Automated Epilepsy Diagnosis Using Interictal Scalp EEG

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Abstract—**Over 50 million people worldwide suffer from epilepsy. Traditional diagnosis of epilepsy relies on tedious visual screening by highly trained clinicians from lengthy EEG recording that contains the presence of seizure (ictal) activities. Nowadays, there are many automatic systems that can recognize seizure-related EEG signals to help the diagnosis. However, it is very costly and inconvenient to obtain long-term EEG data with seizure activities, especially in areas short of medical resources. We demonstrate in this paper that we can use the interictal scalp EEG data, which is much easier to collect than the ictal data, to automatically diagnose whether a person is epileptic. In our automated EEG recognition system, we extract three classes of features from the EEG data and build Probabilistic Neural Networks (PNNs) fed with these features. We optimize the feature extraction parameters and combine these PNNs through a voting mechanism. As a result, our system achieves an impressive 94.07% accuracy.**

Index Terms—**Epilepsy, Electroencephalogram (EEG), Probabilistic Neural Network (PNN), seizure.**

I. INTRODUCTION

EPILEPSY is the second most common neurological disorder, affecting 1% of world population [1]. Eighty-five percent of patients with epilepsy live in the developing countries [2]. In some areas of the world, patients with seizures routinely experience discrimination in their schools, work places and communities [3]. Electroencephalogram (EEG) is routinely used clinically to diagnose epilepsy [4]. Long-term video-EEG monitoring can provide 90% positive diagnostic information [5] and has become the golden standard in epilepsy diagnosis. For the purpose of this research, we define the term "the diagnosis of epilepsy" as the determination of whether a person is epileptic or non-epileptic [6], i.e., whether the patient's epilepsy is the result of an abnormal electrical discharge that corresponds to the clinical behavior that is observed on the synchronized video record.

Traditional diagnostic methods rely on experts to visually inspect lengthy EEG recordings, which is time consuming and problematic due to the lack of clear differences in EEG activity between epileptic and non-epileptic seizures [7], particularly in seizures of electrical onset in the frontal region, where the electrical charges in the brain may be minimal or invisible on the EEG recorded from the scalp surface, leading to misdiagnosis or to the seizures being considered non-epileptic. Many automated seizure recognition techniques, therefore, have emerged [7]–[18]. The approach of using automatic seizure recognition/detection algorithms would still require the recording of clinical seizures. Therefore, very long continuous EEG recordings, preferably with synchronized video for several days or weeks, are needed to capture the seizures. The long-term EEG recordings can greatly disturb patients' daily lives. Another clinical concern is that unfortunately, 50-75% of epilepsy patients in the world reside in areas where medical resources and trained clinicians are seriously lacking to make such a process possible [2]. Consequently, an automated EEG epilepsy diagnostic system would be very valuable if it does not require data containing seizure activities (i.e., ictal). However, to the authors' best knowledge, we are not aware of any report on automated epilepsy diagnostic system using only interictal *scalp EEG* data.

Previous research has attempted to create automated epilepsy diagnostic systems using interictal EEG data [14], [19]. However, in those trials, only *intracranial* EEG data from patients are used, and the EEG artifacts have been carefully removed manually. It is very expensive to obtain intracranial EEG recordings that are relatively artifact free for every epilepsy patient, which is especially impractical in poor and rural areas. Therefore, we have built an automated epilepsy diagnostic system with very good accuracy that can work with scalp EEG data containing noise and artifacts.

Artificial Neural Networks (ANNs) have been used for seizure-related EEG recognition [11]–[16]. We use in this work one kind of ANN as the classifier, namely the Probabilistic Neural Network (PNN), for its high speed, high accuracy and real-time property in updating network structure [20]. It is very difficult to directly use raw EEG data as the input of an ANN [21]. Therefore, the key is to parameterize the EEG data into features prior to the input into the ANN. We use features that are used in previous studies on seizure-related EEG, namely, the power spectral feature, fractal dimensions and Hjorth parameters. A simple classifier voting scheme [22] and parameter optimization are used to improve the accuracy. The system diagram of our approach is as shown in Fig. 1.

Our system on distinguishing interictal scalp EEG of

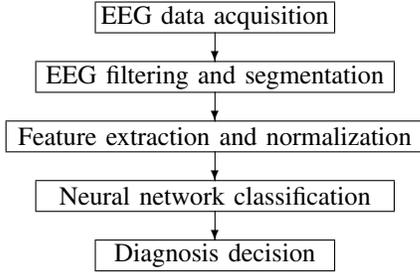Corresponding author's email: forrest.bao @ gmail.com

Fig. 1. Flow diagram of our EEG classification scheme

epileptic patients vs. the scalp EEG of healthy people has a best accuracty rate of 94.07%.

II. DATA ACQUISITION

We compose a data set[1] based on 22-channel routine scalp EEG recordings from Dept. of Neurosurgery, Jiangsu Provincial Hospital of Chinese Medicine, China. The data is from 6 normal people and 6 epileptic patients (in interictal period). Our interictal EEG data is not obtained from continuous 24hr scalp-EEG recordings, but from routine EEG recordings from patients and normal people. Even though the patient number is limited in this study, our EEG data size includes 5 days of data, so the results achieved in this work should be statistically significant. It is recorded at 200Hz sampling rate, using the standard international 10-20 system with referential montage. Similar to another research [14], EEG recordings are cut into segments of 4096 (i.e., 2^{12}). Our complete data set has 22,353 segments per channel, and 491,766 segments in total. The scalp EEG data contains noise and artifacts, which was *not* removed before performing our analysis. Please note that because the drug effects, ages and prior medical histories of patients, etc. may heavily affect the EEG of the epilepsy patients and normal people, and that our sample size under study is quite small, it remains to be seen if our impressive diagnosis results reported here can be extrapolated to a large sample size of patients in the future.

III. FEATURE EXTRACTION

Three classes of features are extracted to characterize the EEG signal: Power Spectral Features, describing its energy distribution in the frequency domain; Fractal Dimensions outlining its fractal property; and Hjorth Parameters, modeling its chaotic behavior.

A. Power Spectral Features

As one can see from Fig. 2, power spectrum is a good way to distinguish different kinds of EEG.

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[1]Human subject data used in this research has been approved and are already exempt by Protection of Human Subjects Committee IRB committee of Texas Tech University under "501209 Diagnosis, Monitoring, Seizures Prediction and Intervention for Epilepsy Patients Using an Intelligent Scalp-EEG Signal Analysis System."

To a time series $x_1, x_2, \cdots, x_N$, its Fast Fourier Transform (FFT) $X_1, X_2, \cdots, X_N$ is estimated as

$$X_k = \sum_1^N x_n W_N^{kn}, \quad k = 1, 2, \cdots, N,$$

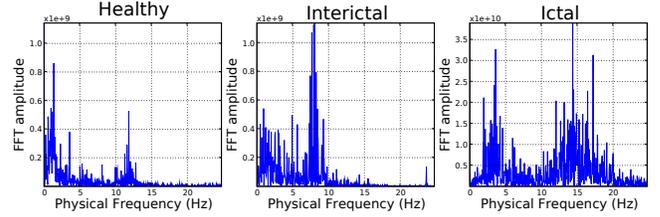where $W_N^{kn} = e^{\frac{-j2\pi kn}{N}}$, and N is the series length.

Fig. 2. Typical FFT results of 3 EEG segments (Raw data in μV)

Based on the FFT result, Power Spectral Intensity (PSI) of each f_{step} Hz bin in a given band f_{low}-f_{up} Hz is evaluated as

$$PSI_k = \sum_{i=\lfloor N\frac{f_{min}}{f_s}\rfloor}^{\lfloor N\frac{f_{max}}{f_s}\rfloor} X_i, \quad k = 1, 2, \cdots, K, \quad (1)$$

where $f_{min} = 2k$, $f_{max} = 2k+2$, $K = (f_{up} - f_{low})/f_{step}$, f_s is the sampling rate, and N is the series length. f_{min} and f_{max} are the lower and upper boundaries of each bin, respectively.

We use Relative Intensity Ratio (RIR) as the Power Spectral Features. It is defined as

$$RIR_j = \frac{PSI_j}{\sum_{k=1}^K PSI_k}, \quad j = 1, 2, \cdots, (f_{up} - f_{low})/f_{step}.$$

B. Petrosian Fractal Dimension (PFD)

PFD is defined as:

$$PFD = \frac{\log_{10} N}{\log_{10} N + \log_{10}(\frac{N}{n+0.4N_\delta})},$$

where N is the series length, and N_δ is the number of sign changes in the signal derivative [23].

C. Higuchi Fractal Dimension (HFD)

Higuchi's algorithm [24] constructs k new series from the original series $x_1, x_2, \cdots, x_N$ by

$$x_m, x_{m+k}, x_{m+2k}, \cdots, x_{m+\lfloor \frac{N-m}{k}\rfloor k}, \quad (2)$$

where $m = 1, 2, \cdots, k$.

For each time series constructed from Eq. (2), the length $L(m,k)$ is computed by

$$L(m,k) = \frac{\sum_{i=2}^{\lfloor \frac{N-m}{k}\rfloor} |x_{m+ik} - x_{m+(i-1)k}|(N-1)}{\lfloor \frac{N-m}{k}\rfloor k}.$$

The average length $L(k)$ is computed as

$$L(k) = \frac{\sum_{i=1}^k L(i,k)}{k}.$$

This procedure repeats k_{max} times for each k from 1 to k_{max}, and then uses a least-square method to determine the slope of the line that best fits the curve of $\ln(L(k))$ versus $\ln(1/k)$. The slope is the Higuchi Fractal Dimension. In this paper, $k_{max} = 5$.

D. Hjorth Parameters

To a time series $x_1, x_2, \cdots, x_N$, the Hjorth mobility and complexity [25] are respectively defined as $\sqrt{\frac{M2}{TP}}$ and $\sqrt{\frac{M4 \cdot TP}{M2 \cdot M2}}$, where $TP = \sum x_i/N$, $M2 = \sum d_i/N$, $M4 = \sum(d_i - d_{i-1})^2/N$, and $d_i = x_i - x_{i-1}$.

IV. Probabilistic Neural Network

In machine learning, a classifier is essentially a mapping from the feature space to the class space. An Artificial Neural Network (ANN) implements such a mapping by using a group of interconnected artificial neurons simulating the human brain. An ANN can be trained to achieve expected classification results against the input and output information stream, so there may not be a need to provide a specified classification algorithm.

PNN is a kind of distance-based ANN that uses a bell-shape activation function. Compared with traditional back-propagation (BP) neural network, PNN is considered more suitable to medical application since it uses Bayesian strategy, a process familiar to medical decision makers [26]. Decision boundaries of PNN can be modified in real-time as new data becomes available [20]. There is no need to train the network over the entire data set again, so we use PNN to enable quick updates of our network as more patients' data becomes available.
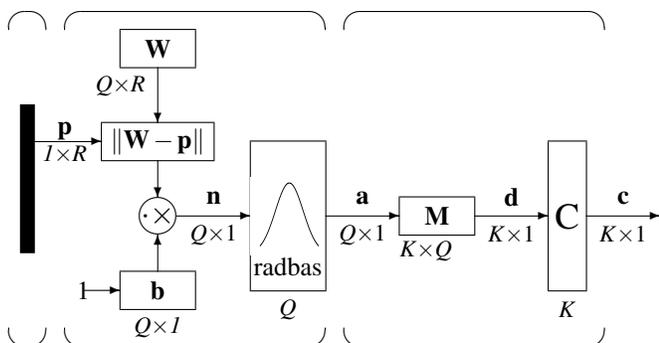

Fig. 3. PNN structure, R: number of features, Q: number of training samples, K: number of classes. The three layers are input layer, radial basis layer and competitive layer respectively from left to right.

Our PNN has three layers: the Input Layer, the Radial Basis Layer which evaluates distances between the input vector and rows in the weight matrix, and the Competitive Layer which determines the classification with maximum probability of correctness. The network structure is illustrated in Fig. 3 and described in greater details below. Dimensions of matrices are marked under their names.

A. Input Layer

The input vector, denoted as $\mathbf{p}$, is presented as a black vertical bar in Fig. 3.

B. Radial Basis Layer

In the Radial Basis Layer, the vector distances between input vector $\mathbf{p}$ and the weight vector, made up of each row of the weight matrix $\mathbf{W}$ are calculated. Here, the vector distance is defined as the dot product between two vectors [20]. The dot product between $\mathbf{p}$ and the i-th row of $\mathbf{W}$ produces the i-th element of the distance vector matrix, denoted as $||\mathbf{W} - \mathbf{p}||$. The bias vector $\mathbf{b}$ is then combined with $||\mathbf{W} - \mathbf{p}||$ by an element-by-element multiplication, represented as "$\cdot \times$" in Fig. 3. The result is denoted as $\mathbf{n} = ||\mathbf{W} - \mathbf{p}|| \cdot \times \mathbf{b}$.

The transfer function in PNN has built into a distance criterion with respect to a center. In this paper, we define it as $\text{radbas}(n) = e^{-n^2}$. Each element of $\mathbf{n}$ is substituted into the transfer function and produces corresponding element of $\mathbf{a}$, the output vector of Radial Basis Layer. We can represent the i-th element of $\mathbf{a}$ as $\mathbf{a}_i = \text{radbas}(||\mathbf{W}_i - \mathbf{p}|| \cdot \times \mathbf{b}_i)$, where $\mathbf{W}_i$ is the i-th row of $\mathbf{W}$, and $\mathbf{b}_i$ is the i-th element of bias vector $\mathbf{b}$.

1) Radial Basis Layer Weights: Each row of $\mathbf{W}$ is the feature vector of one trainging sample. The number of rows is equal to the number of training samples.

2) Radial Basis Layer Biases: All biases in the radial basis layer are set to $\sqrt{\ln 0.5}/s$, resulting in radial basis functions that cross 0.5 at weighted inputs of $\pm s$, where s is the spread constant of PNN. According to our experience, $s = 0.1$ can typically result in the highest accuracy.

C. Competitive Layer

There is no bias in the Competitive Layer. In this layer, the vector $\mathbf{a}$ is first multiplied by the layer weight matrix $\mathbf{M}$, producing an output vector $\mathbf{d}$. The competitive function $\mathbf{C}$ produces a 1 corresponding to the largest element of $\mathbf{d}$, and 0's elsewhere. The index of the 1 is the class of the EEG segment. $\mathbf{M}$ is set to a $K \times Q$ matrix of Q target class vectors. If the i-th sample in the training set is of class j, then we have a 1 on the j-th row of the i-th column of $\mathbf{M}$.

V. Combining Classifiers Using Voting

A simple voting scheme [22] is used to improve the classification accuracy in this paper. We implement this scheme by first building one component classifier for each channel and then combining them as follows. Given 22 segments collected at the same time (from different channels), each of them will be classified by the component classifier for the same channel. The component classifier of each channel will judge whether the given EEG segment is epileptic. The final classification decision will be based on the collective vote of each component classifier combined. The voting rule we use here is the majority rule; i.e., if 11 or more classifiers vote epileptic, then our final system voting result will be epileptic. Fig. 4 shows how our combined classifier works.

VI. Experimental Results

In the experiments, we use the MATLAB^TM Neural Network Toolbox to implement our PNN. The data used in
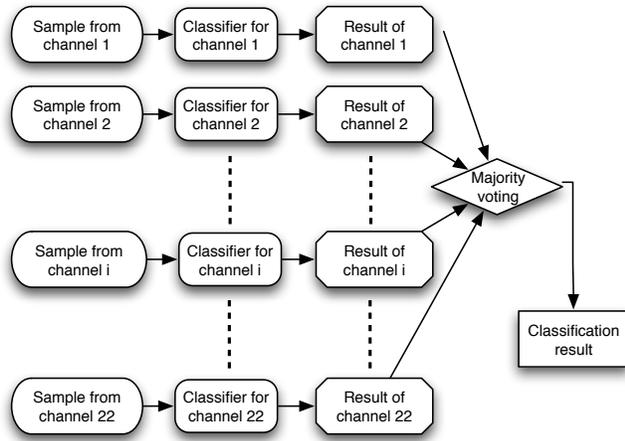
Fig. 4.   Classification Voting Scheme

ch.	RIRs, FDs & Hjorth's	FDs & Hjorth's	FDs	RIRs	Hjorth's	RIRs & FDs	RIRs & Hjorth's
Fp1	76	63	58	72	63	75	73
Fp2	78	62	58	73	54	77	74
F3	75	61	56	71	59	73	73
F4	80	64	59	76	62	79	77
C3	81	67	62	77	58	80	78
C4	77	63	58	73	59	76	74
P3	76	62	55	73	57	75	74
P4	81	64	60	77	59	80	78
O1	79	62	55	76	58	78	76
O2	81	61	56	75	56	78	79
F7	80	66	57	76	63	79	78
F8	85	70	57	81	61	82	84
T3	81	67	66	76	59	78	79
T4	81	62	60	78	53	80	79
T5	79	67	59	72	59	75	77
T6	78	67	57	70	62	74	75
A1	80	66	58	72	61	77	77
A2	80	61	56	72	60	76	75
Fz	81	65	59	78	54	80	79
Pz	79	65	57	73	56	77	75
Cz	81	66	62	77	56	80	78
Oz	82	61	59	77	54	80	79

Parameters	Values
segment length	4096 or 8192 samples
cut-off frequency of filters	40, 46, 56 or 66 Hz
spectral band and bin	band: 2-32 Hz, bin:1 Hz band: 2-34 Hz, bin: 2 Hz band: 2-34.5 Hz, bin: 2.5 Hz

the experiments is labeled as interictal (positive) or healthy (negative). The interictal data set has the same size as the healthy one. The testing method for our PNN is the Leave-One-Out Cross-Validation (LOOCV) [22], where exactly one sample is used as the test sample, while remaining samples are used as training samples. This process repeats until every sample has been used as a test sample exactly once.

As expected, different parameters used in feature extraction can lead to different classifier performances. The experimental results below use default feature extraction parameters in Sec. VI-A and optimized parameters in Sec. VI-B.

A. Classification using default feature extraction parameters

The features are extracted using the default parameters described in Sec. II. We have carried out experiments to find the best features to use for classification. We use all possible combinations of these features to build the PNN classifier: RIRs, Fractal Dimension (FDs) and Hjorth parameters (Hjorth's). The performance of each PNN with a specific combination of features is tested using LOOCV against each channel. The results are listed in Table I, where each entry is the accuracy of LOOCV of the PNN with the features for that column against the data set of the channel corresponding to that row.

From Table I, it is clear that the first feature combination (i.e., using all features) yields the highest accuracy, and thus we decide to use all extracted features in later experiments to build our classifiers.

The accuracy of our combined classifier increases to 84.27% while the true and false positive rates increase to 85.36% and 83.18% respectively. Thus, the sensitivity and specificity are 83.33% and 84.69%, respectively.

B. Optimizing feature extraction parameters

In Sec. II and Sec. III, there are some parameters that can be changed: the segment length of the EEG signal, the cut-off frequency of filters, and the bin(f_{step}) and band (f_{low} and f_{up}) in Eq. (1). A combination of those parameters is called a *configuration*. In this subsection, we will show that such configuration is important to the classification. Optimized configuration can lead to better accuracy. Different feature extraction parameters used in this paper are listed in Table II.

Table III shows the accuracies of combined PNN-based classifier in different configurations. The cut-off frequencies of 56 and 66 Hz are not tested for segment length 4096, because we find longer segmentation can give higher accuracy. An interesting finding is that after the filter cut-off frequency reaches above 46 Hz, the accuracy of our combined PNN classifier does not significantly increase. One possible explanation is that many spikes may exist in interictal EEG and most spikes reside in a frequency range of 15 to 50 Hz. Increasing the filter cut-off frequency above 50Hz may also introduce line noise from power supply or other sources, which will not benefit EEG signal quality [27]. Table V shows the highest accuracy is 94.07%.

VII. CONCLUSIONS

In this paper, an automated and robust interictal scalp EEG recognition system for epilepsy diagnosis using only interictal data is developed and validated. Three classes of features are extracted, and a PNN is employed to make a classification using those features. To improve the accuracy,

TABLE III
ACCURACY OF VOTED CLASSIFIER (PNN) IN DIFFERENT
CONFIGURATIONS

Length	cut-off freq.	band and bin (f_{low}-f_{up}, f_{step})		
		2-32, 1	2-34, 2	2-34.5, 2.5
4096	40	86.41	84.27	83.41
	46	91.77	89.81	89.23
8192	40	90.19	87.80	86.86
	46	93.73	91.93	91.92
	56	*94.07*	92.14	91.37
	66	93.78	91.96	91.13

we optimize the feature extraction parameters and design a final classifier that combines several PNN-based classifiers. Our system can reach an accuracy of 94.07%. Compared with the existing approaches on epilepsy diagnosis, our approach does not require the occurrence of seizure activity during EEG recording. This merit reduces the difficulties in EEG collection since interictal data is much easier to collect than ictal data. Therefore, our epilepsy diagnosis system can be very helpful for areas where medical resources are limited.

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