Novel Feature Extraction Method Based on Weight Difference of Weighted Network for Epileptic Seizure Detection

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Abstract— **The extraction method of classification feature is primary and core problem in all epileptic EEG detection algorithms, since it can seriously affect the performance of the detection algorithm. In this paper, a novel epileptic EEG feature extraction method based on the statistical parameter of weighted complex network is proposed. The EEG signal is first transformed into weighted network and the weight differences of all the nodes in the network are analyzed. Then the sum of top quintile weight differences is extracted as the classification feature. At last, the extracted feature is applied to classify the epileptic EEG dataset. Experimental results show that the single feature classification based on the extracted feature obtains higher classification accuracy up to 94.75%, which indicates that the extracted feature can distinguish the ictal EEG from interictal EEG and has great potentiality of real-time epileptic seizures detection.**

I. Introduction

Epilepsy is one of the most common neurological disorders, which seriously affects the life and work of patients. With respect to neuronal firing pattern, brain activity during an epileptic seizure stage differs greatly from that in the normal state. The electroencephalogram (EEG), which is a highly complex signal, is mainly sources of information that is used to study brain function. It plays a significant role in the diagnoses of neurological disorders such as epilepsy. The traditional detection of the epileptic seizure requires time-consuming observation and analysis of the entire length of the EEG data by an expert, which is a tedious and subjective diagnostic process. Computer aided technologies have set out to settle this problem, and thus epileptic EEG automatic detection have been researched for several years.

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The techniques developed for automatic detection, based on EEG, transform the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem. For ideal classification problems, the classification feature contains only the intrinsic information of the sample, which means that the extracted feature gets better classification performance when it obtains more essential information. Because of the growing awareness that the electrical activities of the brain are complex nonlinear dynamic systems [1], the nonlinear features can better describe the nature of EEG, compared with the traditional other features. Numerous nonlinear features of EEG signals have been proposed recently [2]-[4]. Based on largest Lyapunov exponent, reference [2] discussed the detection and prediction of epileptic seizure. Reference [3] analyzed the correlation dimensions of epileptic EEG, and concluded that the correlation dimension of the epileptic EEG was larger than the normal EEG's. The Hurst index of the epileptic EEG was discussed in [4] and the results shown that the normal EEG was uncorrelated whereas the epileptic EEG was long range anticorrelated. Spectral entropy and embedding entropy, which measured the system complexities, were introduced to epilepsy detection in reference [5]. The classifiers have also been widely applied into the epilepsy detection algorithm in reference [6]-[11]. These literatures get a conclusion that if a classification feature can clearly distinguish two categories, with the classification feature combined with classifier, the classification algorithm will obtain even better classification performance.

Recently, complex networks theory provided a new perspective for nonlinear time series analysis. Zhang and Small [12] proposed an algorithm that transformed the pseudoperiodic time series into complex networks. A bridge between nonlinear time series analysis and complex networks theory has been built. Reference [13] converted time series into complex network based on time delay embedding theory, and shown, compared with pseudoperiodic time series, that the chaos attractor reveals a more heterogeneous structure and exhibits small world feature. The correlation networks of time series under different dynamics, which had different degree distributions, were constructed by Yue Yang *et al.* [14]. The transform was based on the time delay embedding theory and the similarity of two nodes was measured by correlation coefficient. Lacasa *et al.* [15] first proposed the visibility graph algorithm, which could convert arbitrary time series into a graph. Tang *et al.* [16] applied the complex networks theory into the analysis of the topology characteristics of the nonstationary traffic flow time series network. This emerging

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research area should be taken seriously, since the complex networks theory accumulated plenty of statistical properties and many of them have not been exploited.

In this study, based on the time series' weighted complex network, a new feature for epileptic seizure detection is proposed. Firstly, the EEG signals are converted to the weighted networks. Then the ranked weight differences (wd_r) of the converted networks are obtained and the sum of top quintile wd_r is extracted as the classification feature to classify the epileptic EEGs. The experimental results show that the extracted feature can distinguish the ictal EEGs from the interictal EEGs.

This paper has been organized as follows. Section 2 describes the EEG signal benchmark dataset used in the present paper and presents the algorithm of converting the time series into weighted network. The algorithm of feature extraction for epileptic automatic detection is also introduced in this section. In Section 3, the evaluation parameters and the experimental results are presented. Finally, some conclusions are included in Section 4.

I. MATERIALS AND METHODS

A. Data Description

In this study, the publicly-available database introduced in [17] is used for testing the extracted feature performance. The EEG data set D and set E are used in this work, each of which contained 100 single-channel EEG data of 23.6 s duration. The set D was composed of intracranial EEG recordings during interictal periods. The intracranial EEG signals in set E were recorded during ictal periods. They were all measured through using deep electrodes placed within the epileptogenic zone of the brain. The EEGs in two sets were taken from five epileptic patients experiencing pre-surgical diagnosis. Each datum had 4097 sampling points. Fig. 1 (a) and (b) depict examples of interictal EEG and ictal EEG, respectively.

B. Approach for Converting the Time Series into Weighted Network

Various statistical properties in complex network theory may dig up information, which cannot be obtained by classical nonlinear time series analysis methods. Weighted network is one type of complex networks, which consists of a node set and the weight sets for every nodes in the network.

The time series, $\{u_i\}_{i=1}^{N}$, is first mapped into the node set of the weighted network. Here N is the length of time series. Through the time delay embedding process for a time series, the node set can be constructed [13]

$$\vec{x}_i = (u_i, u_{i+\tau}, ..., u_{i+(m-1)\tau}), i \in [1, M]. \quad (1)$$

where the m is embedding dimension, τ is time delay and M=N–(M–1)τ is the number of obtained vectors. Then the obtained M vectors compose the node set of the weighted network.

The weights of two nodes in the network are measured by the Euclidean distance

$$w_{ij} = \left\| \vec{x}_i - \vec{x}_j \right\|. \quad (2)$$

After a pair-wise test of all the nodes, the time series weighted network (TSWN) is constructed and a symmetric distance matrix is obtained, which is represented by $W=(w_{ij})_M$ and is called as weight matrix. The node in phase space represents a state of the time series and the distance between two nodes measures the similarity of the two states. Two nodes having a smaller distance (much nearer in phase space) have bigger similarity.

C. Feature Extraction Method Based on the Time Series' Weighted Network

The weight matrix contains the information of the entire TSWN, thus the analysis of TSWN can be implemented by studying the weight matrix. The weight difference of the ith node ($wd(i)$) measures the sum of normalized weights difference among the ith node's weight set (WS_i) and is defined as

$$wd(i) = \sum_{j=1}^{M} \left(\frac{w_{ij}}{s(i)} \right)^2, \quad (3)$$

where the $s(i)$ represents the vector strength of the ith node and is defined as

$$s(i) = \sum_{j=1}^{M} w_{ij}. \quad (4)$$

According to the (3), with the increasing of the difference of weights in the WS_i, the value of $wd(i)$ increase. The $wd(i)$ gets the 1/M only when the weights in the WS_i have the same value. In this way, the value of $wd(i)$ measures the similarity degree of the weights in the WS_i, and the smaller the $wd(i)$, the more similar are the weights in the WS_i. Through the analysis of the weight differences of all the nodes in the TSWN, the complexity (irregular) of the overall TSWN can be obtained. Therefore, it can be used as a tool to distinguish the time series with different dynamics, which have different network structures.

In order to facilitate subsequent analysis, the weight difference values of the TSWN are arranged by an increasing order, represented by the symbol "wd_r",

$$wd_r = \text{rank}\{wd(i) \,|\, i \in [1, M]\}. \quad (5)$$

According the awareness that the dynamic structure of interictal EEG signal shows more complex than the ictal EEG dynamic structure [1], the sum of the top α smaller weight differences is extracted as feature and is defined as

$$wd_r^{\alpha} = \sum_{i=1}^{\alpha} wd_r(i), \quad (6)$$

where the α represents the number of nodes for feature extraction. The top nodes are taken into consideration because of smaller weight differences play an important role in the TSWN. Based on the extracted feature, the single feature automatic detection scheme can be established.

II. Result and Discussion

A. Performance Evaluation Parameters

The performance of the proposed algorithm is evaluated by computing parameters such as sensitivity, specificity, and overall accuracy, respectively defined as follows [6]: Specificity (*SPE*): number of true negative decisions/number of actually negative cases; Sensitivity (*SEN*): number of true positive decisions/number of actually positive cases; Overall accuracy (*ACC*): number of correct decisions/total number of cases. A true negative decision occurs when both the classifier and the physician suggested the absence of a positive detection. A true positive decision occurs when the positive detection of the classifier coincided with a positive detection of the physician.

B. Experiment Results and Discussion

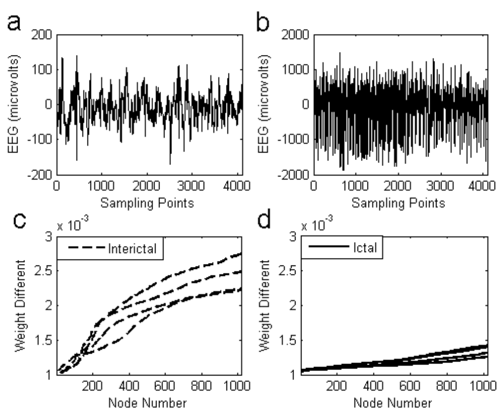

Fig. 1. Plots of epileptic EEG signals for (a) interictal, and (b) ictal. And the wd_rs of four subsegments of these two EEGs are respectively shown in (c) and (d).

In experimental section, the m and τ are selected as 8 and 1 for embedded process [18]. In performance evaluation process, the interictal EEG and the ictal EEG are regarded as the positive case and the negative case, respectively. All the data in two sets are divided into four equal-length non-overlapping sections (each section has 1024 points), which are regarded as four independent samples. The 400 interictal and 400 ictal samples constitute the test set.

The TSWNs of the 800 samples are constructed and also the corresponding wd_rs are obtained. Fig. 1 (c) and (d) show the four wd_rs of the one interictal EEG and four wd_rs of the one ictal EEG, which are drawn in Fig.1 (a) and (b), respectively. It can be clear found that wd_rs of ictal EEG are approximate horizontal curves, whereas the shapes of the interictal EEGs' wd_rs have an apparent increasing trend. That is to say, the ictal EEG TSWN has more small weight differences, whereas the interictal EEG TSWN has more large weight differences. That means that the interictal EEG TSWN is more complex than the ictal EEG TSWN. This confirms the conclusion that the time series dynamic under epileptic interictal period is more complex than epileptic ictal period [1]. After a one by one observation, the similar result is found. The observation result indicates that the different dynamics of the EEG signals under different brain conditions can be distinguished through different wd_rs shapes in TSWN domain. Therefore the wd_r^{210} (around one-fifth of the total number of nodes) can be extracted as the classification feature.

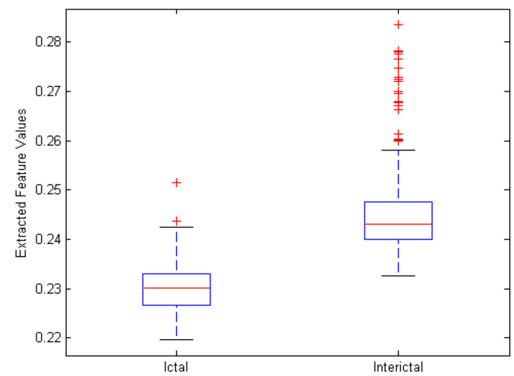

Fig. 2. The boxplots for wd_r^{210}s of the ictal EEGs and interictal EEGs.

Fig. 2 depicts the boxplots of wd_r^{210} values of two kind EEG signals. It can be found that the wd_r^{210}s of ictal EEG are mainly distributed in [0.2424, 0.2197], compared with the [0.2581, 0.2326] of interictal EEGs. The main body of the wd_r^{210} of ictal EEG is lower than the interictal EEG's.

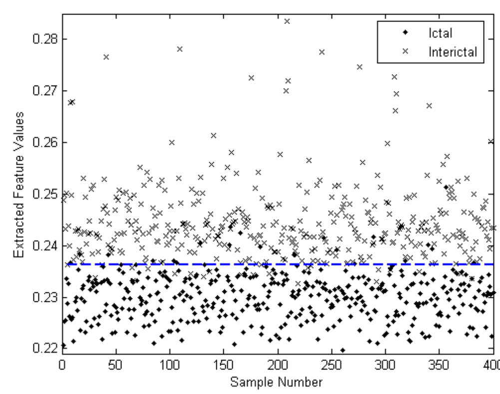

Fig. 3. Result of the single feature automatic detection scheme based on the extracted feature, where 'x' is for the feature values of the samples in interictal set and '•' is for the feature values of the samples

The distribution of total wd_r^{210}s is shown in the Fig. 3, where each 'x' represents the wd_r^{210} of one interictal sample and each '•' represents the wd_r^{210} of one ictal sample. It can be found that the wd_r^{210}s of ictal samples are smaller than the interictal samples except several special samples. Only 20 ictal samples and 22 interictal samples are put into wrong cases when the samples are classified by the dashed line (0.2363). The classification accuracy is 94.75%. In order to compare the classification performance of the extracted feature, the approximate entropy and sample entropy, listed in Table I, are also used as extracted feature to classify the same test set. It can be seen from Table I, the wd_r^{210} shows the best performance not only in classification *SEN* and *SPE*, but also in *ACC*.

The correlation between the accuracy of the extracted feature and the parameter α are summarized in Table Ⅱ. The recognition accuracies of the feature first increase with the increase of the parameter α, and then decrease after they reached the peak accuracy value (94.75%, when α=210).

TABLE I. RESULT OF THE SINGLE FEATURE AUTOMATIC DETECTION ALGORITHM BASED ON THE EXTRACTED FEATURE

Feature	*SEN* (%)	*SPE* (%)	*ACC* (%)
Approximate Entropy	83.00	91.50	87.25
Sample Entropy	91.50	84.00	87.75
wd_r^{210}	95.00	94.50	94.75

TABLE II. THE CORRELATIONS BETWEEN THE ACCURACYIES OF THE EXTRACTED FEATURE AND THE PARAMETER.

α	100	210	300	400	500
ACC (%)	87.25	94.75	92.87	90.50	87.88
α	600	700	800	900	1000
ACC (%)	82.25	77.12	71.75	66.75	62.87

Table Ⅲ lists the accuracies of several established epilepsy automatic detection algorithms, which are combined with the classifier and are applied to the same epilepsy dataset. Here, the DFA-α is the scaling exponent of the detrended fluctuation analysis of epileptic EEG. The results of approximate entropy + SVM and sample entropy + SVM are obtained based on the results listed in Table I. Table Ⅲ shows that the single feature classification algorithm based on the extracted feature proposed in this study has the highest classification accuracy compared with other classification algorithms combined with classifier. To some extent the result shows that the feature, wd_r^{210}, extracts more essential information than other features listed in Table Ⅲ, which makes wd_r^{210} fit the main purpose of the feature extraction method.

TABLE III. CLASSIFICATION ACCURACIES OF SEVERAL DETECTION ALGORITHMS

Feature	*ACC* (%)
DFA-α + SVM[10]	82.00
Hurst + SVM[11]	87.25
Approximate Entropy + SVM	89.00
Sample Entropy + SVM	91.00
Proposed approach in the present paper	94.75

III. CONCLUSION

This paper develops a novel feature extraction method for epileptic EEG which can be used for classifying the interictal and the ictal EEG subjects. The proposed algorithm firstly mapped the EEG signal into the phase space according to time delay embedding theory and the TSWN is constructed based on the embedded attractor. Then the weight differences of all the nodes in the TSWN are analyzed and the sum of top quintile wd_rs is defined and extracted as the classification feature. Finally, the extracted feature is applied into the single feature classification for epileptic EEG. Experimental results show that the extracted feature can clearly describe the essential difference between the two kind signals and obtains the higher classification accuracy about 94.75%. Taking into account the advantage, the proposed extracted feature in the present paper shows the great potential for real-time detection of epileptic seizure.

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