

Analysis of EEG signal for detection of Epilepsy Seizure

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Abstract: There are certain parts of our country where the patients are suffering from Epilepsy seizure. Artificial Neural Network (ANN) have been widely accepted tool for complex decision making problems. ANN has ability to take its own decision based on its train data. In this paper, ANN is used for this purpose the EEG signal Analysis of Epilepsy Seizure. The electroencephalogram (EEG) signal plays an important role in the diagnosis of epilepsy. Two different types of neural networks, namely, Elman and probabilistic neural networks, are considered in this paper. This paper proposes a neural-network-based automated epileptic EEG detection system that uses approximate entropy (ApEn) as the input feature. ApEn is a statistical parameter that measures the predictability of the current amplitude values of a physiological signal based on its previous amplitude values. During an epileptic seizure the value of the ApEn drops sharply during an and this fact is used in the proposed system

Keywords: Approximate entropy (ApEn), artificial neural network (ANN), electroencephalogram (EEG), Elman network (EN), epileptic seizure, probabilistic neural network (PNN), seizure.

I. Introduction

Approximately 1% of the people in the world suffer from epilepsy. As epilepsy is a condition related to the brain's electrical activity, the electroencephalogram (EEG) signal is used for the purpose of the epileptic detection. A common form of recording used for this purpose is an ambulatory recording that contains EEG data for a very long duration of even up to one week. It involves an expert's efforts in analyzing the entire length of the EEG recordings to detect traces of epilepsy [1]. Also clinical practice involves diagnosis of the patient condition from the information collected during the query session, physical examination and laboratory test data, and then suggesting the most appropriate therapy based on the collected data. Correctness of such practice mainly depends on the knowledge and the skill acquired by the clinician through many years of practice.

II. System Design

Electroencephalogram (EEG) is a record of the electric signal generated by the cooperative action of brain cells, or more precisely, the time course of extracellular field potentials generated by their synchronous action. The amplitude of EEG of a normal subject in the awake state recorded with the scalp electrodes is 10–100 Micro volts. In case of epilepsy, the EEG amplitudes may increase by almost an order of magnitude. The EEG recordings of patients suffering from epilepsy show two categories of abnormal activity: inter-ictal, abnormal signals recorded between epileptic seizures; and ictal, the activity recorded during an epileptic seizures shown in fig 2.1

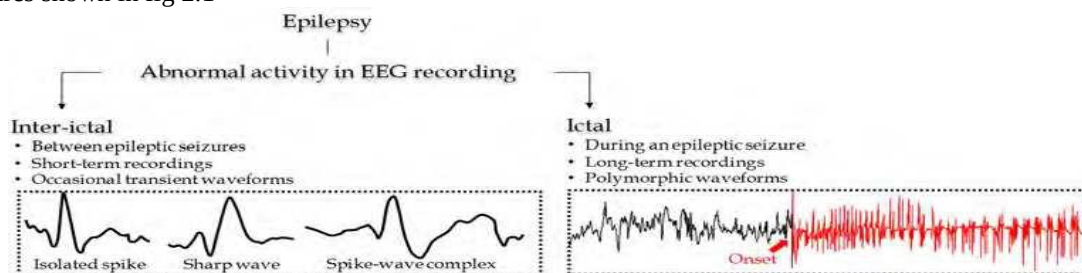


Figure 2.1: Epilepsy seizure abnormal activity

The EEG signature of an inter-ictal activity is occasional transient waveforms, as either isolated spikes, spike trains, sharp waves or spike-wave complexes. Given that ictal recordings (recording during an epileptic seizure) are rarely obtained, EEG analysis of patients suffering from epilepsy usually relies on inter-ictal findings[8]. The block diagram of the proposed neural network based automated epileptic detection system is shown in Fig.2.2



Figure 2.2: Block diagram of the proposed system.

A. EEG Data Acquisition

Two sets of EEG data corresponding to the normal and epileptic subjects are used as the experimental data set for the proposed neural network based detection system. Each data set contains 100 single-channel EEG segments, with a segment duration of 23s. These segments are selected and cut out from the continuous multichannel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. The first set of the EEG data corresponding to the normal subjects is taken from the surface EEG recordings of five healthy subjects. The second set of the EEG data consists of epileptic EEG signals obtained from five different epileptic patients, recorded during the occurrence of the epileptic seizures from intracranial electrodes[1].

The EEG signals are recorded with 128-channel amplifier system, using an average common reference. After a 12-bit analog-to-digital conversion, the data are written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz with bandpass filter settings at 0.53–40 Hz (12 dB/octave). Fig. 3.1.2(a) and (b) shows specimens of the normal and epileptic EEG signals, respectively[1].

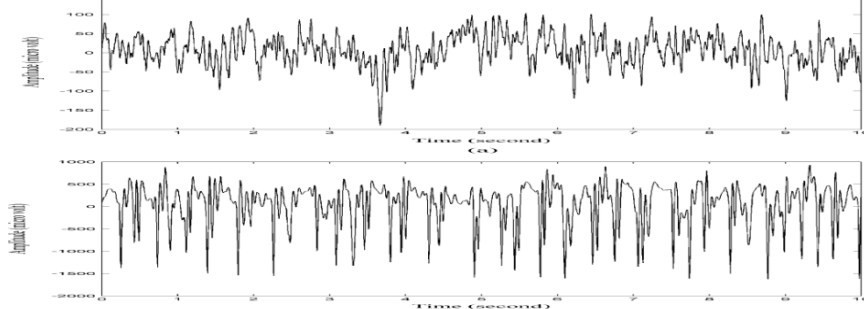


Figure 2.1.1: Specimens of the EEG signal. (a) Normal EEG. (b) Epileptic EEG

B. Wavelet Transformation

Wavelet transform (WT) forms a general mathematical tool for signal processing. 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 information [3]. The procedure of multi resolution decomposition of a signal $x(n)$ is schematically shown in the Figure 3.2.1.

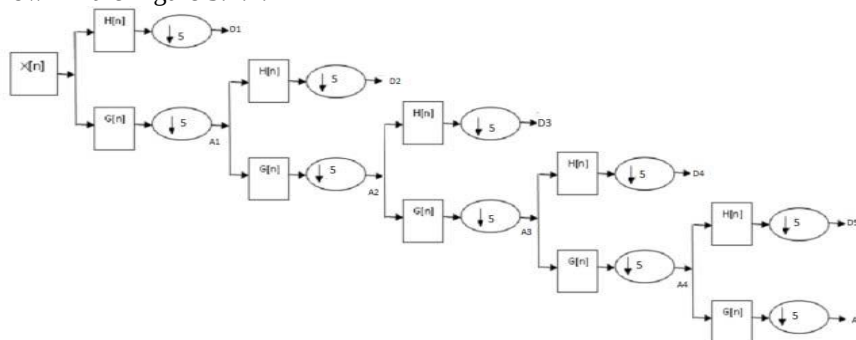


Figure 2.2.1: Scheme of five level wavelet decomposition.

C. Feature Extraction

The proposed system makes use of a single feature called ApEn for the epileptic detection. The ApEn is a time-domain feature that is capable of classifying complex systems. The value of the ApEn is determined as shown in the following steps:

- 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

$$x(i) = [x(i), x(i+1), x(i+2), \dots, x(i+m-1)] \text{ for } 1 \leq i \leq N-m,$$
 where m represents the number of samples used for the prediction.
- 3) Let r represent the noise filter level that is defined as $r = k \times \text{SD}$
 for $k = 0, 0.1, 0.2, 0.3, \dots, 0.9$ (1)
 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:

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

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

$$C_i^{m+1}(r) = \frac{\sum_{j=1}^{N-m} k_j}{N-m} \quad (2)$$

with conditions depicted by (A)

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

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

$$\Phi^m(r) = \frac{\sum_{i=1}^{N-m} \ln(C_i^m(r))}{N-m} \quad (3)$$

$$\Phi^{m+1}(r) = \frac{\sum_{i=1}^{N-m} \ln(C_i^{m+1}(r))}{N-m} \quad (4)$$

- 6) $\text{ApEn}(m, r, N)$ is calculated using $\Phi^m(r)$ and $\Phi^{m+1}(r)$ as follows:

$$\text{ApEn}(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \quad (5)$$

$$= \frac{\sum_{i=1}^{N-m} \ln(C_i^m(r))}{N-m} - \frac{\sum_{i=1}^{N-m} \ln(C_i^{m+1}(r))}{N-m} \quad (6)$$

$$= \frac{1}{N-m} [\sum_{i=1}^{N-m} \ln(C_i^m(r)) - \sum_{i=1}^{N-m} \ln(C_i^{m+1}(r))] \quad (7)$$

$$= \frac{1}{N-m} \left[\sum_{i=1}^{N-m} \ln \left(\frac{C_i^m(r)}{C_i^{m+1}(r)} \right) \right] \quad (8)$$

The flowchart for the calculation of $\text{ApEn}(m, r, N)$ is shown below. Small values of ApEn imply strong regularity in a data sequence and large values imply substantial fluctuations [1].

The ApEn graph of normal and epileptic patient is plot. The ApEn plot of epileptic patients had a common pattern. It has a slightly wide spike followed by abrupt drop in its value as shown in fig 2.3.1 The Neural network is trained to identify this pattern[2].

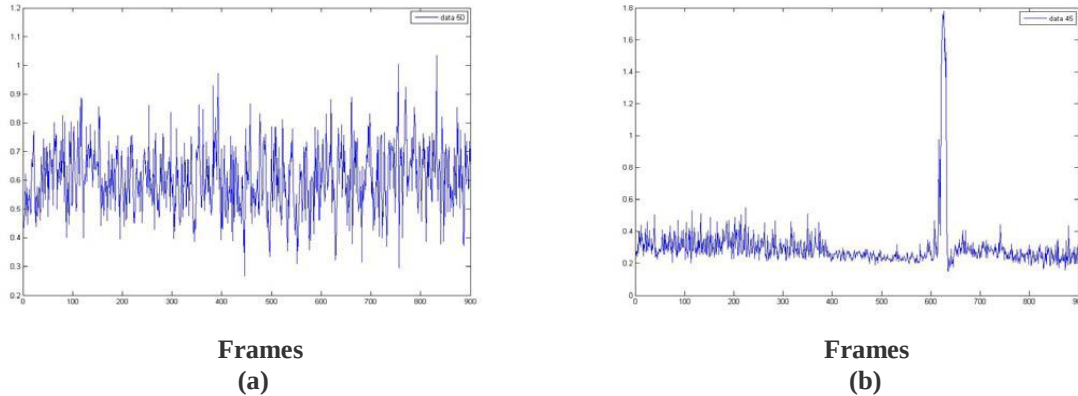


Figure 2.3.1: ApEn graph of (a) non epileptic, (b) epileptic patient

D. Neural Network Classifier

Two different types of ANNs, namely, EN and PNNs are employed in this paper for the detection of epilepsy. A brief description of the configuration, target, and threshold values used the two neural networks are given as follows[1].

D.1. Elman Network

It is a special type of recurrent neural network. It is a two-layered backpropagation network with a feedback connection from the output of the hidden layer to its input. This feedback connection allows EN to recognize and generate temporal patterns, as well as spatial patterns. Fig.3.4.1 illustrates the architecture of a recurrent neural network[1].

The ApEn values corresponding to the normal and epileptic EEG signals are used as the inputs for the neural network. For the two-layered EN, the activation functions used are tan-sigmoidal and log-sigmoidal for the hidden and output layers, respectively. Gradient descent algorithm with an adaptive learning rate is used for

training the EN. The network is trained with a target value of 0 for normal EEG and 1 for epileptic EEG. The range of the output values used for the classification are 0–0.3 for the normal EEG and 0.7–1 for the epileptic EEG[1]. The neural network training parameters are as shown in Table 3.4.1

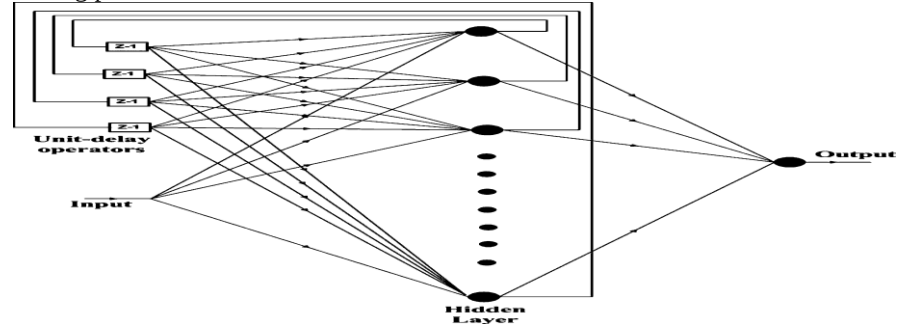


Figure 2.4.1.1: Architecture of a recurrent neural network.

D.2. Probabilistic Neural Network

It is a type of radial basis network. It is a feedforward neural network with two middle layers called radial basis and competitive layers. The two layers employ radial basis and compete activation functions, respectively. Fig. 3.4.2 shows the architecture of a PNN. The ApEn values corresponding to the normal and epileptic EEG signals are used as the input for the neural network. The network's target values correspond to a value of 1 for normal EEG and 2 for epileptic EEG[1].

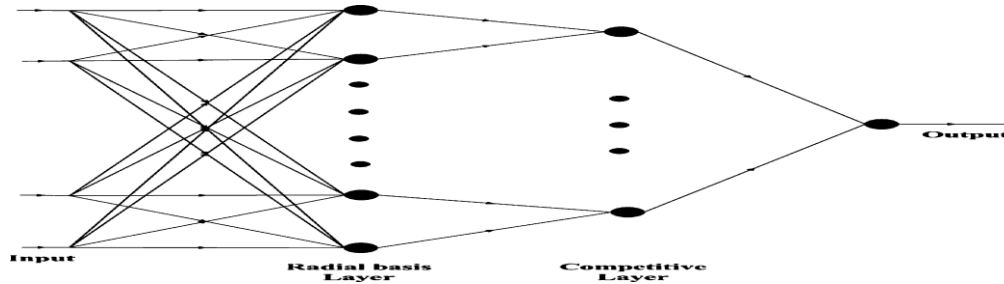


Figure 2.4.2.1: Architecture of a PNN.

An AI-based classifier is essentially a mapping $f: R^m \rightarrow Z^n$ from the feature space to the discrete class space. An Artificial Neural Network (ANN) implements such a mapping by using a group of interconnected artificial neurons simulating human brain. An ANN can be trained to achieve expected classification results against the input and output information stream, so there is not a need to provide a specified classification algorithm. The real-time property of PNN is also crucial to our research. In PNN, decision boundaries can be modified in real-time as new data become available. There is no need to train the network over the entire data set again. So we can quickly update our network as more and more patients' data becomes available. Our PNN has three layers: the Input Layer, the Radial Basis Layer which evaluates distances between input vector and rows in weight matrix, and the Competitive Layer which determines the class with maximum probability to be correct. The network structure is illustrated in Fig. 3.4.3, using symbols and notations in. Dimensions of arrays are marked under their names.

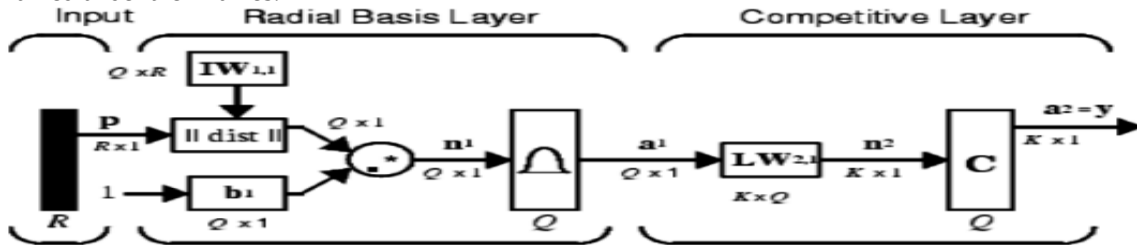


Figure 2.4.2.2: PNN Classifier

D.3. Radial Basis Layer:

In Radial Basis Layer, the vector distances between input vector p and the weight vector made of each row of weight matrix W are calculated. The bias vector b is then combined with $\|W - p\|$ by an element by- element multiplication, represented as “ $\cdot$ ” in Fig. 5. Here we define a function as $\text{radbas}(n) = e^{-n^2}$. Each element of n is substituted into (2) and produces corresponding element of a , the output vector of Radial Basis Layer. We can represent the i -th element of a as $a_i = \text{radbas}(\|W_i - p\| \cdot b_i)$ (3) where W_i is the i -th row of W and b_i is the i -th element of bias vector b [6].

1) Radial Basis Layer Weights: Each row of W is the feature vector of one training sample. The number of rows equals to the number of training samples.

2) Radial Basis Layer Biases: All biases in radial basis layer are set to $\frac{\sqrt{\ln 0.5}}{s}$ resulting in radial basis functions that cross 0.5 at weighted inputs of $\pm s$, where s is the spread constant of PNN. In this paper, s is set to 0.1[6].

D.4. Competitive layer:

There is no bias in Competitive Layer. In this layer, the vector a is first multiplied by 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. M is set to $K \times Q$ matrix of Q target class vectors. If the i -th sample in training set is of class j , then we have a 1 on the j -th row of i -th column of M [6].

E. Performance Evaluation Parameters

The performances of EN and PNN are evaluated by using three parameters, namely, sensitivity (SE), specificity (SP), and overall accuracy (OA), which are defined in eq(9), (10), and (11), respectively.

1) Sensitivity (SE) :

$$SE = \frac{TN_{CP}}{TN_{AP}} \quad (9)$$

where TN_{CP} represents the total number of correctly detected positive patterns and TN_{AP} represents the total number of actual positive patterns. A positive pattern indicates a detected seizure.

2) Specificity (SP) :

$$SP = \frac{TN_{CN}}{TN_{AN}} \quad (10)$$

where TN_{CN} represents the total number of correctly detected negative patterns and TN_{AN} represents the total number of actual negative patterns. A negative pattern indicates a detected nonseizure.

3) Overall accuracy (OA)

$$OA = \frac{TN_{CDP}}{TN_{APP}} \quad (11)$$

where TN_{CDP} represents the total number of correctly detected patterns and TN_{APP} represents the total number of applied patterns. A pattern indicates both seizure and nonseizure[1].

III. Conclusion

Neural Network and ApEn is used as an input feature for implementation of detection of epilepsy. Since, it is using a single input feature, it is having low computational burden and best suited for the real-time detection of epileptic seizures. Though the use of ANNs increases the computational complexity, the high overall detection accuracies expected from this system surpasses its disadvantage as in any automated seizure detection system, since the detection of the seizure with high accuracy is of primary importance. This is because it is known that ApEn possesses good characteristics such as robustness in the characterization of the epileptic patterns and low computational burden. Hence, an automated system using ApEn as the input feature is best suited for the real time detection of the epileptic seizures.

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