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Implementation of Probabilistic Neural Network using Approximate Entropy to Detect Epileptic Seizures

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Abstract - Epileptic seizures detection is largely based on analysis of Electroencephalogram signals. The ambulatory EEG recordings generate very lengthy data which require a skilled and careful analysis. This tedious procedure necessitates the use of automated systems for epileptic seizure detection. This paper proposes one such automated epileptic seizure detection technique based on Probabilistic Neural Network (PNN) by using a time frequency domain characteristics of EEG signal called Approximate Entropy (ApEn). Our method consists of EEG data collection, feature extraction and classification. EEG data from normal and epileptic subjects was collected, digitized and then fed into the PNN. For feature extraction, the wavelet coefficients are derived using Discrete Wavelet Transformation. For the feature selection stage a new methodology is proposed, which is, comparing the ApEn values of wavelet coefficients of different EEG data. The experimental results portray that this proposed approach efficiently detects the presence of epileptic seizures in EEG signals and showed a reasonable accuracy.

Keywords - *Electroencephalogram, Epilepsy, Approximate Entropy, Epileptic Seizure, Probabilistic Neural Network, Discrete Wavelet Transformation.*

I. INTRODUCTION

Epilepsy is a disorder of the brain characterized by an enduring predisposition to generate unprovoked, recurring epileptic seizures that disturb the nervous system¹. Seizures or convulsions are temporary alterations in brain functions due to abnormal electrical activity of a group of brain cells that present with apparent clinical symptoms and findings. Epilepsy may be caused by a number of unrelated conditions, including damage resulting from high fever, stroke, toxicity, or electrolyte imbalances. Nearly 1% of world's total population experience at least one seizure in its life time². Unfortunately, the occurrence of an epileptic seizure is not predictable and its process is not completely understood yet. Electroencephalogram (EEG) as a representative signal of the electrical activity of the nerve cells, has been the most utilized signal to clinically assess brain activities, and the detection of epileptic discharges. However the detection of epilepsy, which includes visual scanning of EEG recordings for seizures, is very time consuming especially in the case of long recordings. Automated diagnostic systems for epilepsy have been developed using different approaches. Earlier methods of automatic seizure detection using EEG were based on Fourier

transformation which detects some characteristic waveforms that fall primarily within four frequency bands. Though useful for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Other methods like parametric method for power spectrum estimation, reduces the spectral loss problems and gives better frequency resolution. Being non stationary signals, the parametric methods are not suitable for frequency decomposition of EEG. The discrete wavelet transform is a powerful method proposed in the late 1980s to perform time-scale analysis of non-stationary signals and well suited to locate transient events like epileptic seizures².

Several workers have proposed Artificial neural network (ANN) based detection systems for epileptic diagnosis. Amplitude of EEG, Average duration, average power spectrum, dominant frequency, spike amplitude and spike rhythmicity are some of the previously described inputs to an adaptive structural neural network³⁻⁷. The method proposed by N. Pradhan *et al.*, uses a raw EEG signal as an input to a learning vector quantization (LVQ) network⁸. This paper discusses an automated epileptic EEG detection system using probabilistic neural networks (PNN), and a time-domain feature of the EEG signal called approximate

entropy (ApEn) that reflects the nonlinear dynamics of the brain activity. ApEn drops abruptly due to the synchronous discharge of large groups of neurons during an epileptic activity. So, it is a suitable feature for using it in the implementation of automated detection of epilepsy⁹⁻¹⁰. ApEn is a statistical parameter to quantify the randomness of a time series data of physiological signals. The entropy estimators are broadly classified into two categories -spectral entropies and embedding entropies. The spectral entropies use the amplitude components of the power spectrum of the signal as the probabilities in entropy calculations. It quantifies the spectral complexity of the time series. The embedding entropies use the time series directly to estimate the entropy. Approximate Entropy is a kind of embedding entropies.

In this paper, approximate entropy based epileptic detection system of wavelet transformation proposed by Muthanantha et al is used with modified approach¹¹. The methodology is applied to two different groups of EEG signals and its 5 constituent EEG sub bands. The approximate entropy of the wavelet coefficient are used to represent the time frequency distribution of the EEG signals in each sub band and PNN is used to detect epileptic EEG signals.

II. METHODOLOGY

Fig. 1 shows the flow diagram of the proposed neural network based automated epileptic detection system.

Fig. 1 : Data flow diagram of the proposed system

As shown in Figure 1 the epileptic seizure detection system consists of three main modules: a feature

extractor that generates a wavelet based feature from the EEG signals, feature selection that composes composite features, and a feature classifier (PNN) that outputs the class based on the composite features.

A. EEG data acquisition:

Two sets of EEG data corresponding to the healthy and epileptic subjects collected at NIMHANS, Bangalore were used as the experimental data set for the study. The signals were analyzed in three groups: group H (healthy subjects) and group GE generalized epilepsy and EE ECT epileptic subjects. Group H contains 50 single channel EEG segments and group GE, EE in total contains 50 single channel EEG segments of 8sec duration each sampled at 128Hz. As such, each data segment contains $N=1024$ data points collected with 25 channels. Each EEG signal is considered as a separate EEG signal resulting in a total of 100 EEG signals. These data were loaded and saved in the working directory for the testing and training of PNN. The EEG data were collected using the standard electrode placement technique from the surface. Fig. 2 shows a representative signal of healthy subject and epileptic subject from each group.

Fig. 2 : Sample unfiltered EEGs Healthy H , ECT Epilepsy EE and generalized epilepsy GE (from top to bottom)

B. Wavelet transformation:

Wavelet transform (WT) forms a general mathematical tool for signal processing with many applications in EEG data analysis. Its basic use includes time-scale signal analysis, signal decomposition and signal compression. The multi scale feature of WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. Discrete wavelet transformation (DWT) employs two sets of functions called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. The

decomposition of the signal into the different frequency bands is simply obtained by successive high-pass and low pass filtering of the time domain signal. Therefore the signal can be reconstructed as a linear combination of the wavelet functions weighted by the wavelet coefficients. The key feature of wavelet is the time – frequency localization. It means that most of the energy of the wavelet is restricted to a finite time interval. The wavelet technique applied to the EEG signal will reveal feature related to the transient nature of the signal. The wavelet transformation analyses the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information¹². All wavelet transforms can be specified in terms of a low pass filter, which satisfies the standard quadrature mirror filter condition. The procedure of multi resolution decomposition of a signal $x(n)$ is schematically shown in the Figure 3. The down-sampled outputs of first high-pass and low-pass filters provide the detail, D1 and the approximation, A1, respectively. The first approximation, A1 is further decomposed and this process is continued till 5th level approximation d5 is achieved. The number of decomposition levels is chosen based on the dominant frequency component in the signal. In the present study, the number of decomposition levels was chosen to be 5 as the EEG signals having epileptic seizures are extracted and saved in graphical form in .dat file after sampling at 128 Hz.

The smoothing feature of Daubechies wavelet for order 4 (Db4) made it more appropriate to detect changes of EEG signal. Hence, the wavelet coefficients were computed using db4 in present study. The proposed method was applied on all data sets; (group H, GE and EE). The EEG sub bands of a5, d5, d4, d3, d2 and d1 are shown in Figure 4.

Fig. 3 : Scheme of five level wavelet decomposition

Fig. 4 : A multi resolution Wavelet Decomposition up to five levels

The detail at level j is defined at

$$D_j = \sum a_j \cdot k \cdot \Psi_j \cdot k(t)$$

And the approximation at level J is defined as

$$A_j = \sum D_j$$

It becomes obvious that

$$A_{j-1} = A_j + D_j$$

$$\text{and } f(t) = A_j + \sum_{j \leq J} D_j$$

C. Feature Extraction

The proposed system makes use of a single feature called ApEn for the epileptic detection. The ApEn is a wavelet domain feature that is capable of classifying complex systems. The value of the ApEn is determined as following^{11, 13-14}.

- 1) Let the data sequence containing N data points be $X = [x(1), x(2), x(3), \dots, x(N)]$.
- 2) Let $x(i)$ be a subsequence of X such that $x(i) = [x(i), x(i+1), x(i+2), \dots, x(i+m-1)]$ for $1 \leq i \leq N-m$, where m represents the number of samples used for the prediction.

- 3) Let r represent the noise filter level that is defined as: $r=k \times SD$ for $k = 0, 0.1, 0.2, 0.3, \dots, 0.9$ where SD is the standard deviation of the data sequence X .
- 4) Let $\{x(j)\}$ represent a set of subsequences obtained from $x(j)$ by varying j from 1 to N . Each sequence $x(j)$ in the set of $\{x(j)\}$ is compared with $x(i)$ and, in this process, two parameters, namely $C_i^m(r)$ and $C_{i+m+1}(r)$ are defined as follows:

$$C_i^m(r) = \frac{\sum_{j=1}^{N-m} k}{N-m}$$

$$\text{where } k = \begin{cases} 1, & \text{if } |x(i) - x(j)| \leq r \text{ for } 1 \leq j \leq N-m \\ 0, & \text{otherwise} \end{cases}$$

$$\text{and } C_{i+m+1}(r) = \frac{\sum_{j=1}^{N-m} k}{N-m}$$

- 5) We define $\Phi_m(r)$ and $\Phi_{m+1}(r)$ as follows:

$$\Phi_m(r) = \frac{\sum_{i=1}^{N-m} \ln(C_i^m(r))}{N-m}$$

$$\Phi_{m+1}(r) = \frac{\sum_{i=1}^{N-m} \ln(C_i^{m+1}(r))}{N-m}$$

The values of ApEn indicates the irregularity of the system as small values imply strong regularity and large values imply substantial fluctuations. In the proposed approach, ApEn is calculated for one approximation and for detailed information such as D4 and D5.

D. Feature Selection

For feature selection, we divided data into two different sets: the training set and the testing set.

In the training set we have 14 different EEG signals from channel 1 belonging to the general EEG signals and ECT EEG signals in which nZ1, nZ2, nZ3, nZ4, nZ5, nZ6, nZ7 are the normal EEG signals Z1, Z2 are generalized epileptic EEG signals and Z3, Z4, Z5, Z6, Z7 are ECT epileptic EEG signals. Now we decomposed the signal up to 5 levels and calculated the ApEn values of all the coefficients (A2, D4, D5). Hence, we get 42 ApEn values for the training set.

In the testing set there are 100 EEG signals of which there are 50 normal EEG signals, 20 generalized epileptic signals and 30 ECT epileptic signals for different odd channels. These signals were again decomposed up to 5 levels and hence the 300 ApEn values were calculated for the testing set. Table 1 shows

extracted feature (mean ApEn) for the subbands of training set.

Table 1 Feature extraction of sample data set

Set	Wavelet Sub bands	ApEn
GENERALISED EPILEPSY (GE)	A2	-0.0042
	D4	0.1430
	D5	0.31335
ECT EPILEPSY (EE)	A2	-0.0042
	D4	0.06838
	D5	0.32742
HEALTHY (H)	A2	-0.0042
	D4	0.1686714
	D5	0.3039429

E. Probabilistic Neural Network Classifier (PNN)

The classification of EEG signals into healthy and epileptic signals is done using the probabilistic neural network. The three layers of PNN are: 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 (Figure 5). Dimensions of matrices are marked under their names.

Fig. 5 : PNN Classifier

- 1) **Input layer** : The input vector, denoted as p , is presented as a black vertical bar in Figure 5. The input layer unit simply distributes the input to neurons in the pattern layer. On receiving a pattern x from input layer, the neuron x_{ij} of the pattern computes its output using the below formula

$$\phi_{ij}(x) = \frac{1}{(2\pi)^{0.5d} \sigma^d} \exp\left(-\frac{(x - x_{ij})^T (x - x_{ij})}{2\sigma^2}\right)$$

Where d denotes dimension of the pattern vector x , is the smoothing parameter and x_{ij} is the neuron vector.

2) **Radial Basis Layer** : In the Radial Basis Layer, the vector distances between input vector p and the weight vector, made up of each row of the weight matrix QXR are calculated. Here, the vector distance is defined as the dot product between p and the i^{th} row of W produces the i^{th} element of the distance vector matrix, denoted as $||\text{dist}||$. The bias vector b is then combined with $||\text{dist}||$ by an element-by-element multiplication, represented as “ $\cdot$ ” in Figure 5. The result is denoted as $n=||\text{dist}|| \cdot b$. 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 n is substituted into the transfer function and produces corresponding element of a , the output vector of Radial Basis Layer. We can represent the i^{th} element of a as $a_i = \text{radbas}((||\text{dist}|| \cdot b)_i)$. Where W_i is the i^{th} row of W , and b_i is the i^{th} element of bias vector b .

3) **Competitive Layer** : There is no bias in the Competitive Layer. In this layer, the vector a is first multiplied by the layer weight matrix M , producing an output vector d . The competitive function C produces a 1 corresponding to the largest element of d , and 0's elsewhere. The index of the 1 is the 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 M . The decision layer classifies the pattern x in accordance with Bayes decision rule based on the output of all summation layer neurons using

$$\hat{C}(x) = \arg \max \{p_i(x)\}, i=1,2,3,\dots,m$$

Where $\hat{C}$ denotes the estimated class of pattern x , and m is total number of classes in training samples. Hence, PNN employed in this work possesses 30 nodes in the input layer and 2 nodes in the output layer (the number of nodes in the output layer is the number of classifications of EEG signals). The performance of the PNN model was evaluated in terms of training performance and classification accuracies and the results confirmed that the proposed scheme has potential in classifying the EEG signals.

III. RESULTS AND DISCUSSION

ApEn values are computed for healthy, generalized epileptic and ECT epileptic signals and are fed as inputs to the two neural networks. This is achieved by using $m=3$, $r=3$ and $N=1024$ where m is no. of groups, r is similarity criterion between repetitive patterns of length m in total data points i.e. N . Among the available 100 EEG signals 21 are used for training and remaining are used for testing the performance the neural network. The potentiality of the ApEn to discriminate the two signals namely healthy, generalized epileptic and ECT epileptic EEG signals depends on the values of m , r and N . Table 2 shows the results of overall accuracy of this PNN

classifier system in detecting healthy, generalized and ECT epileptic EEG signals.

Table 2 Accuracy of PNN classifier in detecting EEG signals

Sl. N		Total	Correctly detected	Incorrectly Detected	Accuracy (in %)
1	Generalized epilepsy	20	18	2	90
2	ECT epilepsy	30	23	7	73
3	Healthy	50	34	16	68

As the table 2 shows, the designed PNN classifier has a very high accuracy of 90% in detection of generalized epilepsy whereas the accuracy for detecting healthy EEG signals was slightly lower (68%). Table shows that our wavelet based ApEn classifier has good potential in the characterization of the generalized epileptic patterns and ECT epilepsy. The results suggest that wavelet based system ApEn as the input feature is best suited for the real time detection of the epileptic seizures in less time and less computation burden. When the signals are fed to the PNN model, some are correctly detected, and some are incorrectly detected. The results of this study are based on data sets corresponding to seven different subjects only. By increasing the number of subjects the detection accuracy of the classifier may even be improved. The optimum ApEn parameter values obtained may not be useful for a generalized case where no. of subjects are large. This problem will not arise in the proposed PNN-based method as it has performed well irrespective of the ApEn parameter values used.

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