International Journal of Computer and Communication Technology

Volume 3 | Issue 4 Article 4

October 2012

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Recommended Citation

VOLLALA, SATYANARAYANA and GULLA, KARNAKAR (2012) "AUTOMATIC DETECTION OF EPILEPSY EEG USING NEURAL NETWORKS," *International Journal of Computer and Communication Technology*: Vol. 3 : Iss. 4 , Article 4.
DOI: 10.47893/IJCCT.2012.1149
Available at: https://www.interscience.in/ijcct/vol3/iss4/4

AUTOMATIC DETECTION OF EPILEPSY EEG USING NEURAL NETWORKS

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Abstract - The electroencephalogram (EEG) signal plays an important role in the diagnosis of epilepsy. The EEG recordings of the ambulatory recording systems generate very lengthy data and the detection of the epileptic activity requires a time-consuming analysis of the entire length of the EEG data by an expert. The traditional methods of analysis being tedious, many automated diagnostic systems for epilepsy has emerged in recent years.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. It is known that the value of the ApEn drops sharply during an epileptic seizure and this fact is used in the proposed system.Two different types of neural networks, namely, Elman and probabilistic neural networks are considered. ApEn is used for the first time in the proposed system for the detection of epilepsy using neural networks. It is shown that the overall accuracy values as high as 100% can be achieved by using the proposed system.

Keyword: *Approximate entropy (ApEn), artificial neural network (ANN), electroencephalogram (EEG), Elman network (EN), epilepsy, probabilistic neural network (PNN), seizure.*

I.INTRODUCTION

EPILEPSY is the second most common neurological disorder, affecting 1% of world population [2]. The electroencephalogram (EEG) signal is used for the purpose of the epileptic detection as it is a condition related to the brain's electrical activity [16]. Eighty five percent of patients with epilepsy live in the developing countries [3]. Electroencephalogram (EEG) is routinely used clinically to diagnose epilepsy [4]. Long-term video-EEG monitoring can provide 90% positive diagnostic information [5] and it 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]. In majority of the cases, the onset of the seizures cannot be predicted in a short period, a continuous recording of the EEG is required to detect epilepsy. The approach of using automatic seizure recognition/detection algorithms would still require the recording of clinical seizures. Therefore, very long continuous EEG recording, preferably with synchronized video for several days or weeks, are needed to capture the seizures.

II. RELATED WORK

In the previous systems, have done maximum process by manual. After that some of researchers introduced automated diagnostic systems for epilepsy have been developed using different approaches. Some of those Example approaches of existing systems and the year of proposed methods are as follows. In 1982, Gotman [14] presented a computerized system for detecting a variety of seizures. In 1991, Murro [15] *et al.* developed an automated seizure detection system based on the discriminant analysis of the EEG signal recorded from the intracranial electrodes. In 1997, Qu and Gotman [16] proposed the use of the nearest-neighbor classifier on EEG features extracted in both the time and frequency domains to detect the onset of the epileptic seizures. In 2004, Gigola *et al*[17] . Used a method based on the evolution of the accumulated energy using wavelet analysis for the prediction of the epileptic seizure onset from the intracranial epileptic EEG recordings.

Artificial Neural Network (ANN) has been used for seizure related EEG recognition. We used in this work one kind of ANN as the classifier, namely the Elmen Neural Network (ENN), for its high speed, high accuracy and real time property in updating network structure. It is very difficult to directly use raw EEG data as the input of an ANN. Therefore, the key is to parameterize the EEG data into features prior to the input into the ANN. A time-domain feature of the EEG signal called approximate entropy (ApEn) that reflects the nonlinear dynamics of the brain activity. Hence, it is a good feature to make use of in the automated detection of epilepsy. In this paper, this feature is applied, for the first time, in the automated detection of epilepsy using neural networks.

III. EXISTING SYSTEM

The method proposed by Pradhan *et al.* uses a raw EEG signal as an input to a learning vector quantization network. In 2004, Nigam and Graupe proposed a new neural network model called LAMSTAR network, and two time-domain attributes of EEG, namely, relative spike amplitude and spike rhythmicity have been used as inputs for the purpose of the detection of epilepsy. The method proposed by Kiymik *et al.* uses a back propagation neural network with periodogram and autoregressive features as the input for the automated detection of epilepsy. Several approaches have been developed elsewhere, with varying success, in attempts to automatically detect epileptic form activity and seizures in the EEG. In most of these, the tendency has been to look for extended amplitude and frequency changes rather than aiming to capture characteristic waveforms. Because of the widely varying morphology of seizures, we also chose to incorporate measures of extended amplitude and frequency changes, as central features in our multi-stage detection algorithm. Probabilistic neural network for epileptic detection is an existing automated system for epileptic EEG detection. In probabilistic neural network, AI-based classifier is used. An AI-based classifier is essentially a mapping from the feature space to the discrete class space.

IV. PROPOSED SYSTEM

The proposed system consists of following various modules which are also shown using a flowchart in Fig 1.

Two sets of EEG data [16] of normal and epileptic subjects from 18 subjects is used. 10 subjects normal and epileptic EEG data is used for training and remaining was used for testing. The depth electrodes are placed symmetrically into the hippocampal formations and strip electrodes are placed onto the lateral and basal regions of the neocortex. The epileptic EEG segments are selected from all the recording sites exhibiting ictal activity [34].

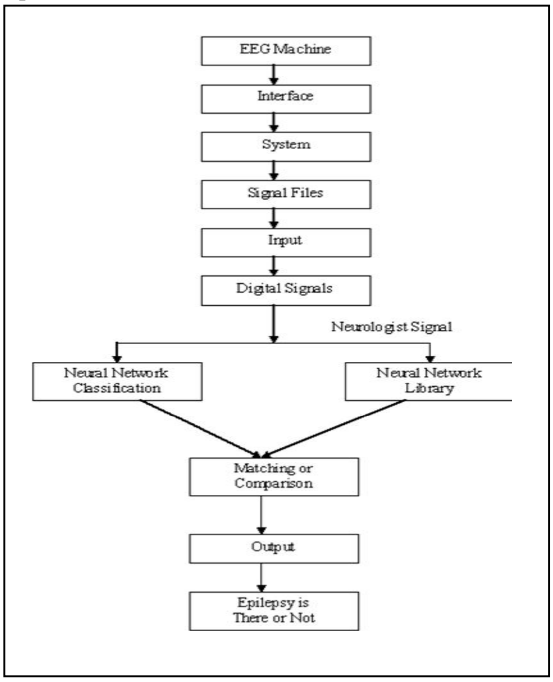


Fig. 1. Proposed System

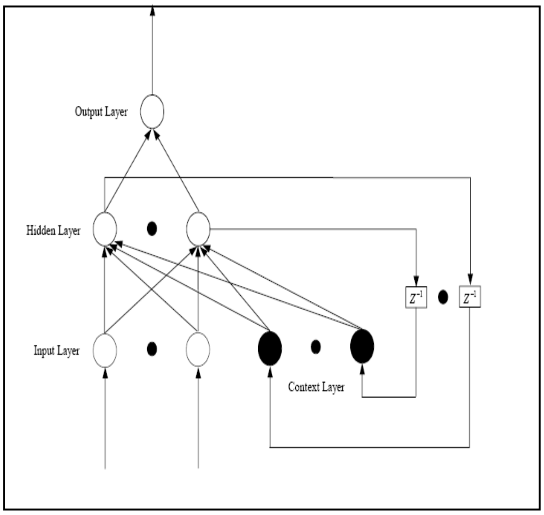
The intracranial epileptic EEG has been chosen for this classification system as the intracranial recordings offer the most precise access to the emergence of seizure. EEG signal is recorded during the occurrence of the epileptic seizures from these intracranial electrodes. EEG signal of normal subjects are obtained using intracranial electrodes. The EEG data acquired and recorded using Neurofile NT Digital Video is greyscaled, sampled at 256 Hz, and digitized into text files of peak values of 128 channels. A line noise of 50hz is present in the data is filtered out using a Notch filter at 50hz(49hz - 51hz).An optional bandpass 0.53 to 40hz filter may be applied to increase sensitivity and remove unnecessary signal frequencies. Notch and Bandpass Filter Order is found using Trial and Error method. The order of filter used is 3*ceil (sampling rate/lower cutoff frequency). Then EEG recordings are visually inspected for artifacts.

V. NEURAL NETWORK CLASSIFIER

Artificial Neural Networks are good classifiers because of their features like robustness, adaptive learning, generalization capability and self-organization. In situation where enough data are available for training the system and where the simple classification algorithm fails the ANNs (Artificial Neural Networks) are useful. To the best of our knowledge, the performance of Elman neural network has not been investigated yet. Elman neural network has been used in this paper for detection of epilepsy. The target, threshold values and description of the configuration used for Elman neural network is given below.

Elman Network: It is a recurrent neural network with two layers the hidden layer and the output layer. It is a backpropagation network with a feedback connection from the output of hidden layer to its input. This means that the function learnt by the network can be based on the current inputs plus a record of the previous states and outputs of the network.

The spatial patterns and temporal patterns are recognized by the ENN due to its feedback connection. The inputs for the neural network are the ApEn values corresponding to the normal and epileptic EEG signals. The ApEn values of epileptic patients have a little wide spike followed by abrupt fall in ApEn value. ENN is used to learn and detect this temporal pattern of ApEn values of epileptic patients. It detects the EEG signal without that particular temporal pattern as non epileptic. The activation functions used for the two-layered ENN are tan-sigmoidal and log-sigmoidal for the hidden and output layers, respectively.



Structure of Elman Neural Networks

90 hidden nodes and one output node is used. The training of the EN is done by using Resilient Backpropogation. Train the network by using the target value 0 and 1 for normal EEG and epileptic EEG, respectively. The classification is done by using the range of values 0-0.3 for the normal EEG and 0.7-1 for epileptic EEG. The MSE Error Goal is set to 0.01, which is sufficient for accurate classification

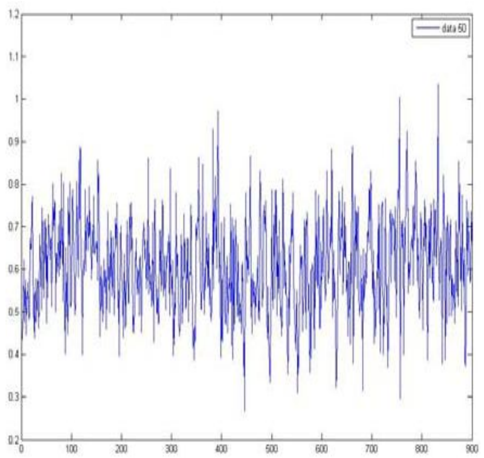


Fig.2

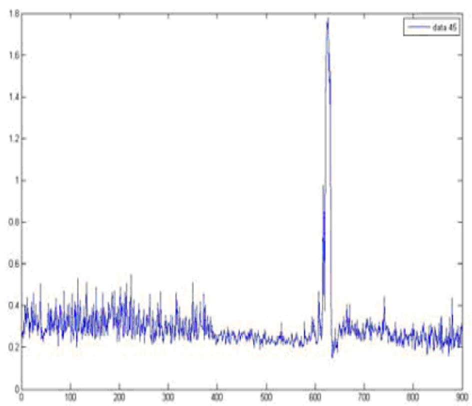


Fig.3

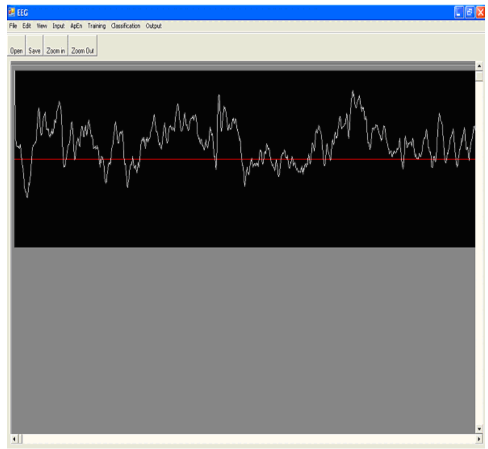


Fig.4

ApEn: 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 [9]. ApEn is a recently formulated statistical parameter to quantify the regularity of a time series data of physiological signals [9].

It was first proposed by Pincus in 1991 [11] and has been predominantly used in the analysis of the heart rate variability [12]–[14] and endocrine hormone release pulsatility [15], estimation of regularity in epileptic seizure time series data, and in the estimation of the depth of anesthesia.

Performance Evaluation Parameters:

The performance of EN is evaluated in terms of the three parameters i.e., Sensitivity (**SE**), Specificity (**SP**) and Overall Accuracy (**OA**), which are defined which are defined in [22], [23], and [24]as:

$$\mathrm{SE}(\%) = \frac{\mathrm{TN}_{\mathrm{CP}}}{\mathrm{TN}_{\mathrm{AP}}} \times 100$$

Where **TNCP** depicts the total number of correctly detected positive patterns and TNAP represents the total number of actual positive patterns. A positive pattern indicates a detected seizure.

$$\mathrm{SP}(\%) = \frac{\mathrm{TN}_{\mathrm{CN}}}{\mathrm{TN}_{\mathrm{AN}}} \times 100$$

Where **TNCN** represents the total number of correctly detected negative patterns and **TNAN** represents the total number of actual negative patterns. A negative pattern indicates a detected nonseizure.

$$\mathrm{OA}(\%) = \frac{\mathrm{TN}_{\mathrm{CDP}}}{\mathrm{TN}_{\mathrm{APP}}} \times 100$$

Where **TNCDP** represents the total number of correctly detected patterns and **TNAPP** represents the total number of applied patterns. A pattern indicates both seizure and nonseizure.

Result : ApEn values are computed for selected combinations of *m*, *r*, and *N*. The values of *m*, *r*, and *N* that are used for the experiments are as follows. ApEn values are computed for both normal and epileptic EEG signals and are fed as inputs to the EN network. Among the available 100 EEG data sets, 60 data sets are used for training and the remaining are used for testing the performance of the neural networks. This choice is made arbitrarily keeping in mind that enough datasets are provided for the neural network to understand the inherent structure of the data so that it can classify the unknown datasets properly. The ApEn values are calculated for each data frame and the number of ApEn values used for training and testing the neural networks.

From 18 patients, a total of 60 datasets were selected, with 30 ictal(epileptic seizures) and 30 interictal(non epileptic) data, for testing. The Performance Evaluation Parameters were calculated and the results obtained as follows:

Overall Accuracy (OA) = 93.43%

Sensitivity (SE) = 96.87%

Specificity (SP) = 90.43%

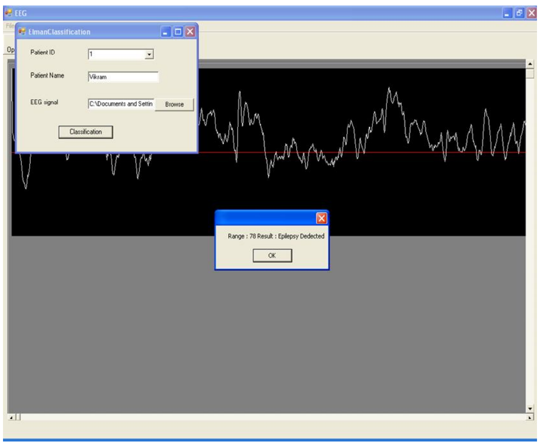


Fig.5

VI. CONCLUSION

Epilepsy is a common neurological disorder not a disease which is not contagious, fainting disorder and cause mental illness. Epileptic person has a tendency to have recurrent seizures which produces non linear dynamic system. By using Elman Neural Network and ApEn as an input feature for implementation of detection of epilepsy. Since, it is using a single input feature so that's why we having low computational burden and best suited for the real-time detection of epileptic seizures. We described one kind of ANN and conception how to implement it. 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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