the pseudo-periodic time series into complex network. A bridge between nonlinear time series analysis and complex networks theory has been built. After that, various types of conversion algorithms were proposed, such as conversion algorithm for transition network [20], correlation network [21], visibility graph [22], recurrence network [23], and directed weighted complex network [24]. Based on these conversion algorithms, different time series, such as periodic, pseudo-periodic time series, chaos series, random, and fractal series [18,19,22], have been converted to complex networks. What more, several statistical properties of complex network have been analyzed, such as degree distribution [18], joint degree distribution, betweenness centrality [25], and super-family phenomena [26]. All of the above references demonstrate that the time series with different dynamics reveal dramatically different statistical property, such as [19] shown that chaos attractor reveals a more heterogeneous structure and exhibits small world feature compared with pseudo-periodic time series. The complex network method has been successfully applied in several practical application fields. Yang et al. [21] analyzed the correlation network of stock time series. Marwan et al. [23] applied the recurrence network in the analysis of marine palaeo-climate record and identified the subtle changes to the climate regime. Tang et al. [27] applied the complex networks theory into the analysis of the topology characteristics of the non-stationary traffic-flow time series network. Through the conversion algorithm, time series can be mapped into the complex network domain, and then we can analyze their different topology structures by plenty of statistical properties of the network and distinguish between them. Complex networks theory that provides us a new perspective for dynamics analysis of nonlinear time series should arouse our attention.

In this paper, a novel classification feature extracting method for epileptic seizure detection is proposed. Firstly, the EEG signal is converted into the complex network. Then the degree distribution of the resulting complex network is calculated. Through the analysis of the shape of degree distribution, the weighted mean value of degree distribution is extracted as the classification feature at last. A classification experiment, which utilizes the extracted feature for distinguishing the ictal EEGs from the interictal EEGs, is used for evaluating the classification performance of the extracted feature. The influences of the parameter selection of feature extraction method have also been investigated in this paper.

This paper has been organized as follows. Section 2 presents the algorithm for converting the time series into complex network, and focuses on describing the feature extraction method for automatic epileptic seizure detection. In Section 3, the EEG signal benchmark dataset and the evaluation parameters used in the classification experiment are described. Then the experimental results are presented in detail. Finally, some conclusions are included in Section 4.

2 Methods

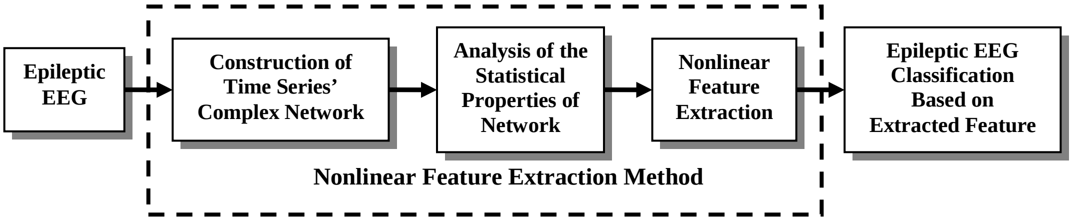

Fig.1 Schematics of the feature extraction method proposed in this paper.

The main idea of extracting feature based on time series' complex network (TSCN) is: (1) map the time series into the complex network domain; (2) use the topology structure statistical properties provided by the complex network theory to analyze this TSCN; (3) extract feature which can clearly describe the difference between various kinds of time series.

2.1 Algorithm for Converting the Time Series into Complex Network

A time series is denoted as $\{s_i \mid i \in [1, m]\}$, where s_i is the i_{th} sampling point in time series and the length of series is m.

A complex network composes of a node set and an edge set.

The node set of TSCN is constructed as

$$\text{NodeSet:} \quad \left\{ n_j = \left(s_{(j-1)\times l+1}, s_{(j-1)\times l+2}, \ldots, s_{(j-1)\times l+l} \right) j = 1,2,\ldots,N \right\}, \tag{1}$$

where n_j represents the j_{th} segment divided from the time series. Obviously, the number of nodes, N, is related to the segment length l (i.e., the dimension of TSCN). Few sampling points at the end of the time series may be abandoned.

The edge set of TSCN is constructed as follows:

Firstly, the similarity between the two nodes, denoted as d_{ij}, is evaluated by Euclidean distance

$$d_{ij} = \frac{1}{l} \times \sqrt{\sum_{k=1}^{k=l} \left(n_i(k) - n_j(k) \right)^2} \tag{2}$$

where $n_i(k)$ is the k_{th} point in n_i. Two nodes with a smaller distance are closer in phase space, which means that the two nodes are more similar. After a pair-wise high-dimensional distance computing between every two nodes in TSCN, a distance similarity matrix is obtained, denoted as $D = \left(d_{ij} \right)_{N \times N}$.

Then the edge between two nodes is determined by

$$a_{ij} = \begin{cases} 1 & d_{ij} < \varepsilon \\ 0 & d_{ij} \geq \varepsilon \end{cases}, \tag{3}$$

where the ε is a predetermined value used to construct an edge between the two nodes which have larger similarity. There is an edge between the i_{th} node and the j_{th} node when $a_{ij} = 1$, whereas $a_{ij} = 0$ means there is no edge between these two nodes. With an appropriate critical value ε selected, matrix D is converted into a binary matrix $A = \left(a_{ij} \right)_{N \times N}$, namely adjacency matrix, which contains the entire information of TSCN.

In the conversion algorithm, the parameter l determines the node dimension i.e., the dimension of the TSCN. The parameter ε determines whether the embedded dynamics of time series can be sufficient encoded into the topological structure of the TSCN or not. When the ε is extremely large, the nodes with weak similarities are also connected, which result in that the physically meaningful correlations of time series are submerged by the noises. With ε decreased, more and more noises can be filtered out. The ε cannot be extremely small, since some connections with physical significance may be filtered out. Moreover, due to a small finite number of connections caused by the extremely small ε, a strong statistical fluctuations may appear.

2.2. Node Degree and Degree Distribution of the Time Series' Complex Network

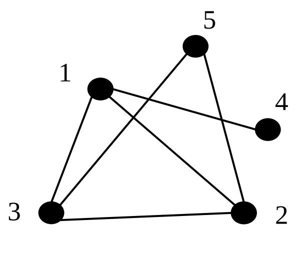

Fig.2 The sample complex network with 5 nodes and 5 edges.

The node degree k of a node is the number of the nodes that directly connected with it.

$$k_i = \sum_{j=1}^{N} a_{ij} \quad i \in [1 \quad N]. \tag{4}$$

The degree distribution (DDF) is defined by a probability function, $P(k)$, which is the probability of a randomly-picked node that happen to have degree k, where each node has an equal probability to be picked. The node degree and degree distribution of the sample complex network are listed in Table 1.

Table 1 The node degree and degree distribution of the sample complex network shown in Fig.2.

	Node Degree k	Degree Distribution $P(k)$
Node 1	3	
Node 2	3	3/5
Node 3	3	
Node 4	1	1/5
Node 5	2	1/5

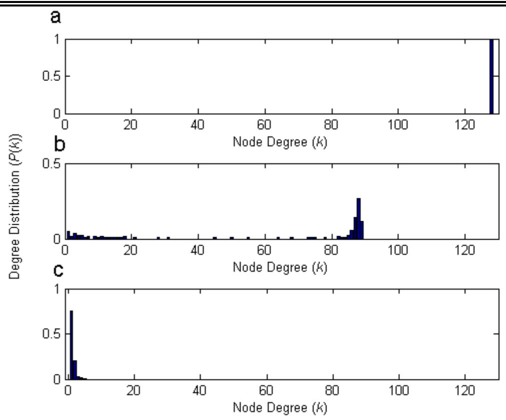

Fig.3 The degree distribution of typical time series: (a) periodic time series, (b) the x component of Rössler system, and (c) Gaussian noise. The length of each time series is 1024 and parameter l is selected as 8.

The DDFs of periodic time series $y_n = \cos(\pi n/4)$, the x component of the well-known chaotic Rössler system given by: $x' = -(y + z)$, $y' = x + 0.398\,y$, $z' = 2 + z(x - 4)$, and Gaussian noise, are shown in Fig.3 (a), (b), and(c), respectively. It can be seen that the time series with different dynamic have obviously different DDF shape.

2.3 Feature Extraction Method Based on Degree Distribution

Time series with different dynamic regimes have different node distribution forms in phase space, which induces the node degree of every nodes are different and the DDFs reveal different shapes. The DDF characterizes the heterogeneous property of networks and consequently can characterize the different dynamics of the networks. In order to determine the importance of the $P(k_i)$ in DDF, the weighted function (WF) is defined as

$$WF = \left\{ wf(i) = e^{-\frac{i^2}{R}} \middle| i \in [0 \quad \max(k)] \right\}, \tag{5}$$

where the parameter R determines the shape of the WF.

According to different shapes of the DDF, an appropriate WF can be constructed to maximized describe the difference. In order to describe the difference between two type signals quantitatively, the *weighted mean value* is defined as

$$wmean = \sum_{i=0}^{\max(k)} WF(i) \cdot P(k_i), \tag{6}$$

and is extracted as a scalar classification feature.

3 Results and Discussion

3.1 Data Description

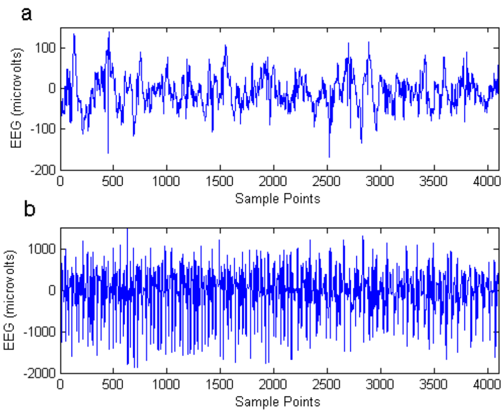

Fig.4 The typical EEG waveforms corresponding to epilepsy: (a) an interictal EEG sample in dataset D, (b) an ictal EEG sample in dataset E. The length of each EEG sample is 4097.

In this paper, we utilize the public database [28], which came from Department of Epileptology, Bonn University, Germany, for evaluating the classification performance of the extracted feature. The EEG dataset D and dataset E, each of which contained 100 single-channel EEG data of 23.6 s time duration, are used in the classification experiment. The dataset D was composed of intracranial EEGs recorded during interictal periods. The EEG signals in dataset E were recorded during ictal periods. They were all measured through using deep electrodes placed within the epileptogenic zone of the brain. The EEGs of two datasets were both taken from five epileptic patients experiencing pre-surgical diagnosis. All EEG signals had 4097 sampling points and were digitized at 173.6 samples per second. Fig.4 (a) and (b) depict example of interictal EEG and ictal EEG, respectively.

3.2 Performance Evaluation Parameters

In experiment section, the interictal EEGs and the ictal EEGs are regarded as the negative class and the positive class, respectively. The classification performance of the extracted feature is evaluated by using parameters such as sensitivity (*SEN*), specificity (*SPE*), and overall accuracy (*ACC*), which are shown in equations (7), (8), and (9), respectively[14].

$$SEN = \frac{TP}{TP + FN}, \tag{7}$$

the number of true positives (*TP*) divided by the total number of ictal EEG signals labelled by the EEG experts. *TP* stands for the ictal EEG signals recognized by both the detection algorithm and the EEG experts. False negative (*FN*) is the number of ictal signals labelled interictal by the detection algorithm.

$$SPE = \frac{TN}{TN + FP}, \tag{8}$$

the number of true negatives (*TN*) divided by the total number of interictal EEG signals labelled by the EEG experts. *TN* stands for the interictal EEG signals recognized by both the detection algorithm and the EEG experts. False positive (*FP*) is the number of interictal signals labelled epileptic by the detection algorithm.

$$ACC = \frac{SEN + SPE}{2}, \tag{9}$$

the mean value of the *SEN* and *SPE*, i.e., the number of correctly recognized EEG signals (*TP*+*TN*) divided by the total number of EEG signals.

3.3 Classification Experiment Results and Discussion

For testing the classification performance of the extracted feature, two hundred interictal EEG samples and 200 ictal EEG samples, which are respectively taken out from the dataset D and dataset E, constitute a test set. Each original datum in the two datasets is divided up into two equal-length sections of 2048 points and these two sections are used as two independent samples. The TSCN dimension *l* is first selected as 8. Then the time series' complex networks (TSCN) of these 400 test samples are constructed and the degree distributions (DDFs) of all the resulting TSCNs are calculated.

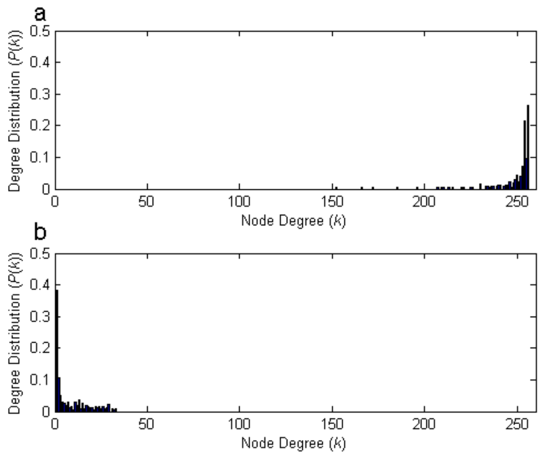

Fig.5 Examples of degree distribution: (a) degree distribution of interictal sample and (b) degree distribution of ictal sample. The length of each test sample is 2048.

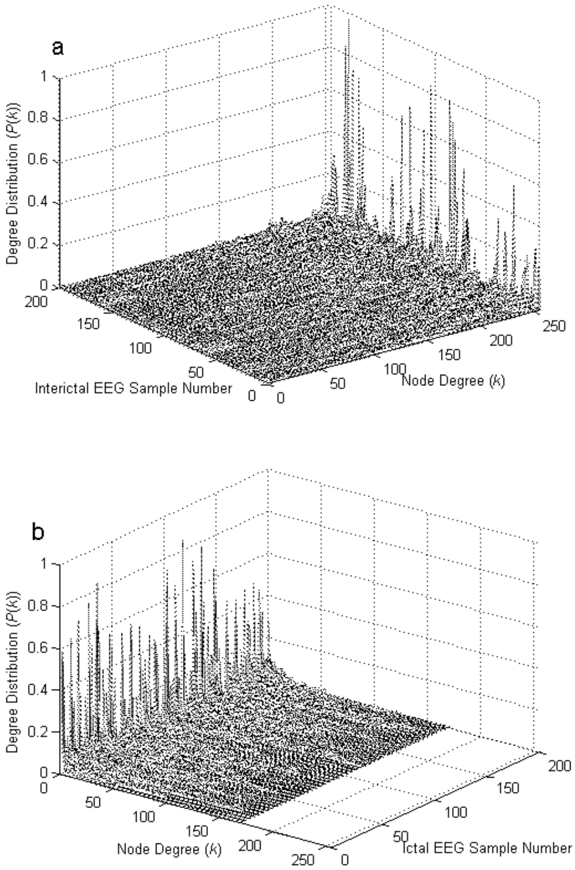

Fig.6 The degree distributions of the resulting complex networks constructed from: (a) 200 interictal samples and (b) 200 ictal samples. The length of each test sample is 2048.

In Fig. 5 (a) and (b), the example of DDFs of interictal sample and ictal sample is presented, respectively. It can be seen from Fig.5 that, for the interictal test sample, mostly node degrees of its network are distributed over the intervals [200 255], which means that the node degrees of interictal test sample are always big. However, the DFF of ictal test sample are distributed over intervals [0 50], which indicates that there are very small node degrees in the TSCN of ictal EEG. The DDFs of the resulting complex networks constructed from the 200 interictal test EEG samples and 200 ictal test EEG samples are shown in Fig.6 (a) and (b), respectively. It can be clear seen that the node degrees of interictal samples are distributed in big node degree value interval, whereas the node degrees of ictal samples are distributed in small degree value interval. From these observation results, we can conclude that the DDF shapes are different between interictal samples and ictal samples.

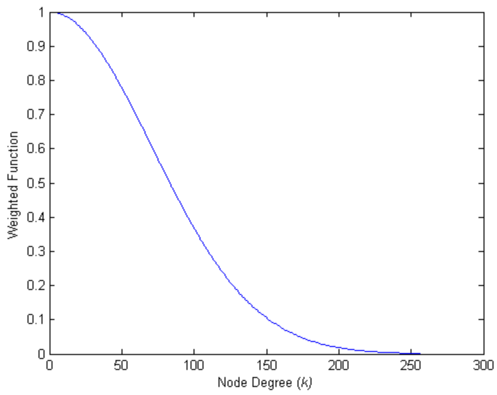

Fig.7 The weighted function used in this experiment.

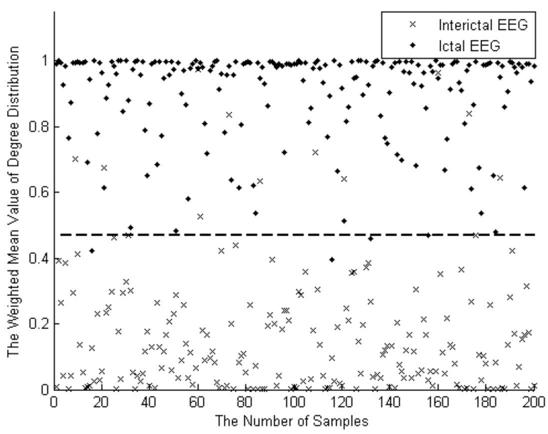

Fig.8 The classification result of the extracted feature by a straight line. The sample length is 2048 and the parameters *l* and *R* are 8 and 10000, respectively. The classification accuracy is 96.50%.

In order to calculate the *weighted mean value* (*wmean*) of every DDF, the Gauss function is selected as the *WF* in this experiment, i.e., $WF=\exp(-(k^2/R))$, k=0,1,…,255, and *R*=10000, shown in Fig.7. The maximum value of node degree is 255, since there are 2048/8=256 nodes in the TSCN. In this way, all the degree values and their appearing probabilities are analyzed under different weights and the *wmean* is then extracted as the feature to classify the epileptic EEGs.

The distribution of 400 *wmean* values of DDF is depicted in Fig.8. In Fig.8, each 'x' represents *wmean* of one interictal test sample and each '•' represents *wmean* of one ictal test sample. It can be found from Fig.8 that the *wmean*s of interictal test samples are smaller than the ictal test samples except several special samples. Only 11 interictal test samples and 3 ictal test samples are put into wrong category when the test samples are classified by the dotted line (0.4679) shown in Fig.8. The classification accuracy is 96.50%.

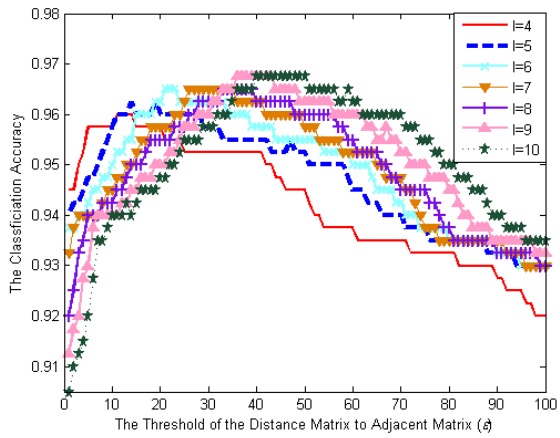

Fig.9 The classification accuracies of the extracted feature were calculated for different TSCN dimensions (*l*). The threshold (*ε*) varies from 50 to 550 in steps of 5.

Table 2 The classification performances of the proposed feature when sample length is 2048.

l	*ε*	*R*	*cth*	*SEN* (%)	*SPE* (%)	*ACC* (%)	*Run Time*(ms)
4	105	50000	0.6580	98.50	93.50	96.00	198.4±0.3
5	120	40000	0.7219	98.50	94.00	96.25	130.1±0.9
6	155	25000	0.6336	98.50	94.50	96.50	87.2±0.5
7	180	15000	0.5501	99.00	94.00	96.50	65.2±0.7
8	215	10000	0.4679	98.50	94.50	96.50	50.0±0.8
9	230	8000	0.4843	99.00	94.50	96.75	39.0±0.8

10	250	5000	0.4952	99.00	94.50	96.75	32.2±0.6

In order to investigate the feature extraction time, the total run time of extracting the feature of the 400 samples has been recorded, and the average time, listed in Table 2, is used as the evaluation of feature extraction time. All the simulations were based on a 2.60 GHz quad-core Inter Pentium processor with 4 GB memory. The code was executed in environment of Matlab 7.0. When the sample length is 2048 and the parameters l and R are respectively selected as 8 and 10000, the feature extraction time for *wmean* is only 50 ms.

In order to investigate whether the TSCN dimension l affects the performance of the extracted feature, we perform a similar experiment, calculating the *wmean* of each test sample with the method described previously. Plots of classification accuracy as a function of threshold (ε) under different l are shown in Fig.9. The performances of the extracted feature, for the TSCN dimension l ranged from 4 to 10 in steps of 1, are listed in Table 2. The parameter ε, R of the weighted function and the classification threshold value (*cth*) are also summarized in Table 2. In Fig.9, we can see that the classification accuracies of the *wmean* under different l first increased with the increasing of the threshold ε, and then decreased after they reached the peak accuracy values. Moreover, through analysis of the detail results summarized in Table 2, we can conclude that the TSCN dimension l has little affect on the performance of the extracted feature, and the peak accuracy under each condition is no less than 96.00 %.

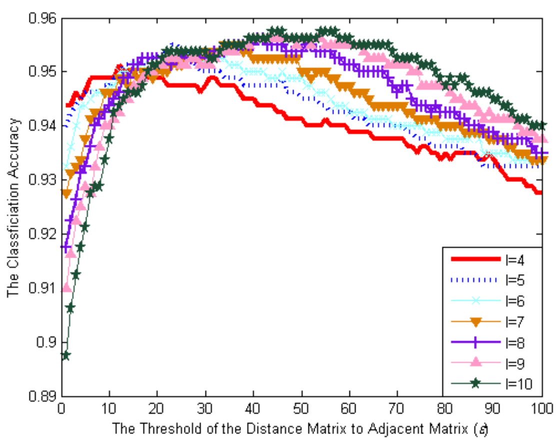

Fig.10 The classification accuracies of the extracted feature were calculated for different TSCN dimensions (l). The sample length, the parameters l, and R are 1024, 8, and 10000, respectively. The threshold (ε) varies from 50 to 550 in steps of 5.

We have also analyzed the effects of data length on the classification performance. For this propose, each datum in the two epileptic EEG datasets (D and E) is divided into four equal-length sections of 1024 points. The 2_{nd} section and the 4_{th} section are regarded as two different test samples. In this way, 200 short ictal samples and 200 short interictal samples constitute a new test set. The same analysis procedure is then applied to the new test set. The classification performances of the proposed feature under the various TSCN dimensions are listed in Table 3. In Fig.10, plots of classification accuracy as a function of threshold ε under different l are illustrated. As can be seen from Fig.10, the similar result can be obtained that the TSCN dimension l has little affect on the performance of the extracted feature. Nevertheless, the peak accuracies of *wmean* under different l are distributed over the intervals [95.00% 95.75%], which are generally lower than the peak accuracies of the *wmean* under long data condition. Since the data length decreased, the feature extraction time is much shorter than the run time under long data condition in general.

Table 3 The classification performances of the proposed feature when sample length is 1024.

l	ε	*R*	*cth*	*SEN* (%)	*SPE* (%)	*ACC* (%)	*Run Time*(ms)
4	110	10000	0.8807	97.25	93.00	95.13	48.5±0.9
5	165	8000	0.8425	98.00	93.00	95.50	31.5±0.8
6	175	6000	0.8647	96.50	94.25	95.37	21.8±0.6
7	220	4000	0.7631	98.00	93.00	95.50	16.4±0.3
8	255	3000	0.7198	97.75	93.25	95.63	12.8±0.4
9	250	2000	0.7734	98.00	93.50	95.50	10.2±0.5
10	270	1500	0.8030	96.50	95.00	95.75	8.5±0.6

Table 4 The classification results of the proposed feature and two other features for comparison. The sample length is 2048.

Feature	*Run Time*(s)	*ACC* (%)
Approximate Entropy$_{(2048)}$	1.9600±0.3600	87.25
Sample Entropy$_{(2048)}$	1.8600±0.3400	87.75
wmean$_{(2048)}$	0.0322±0.0006	96.50

In Table 4, the classification performance of the approximate entropy and sample entropy, which are utilized as extracted feature to classify the same long data test set (2048), are used to compare with the classification performance of the extracted feature. The average run times of these two feature extraction methods are also listed in Table 4. The run time taken by *wmean* is a lot shorter than the run times taken by other two entropies. A conclusion can be drawn from the Table 4 that the extracted feature, *wmean*, shows the best performance: not only highest classification accuracy but also fast computation speed.

Table 5 lists the accuracies of several established epilepsy automatic classification algorithms recently, which are combined with the support vector machine (SVM) classifier and applied to the same epileptic EEG dataset. Here, the DFA-α is the scaling exponent of the detrended fluctuation analysis of epileptic EEG. The results of approximate entropy combined with SVM and sample entropy combined with SVM are obtained based on the results listed in Table 4. Table 5 shows that the single feature classification algorithm based on the *wmean* proposed in this study achieves the highest classification accuracy compared with other established classification algorithms, which combined with classifier.

Table 5 The classification accuracies of different epileptic EEG classification algorithms applied into the same epileptic EEG dataset.

Feature	*ACC* (%)
DFA-α + SVM[10]	82.00
Hurst + SVM[11]	87.25
Approximate Entropy + SVM	89.00
Sample Entropy + SVM	91.00
Single feature classification based on *wmean*	96.50

The above results and conclusions indicate that the extracted feature *wmean* can clearly characterize the difference between the dynamics of the EEG signals under different brain conditions in TSCN domain. Moreover, the short extraction time of *wmean* make it more possible to be applied in clinic.

4 Conclusion

In this paper, we proposed a novel feature extraction method that can be applied in detection of epileptic seizure. The proposed scheme firstly constructs time series' complex network (TSCN). Then the node degrees of all the nodes in TSCN and the degree distribution (DDF) are calculated. At last, through analyzing the difference between the DDFs of various objectives, the *weighted mean value* of the DDF, *wmean*, is defined and extracted as the classification feature. The classification performances of *wmean* under different conditions are evaluated by distinguishing between interictal EEGs and ictal EEGs.

Experimental results show that the *wmean* can clearly describe the essential difference between the two kind signals and achieves higher classification accuracy about 96.50% (sample length is 2048 and TSCN dimension l is 8). The feature extraction times for one EEG sample with 2048 sampling points are all less than about 0.2 s, which is much shorter than the EEG sample's time duration (11.8 s). Higher classification accuracy and fast computation speed indicate the proposed feature's huge potentiality for real-time detection of epileptic seizure.

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