A Novel Direct Feature-Based Seizure Detector: Using the Entropy of Degree Distribution of Epileptic EEG Signals

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Abstract— **The electroencephalogram (EEG) signals with different brain states show different nonlinear dynamics. Recently the statistical properties of complex networks theory have been applied to explore the nonlinear dynamics of time series, which studies the dynamics of time series via its organization. This study combines the complex networks theory with epileptic EEG analysis and applies the statistical properties of complex networks to the automatic epileptic EEG detection. We construct the complex networks from the epileptic EEG series and then calculate the entropy of the degree distribution of the network (NDDE). The NDDE corresponding to the ictal EEG is lower than interictal EEG's. The experiment result shows that the approach using the NDDE as a classification feature obtains robust performance of epileptic seizure detection and the accuracy is up to 95.75%.**

I. INTRODUCTION

Epilepsy is a common neurological disease of the brain which seriously affects the work and life of patients. For correct diagnosis, the doctor need long time observation in patients' EEG, which contains important information about the conditions and functions of the brain, and the long-range EEG replay analysis costs doctors a lot of time and energy. The automatic detection and classification of epileptic EEG have great clinical significance.

Automatic seizure detection to the scalp EEG, including automatic labeling of seizures for faster reporting [1] and activating radioactive tracer injection for improved seizure focus localization using SPEC [2], given the many artifacts found in EEG analysis, and this meant that automated seizure detection was not widely used in standard clinical practice. The seizure detectors, in general, have two classes, including direct feature based seizure detectors [3-4] and more complex seizure detectors using classification algorithms [5-6]. Direct feature based seizure detectors are typically easier to understand and implement than complex classification algorithms which analyze the joint space of several features.

The nonlinear dynamics theory may be a better approach than traditional linear methods in characterizing the nature of EEG, considering the growing evidence that the electrical activities of the brain are complex nonlinear dynamic systems, and several approaches [7-9] have been proposed recently. Reference [7] discussed the nonlinear parameters of the EEG signals under different mental state, such as correlation dimension, largest Lyapunov exponent, Hurst exponent and approximate entropy. Reference [8] proposed a noise reduction method to reduce the noise in the EEG signals. Reference [9] analyzed largest Lyapunov exponent and the approximate entropy before and after the epileptic seizure.

In the past few years, the complex networks theory provided us with a new viewpoint and an effective tool for understanding the nonlinear dynamics of time series. Zhang and Small [10] first proposed a transformation from pseudoperiodic time series to complex networks, and discussed the dynamics of nonlinear time series encoded into the topology of the corresponding networks. Reference [11] discussed several topology statistics of networks, such as the joint degree distribution and the betweenness centrality, which provide different levels statistical characterization of the nonlinear dynamics of time series. Lacasa et al. [12] proposed a simple and fast computational method (the visibility algorithm) to convert arbitrary time series into a graph. Reference [13] illustrated the performance of complex networks to detect the dynamical transitions, and compared with the well established recurrence plot. In Reference [14], Zhongke Gao et al. expanded the analysis of the time series nonlinear dynamics from using the binary networks into using the directed weighted complex networks.

In this study, the NDDE of the time series, as an extracted feature, is proposed and employed to automatically detect the epileptic ictal EEG from the epileptic EEG. At first, the EEG series is transformed into a complex networks and then the degree distribution (DDF) and the classification feature NDDE of the resulting networks are explored. At last, the

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correct classification rate of distinguishing between the EEG of ictal and interictal, by the feature we extracted, is tested. The result demonstrates that NDDE is a robust classification feature in automatic epileptic seizure detection.

II. THE NDDE AS A FEATURE FOR AUTOMATIC DETECTION

A time series denoted as $\left\{s_1, s_2, \cdots, s_j, \cdots, s_m\right\}$, where the s_j is the j_{th} point of the time series and the length of series is m. Firstly, the time series is divided up into nonoverlapping segments according to the local minimum (or maximum) values. Every segment is called as cycle, and all cycles denoted as $\left\{C_1, C_2, \cdots, C_j, \cdots, C_N\right\}$, where C_j means the j_{th} cycle divided from the series. The value of N is related to the number of local minimum (or maximum) values. Each cycle is then treated as a node in the complex networks domain.

From the view of high-dimensional phase space, the distance between two cycles C_i and C_j is described by Euclidean distance, denoted as d_{ij}. The C_i has different length and the Euclidean distance is modified as

$$d_{ij} = \min_{l=0,1\ldots,L_j-L_i}\left(\frac{1}{L_i}\sqrt{\sum_{k=1}^{k=L_i}\left(C_i\left(k\right)-C_j\left(k+l\right)\right)^2}\right), \quad (1)$$

where $C_i(k)$ and $C_j(k)$ is the k_{th} point of C_i and C_j (with length L_i and L_j, respectively, and $L_i<L_j$). After a pair-wise high-dimensional distance computing between every nodes (cycles), a square, symmetric distance matrix is obtained, denoted as $D=\left(d_{ij}\right)_{N\times N}$.

Two nodes with a smaller distance are close in phase space and the 'close' means that the two nodes are similar. The connection state (edge) between two nodes is determined by a predetermined value of th. The rules of converting read

$$a_{ij} = \begin{cases} 1 & \left(d_{ij} < th\right); \\ 0 & \left(d_{ij} \ge th\right). \end{cases} \quad (2)$$

Then the distance matrix D can be converted into a new binary matrix $A=\left(a_{ij}\right)_{N\times N}$, called adjacency matrix, with choosing an appropriate critical value th. The a_{ij} = 1 and a_{ij} = 0 means similarity and dissimilarity between the i_{th} node and the j_{th} node, respectively. The nodes and edges compose the resulting complex network. The topological structure of this network can be described just by the adjacency matrix A.

The parameter th is considered to be a critical parameter and its value determines whether the embedded dynamics of time series can be sufficient encoded in the resulting complex networks or not. With extremely large value of th in the network, the nodes in pairs with weak correlations are also connected, which result in the physically meaningful correlations of time series submerged by the noises. More and more noises can be filtered out by decreasing the value of th. The value of th can not be extremely small, because some of the physically meaningful connections may be filtered out, leading to strong statistical fluctuations due to a small finite number of connections. For exact characterizing the dynamics of time series through resulting network and obtaining the best classification result, the critical value of th need to be found in the interval of ($th \in \left(\min\left(d_{ij}\right), \max\left(d_{ij}\right)\right)$). A proper critical value th can be found by changing the value of th monotonously while keeping the other parameters unchanged and testing the classification accuracy in every situation.

After constructing the complex network from the time series, the DDF of the resulting networks is investigated, denoted as $P(k)$. The DDF is defined as the probability that a node chosen uniformly at random has degree k. The degree k of a node is the number of the nodes directly connected with it. The different dynamics of the time series have different topological structure of the resulting networks and can be distinguished by the shape of DDF. Since the shape of the DDF is hard to quantify, it is inappropriate to take it as a classification feature.

The Shannon entropy is a state function of the system and directly reflects the uniformity and the condition of the system. In statistical mechanics, entropy is a measure of the number of ways in which a system may be arranged, often taken to be a measure of 'disorder' (the higher the entropy, the higher the disorder). Here, the entropy is used to reflect the shape of the DDF, and then the NDDE is used to classify the time series with different dynamics. The NDDE is defined as

$$NDDE = \text{-}p\sum_{i=0}^{i=\max(k)} P(i)\times\log_2 P(i), \quad (3)$$

where the k means the degree of a node. The p is the Boltzmann constant and the value of it is selected as 1. When the DDF has a large fluctuation range (the DDF only has several big probability values), the value of the NDDE is small. Conversely, the value of the NDDE is large, if the DDF only has a lot of small and similar probability values.

III. EXPERIMENT RESULTS AND ANALYSIS

The performance of the proposed approach is illustrated by testing the epileptic EEG data, which obtains from the dataset of the Department of Epileptology at the University Hospital of Bonn. Five sets (set A ~ set E) are in the dataset and the set D and the set E contain only activity measured during seizure free intervals and seizure activity only, respectively. The set D contains 100 ictal EEG data (S001~S100), and set E contains 100 interictal EEG data (F001~F100). Further details of the dataset refer to reference [15].

For the purpose of comparison, 200 simples of ictal EEGs and 200 simples of interictal EEGs are taken out from the sets D and E (every datum in a file is divided into two equal-length sections of 2048 points as two different simples), respectively.

In this study, the maximum value of time series is used to divide time series into individual cycles. The interictal and the ictal EEGs are regarded as the positive class and the negative class, respectively.

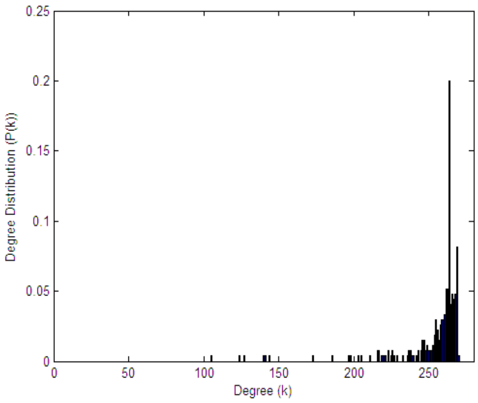

Fig. 1 Degree distribution of an ictal EEG.

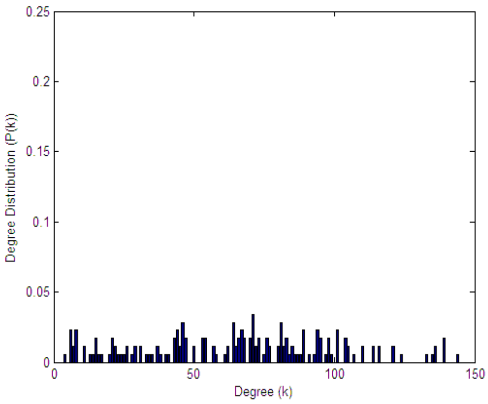

Fig. 2 Degree distribution of an interictal EEG.

Fig. 1 plots the DDF of the networks reconstructed from an ictal EEG signal, and Fig. 2 plots the DDF of the networks reconstructed from an interictal EEG signal.

As can be seen in Fig. 1, the values of DDF mostly locate in a small region $k \in [250, 270]$. The values of $P(k)$ changes from 0 to 0.200. In Fig. 2, the values locate in a large region $k \in [0, 150]$. The values of $P(k)$ changes from 0 to 0.040. The 0.200 and 0.04 are the maximum values of two $P(k)$s, respectively. The DDF of the ictal EEG signal has a fewer numbers of values but a larger maximum value than the interictal EEG signal's DDF. It can be clearly found that the shape of the ictal EEG signal's DDF is different from the shape of the interictal EEG signal.

Fig. 3 plots one of the best classification result showing in the Table I, when the critical value (*th*) is 8. There are two hundred 'square' points and two hundred 'circle' points representing the NDDE values of the interictal EEGs and the NDDE values of the ictal EEGs, respectively. As can be clearly observed from the Fig. 3, the points 'square' are higher than the points 'circle' except for a few points. At 4.738 (the value of the NDDE), represented by the dotted line in the Fig. 3, the classification accuracy is 95.75%.

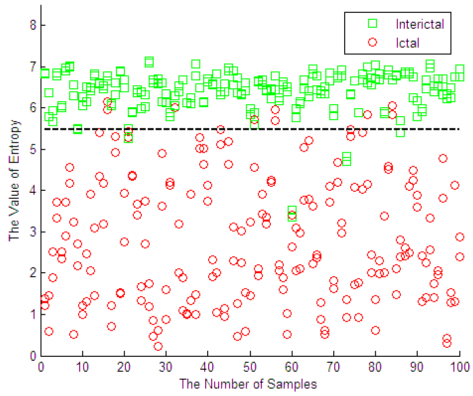

Fig.3 The classification result of the approach under *th* = 8

TABLE I
THE CLASSIFICATION ACCURACY OF THE APPROACH UNDER DIFFERENT CRITICAL VALUE

th	Interictal EEG		Ictal EEG		Accuracy (%)
	Sensitivity (%)	Specificity (%)	Sensitivity (%)	Specificity (%)	
4	95.50	95.00	95.00	95.50	95.25
5	95.50	96.00	96.00	95.50	95.75
6	95.50	96.00	96.00	95.50	95.75
7	95.50	96.50	96.50	95.50	95.75
8	95.00	96.00	96.00	95.00	95.75
9	95.00	96.50	96.50	95.00	95.75
10	95.00	96.50	96.50	95.00	95.75
11	95.50	96.00	96.00	95.50	95.75
12	94.00	97.50	97.50	94.00	95.75
13	95.50	95.50	95.50	95.50	95.50
14	94.50	97.00	97.00	94.50	95.75
15	95.50	95.50	95.50	95.50	95.50
16	95.00	96.00	96.00	95.00	95.50
17	94.50	96.00	96.00	94.50	95.25
18	93.50	96.50	96.50	93.50	95.00

Table I presents the correct classification rates of the approach with the parameter *th* adjusted from 4 to 18. The correct classification rate of the approach remains unchanged at 95.75%, changing the critical value from 5 to 12. An interval of the critical value *th*, in which the correct classification accuracy is unchanged, is found, which demonstrates that the resulting networks can capture the dynamic characteristics of the time series and using the feature NDDE as classification feature has strong robustness. The classification accuracy is higher than 95%, changing the *th* from 4 to 18, which shows the feature extracted is an effective classification feature on the epileptic automatic detection.

IV. Conclusion

Recent works show that complex networks theory may be a powerful tool in dynamic analysis of nonlinear time series. In this study, the DDF of the complex networks is applied to analyze the epileptic EEG, which is nonlinear time series with different dynamics under different states of the brain, and the NDDE of EEG signal is employed as a classification feature to automatically find out the ictal EEG signals from the epileptic EEG signals.

Application to epileptic EEG dataset shows that the extracted feature (NDDE) is robust and effective classification feature in the epileptic automatic detection. The classification accuracies are higher than 95%, with *th* changing from 4 to 18, and the maximum classification accuracy 95.75% is obtained during the *th* changing from 5 to 12.

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