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DETECTION OF EPILEPTIC SPIKES IN EGG SIGNAL USING WAVELET TRANSFORM AND ADAPTIVE NEURO – FUZZY INFERENCE SYSTEM(ANFIS) TECHNIQUES

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ABSTRACT

Diagnostic and warning methods can prove useful for epilepsy infinite recognition, controlling seizure (to prepare for seizure e.g., pull over if driving) and organizing medicine schedule to reduce unwanted side effects of untimely medication. Such methods employ brain electrical activity signals called electro encephalography (EEG). Epileptiform from EEG can be detected either visually (by specialist inspection) or automatically (by using signal processing knowledge). The first method requires plenty of time and precision. Automatic systems, growingly popular in recent decades, have been proposed to reduce time. In this study, an automated system is developed to detect spikes from EEG and classify them into healthy and epileptic categories in order to increase accuracy and precision. Discrete wavelet (DWT) is applied as a feature extraction method and adaptive neuro-fuzzy inference system (ANFIS) is used for classification. A sensitivity of 99% has been obtained.

Keywords: *EEG, DWT, ANFIS, Epileptic spikes detection.*

INTRODUCTION

As the second chronic neurological malfunction, epilepsy is characterized by sudden discharge and transient disturbances of mental function due to excessive discharge of groups of neurons. About one in every 100 persons tolerates a seizure at some time in their life [14]. Unfortunately, the epileptic seizure prediction seems to be difficult and its process is not much understood [23]. Epilepsy is usually controlled, but cannot be treated with medication, although surgery may be considered in difficult cases.

Electroencephalogram (EEG) is the most utilized and available signal to clinically assessed brain activities. EEG is a record of the brain electrical activity generated by the cerebral cortex nerve cells [23].
The epileptic waves have various morphologies with main ingredients like sharp waves, slow waves, and spikes. Usually spikes and sharp waves (SSW) or sharp and slow waves (SWW) appear simultaneously [17]. Excessive discharge is manifested in EEG as epileptic spikes which are significant source of information in diagnosis and localization of epilepsy [17].

As the most important of epileptic waves, spikes are the hardest ones to be recognized. The spikes appear in the range of 1-4 Hz (delta range) with maximum power, but they cannot be seen in normal EEG [2].
One of the problems in detecting epileptic form is that visual investigation of long term EEG by a specialist requires detailed analytical precision and it is very time consuming. Another difficulty is that epileptic spikes are very similar to eye blink and other artifacts and are too subtle to be detected only in the time domain. In this respect, automated system is acquired to reduce inspection time.

Recognition of electroencephalographic changes by automated system has been under study for several years [8,9,22,28]. Abnormalities in the EEG in serious psychiatric disorders are too slight in time domain to be detected by conventional techniques. Such techniques transform the qualitative characteristic into a more objective quantitative signal to feature classification problem. To solve this problem, a range of techniques have been addressed including the analysis of EEG signals for detection of electroencephalographic changes using the autocorrelation function, frequency domain features, time frequency analysis, and wavelet transform (WT) [1,9,13,23]. The results of the studies in the literature demonstrate that the WT is the most promising method to extract features from the EEG signals [1, 13, and 23]. Therefore, this study employed the WT for feature extraction from the EEG signals.

On the other hand, artificial neural networks (ANNs) have been implemented as computational tools for pattern recognition including diagnosis of diseases because of the belief that they have a superior predictive power than signal analysis techniques [5, 12, and 19]. However, fuzzy theory plays an important role in dealing with the uncertainty of making decisions in medical applications. Therefore, fuzzy sets have attracted growing attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics, data analysis, etc. [7, 18, and 21]. A new development in neuro-fuzzy approach is the adaptive neuro-fuzzy inference system (ANFIS), which has shown incredible results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [15, 16]. ANFIS is successfully implemented in biomedical engineering for classification [6, 10, 11, 26] and data analysis [27].

The present study employed automated system for the obvious reason of saving time and enhancing accuracy. Considering the fact that EEG is actually a non-stationary signal and the results from previous studies indicate WT as the best tool for extracting feature from EEG, the present research made use of WT. As a classifier, first order ANFIS (Sugeno) trained by hybrid model was implemented to classify the feature vectors of training dataset. Next sections deal with the material and methods, results and the conclusion of the implemented system.

MATERIALS AND METHODS

This study employed two of the five available EEG dataset (B and E) [3]. From each set, 50% was used for training and the remaining half was devoted to testing. Each contains 100 single-channels EEG signals of 23.6 s with 4097 samples over this period. Each signal was chosen after visual assessment. Set B was taken from scalp EEG recordings (extra-cranially) of five healthy subjects with eyes closed. Set E consisted of seizure activity, selected from all recording sites exhibiting ictal activity. Set E was recorded intra-cranially. Despite using different recording electrodes, the recording parameters were permanent.

The frequency range of all EEGs was 0-85 HZ, so that band pass filter to select the desired frequency band could be applied. B set was chosen because the so-called alpha rhythm in a frequency range of 8–13 Hz, predominant physiological rhythm, could be seen and realized during the relaxed state of healthy subjects with eyes closed [3]. Useful information lies down below 30 HZ frequency. In order to cut out this frequency range, a Butterworth band-pass order 8 filter was applied. To remove electrical interface of 50 HZ frequency, a Butterworth band stop filter (notch) order 8 was used.

EEG signal can be contaminated by artifacts. One of the methods to remove these artifacts is using DWT. Due to eye blinking, head and eyeball moving, most of the artifacts usually lie in low frequencies [29]. In the present work, Bior 3.3 was applied as mother wavelet since it resembled the artifacts [4]. The signal decomposition by DWT was done in 6 levels. Then, the sixth approximation signal including lowest frequency band and not having epileptic spikes information was removed, and EEG signal was finally reconstructed without this approximation.
Each signal was broken down into 16 segments by a rectangular window. Each segment contained 256 samples. No segment has overlapped slide with the next segment.

Wavelet and feature extraction:

Wavelet theory

Wavelet transform (WT) is a time-frequency analysis tool that can be considered as extensions of Fourier transform (FT), except that providing single resolution (time or frequency), it provides multi-scale resolution. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution corresponding to its scale. Each scale emerges a particular coarseness of the signal under study.

The decomposition can continue only until the individual details consist of a single sample or pixel. In practice, one selects a suitable number of levels based on the nature of the signal. The chosen number for decomposition level depends on the dominant frequency of the signal.
Since preprocessed EEG signals contain 0.5-30 HZ frequency component, and epileptic spike information exist in delta frequency band (1-4 HZ), 3 levels of decomposition were chosen for feature extraction step via Daubechies 4 **(**Db4).

Feature extraction

Due to wavelet decomposition, for each segment a large number of features were obtained to reduce the classification speed. In order to reduce features vector dimension, some statistics were applied. Statistical features used in this study to represent time-frequency distribution of EEG segments are as follows:

1. Maximum of wavelet coefficients in each sub-band frequency for each segment
2. Mean of wavelet coefficients in each sub-band frequency for each segment
3. Standard deviation of wavelet coefficients in each sub-band frequency for each segment

These features were calculated over D1, D2, D3 and A3 wavelet coefficients.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is an Adaptive Network Based Fuzzy Sugeno model Inference Engine, first proposed by [15]. This system is intended to allow if-then rules and membership function to be constructed based on the historical data of the metrics. It integrates the adaptive nature for automatic adjustment purposes as well. Figure 1 shows the basic architecture of ANFIS with two inputs and one output. It is a multilayered feed-forward network where each node carries out a particular role on the received input signals. Each node is adapted and trained by modifying its parameters and / or formulas.

Two fuzzy if-then rules based on a first order Sugeno model are considered:

Rule 1: If (x is $A1$) and (y is $B1$) then ($f1 = p1x + q1y + r1$) (1)

Rule 2: If (x is $A2$) and (y is $B2$) then ($f2 = p2x + q2y + r2$) (2)

where x and y are the inputs, Ai and Bi are the fuzzy sets, fi *is* the outputs within the fuzzy area specified by the fuzzy rule, pi, qi and ri are the intended parameters that are determined during the training process. A circle point toward a fixed node, whereas a square indicates an adaptive node.

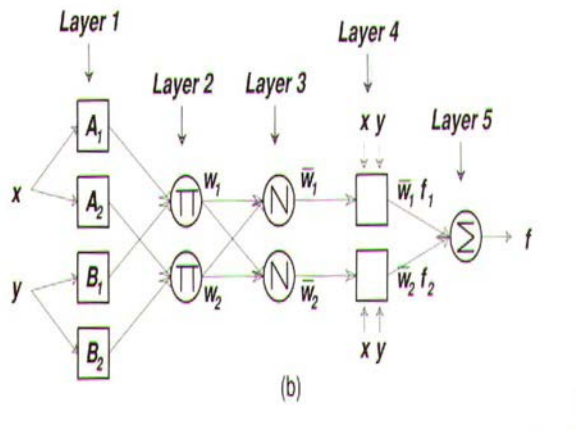

Fig. 1: ANFIS architecture [11]

Jang offered that the functions of the nodes are cluster into 5 different layers.

Layer 1: The membership functions are defined hypothetically, for instance: Generalized bell:

$$\mu_{gbell}(x;a,b,c)= \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \qquad (3)$$

When the values change, the membership function shape also changes consequently. In this layer, the parameters involved in the procedure are known as the premise parameters. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O1i= \mu Ai\ (x),\ i = 1, 2 \qquad (4)$$

$$O1i= \mu Bi-2\ (y),\ i = 3, 4 \qquad (5)$$

Where, $\mu Ai\ (x)$, $\mu Bi-2\ (y)$ can take on any fuzzy membership function.

Layer 2: Here, each output of the node is as the firing strength of the rules in the fuzzy inference system. The outputs of this layer, the so-called firing strengths of the rules, can be represented as:
$$O2i= wi = \mu Ai\ (x)\mu Bi\ (y),\ \ i = 1, 2 \qquad (6)$$

Layer 3: In this layer, the ratio of the i^{th} rule's firing strength is calculated, as shown in (2). The outputs of this layer, the so-called normalized firing strengths, can be presented as:

$$O3i= \bar{w}_i = w_i/ (w1 + w2),\ \ i = 1, 2 \qquad (7)$$

Layer 4: The parameters in this layer are called the consequent parameters. The nodes in this layer adjust with an output node. The outputs of this layer are given by:

$$O4i= \bar{w}_i f_i = \bar{w}_I (p_i x + q_i y + ri),\ \ i = 1, 2 \qquad (8)$$

Layer 5: In this layer, nodes are fixed and sum all incoming signals from the preceding layers. The final output of the model is given by:

$$O5i=\sum_i \bar{w}_i f_i=\frac{\sum_i wi\ fi}{\sum_i wi}, \qquad i = 1, 2 \qquad (9)$$

ANFIS uses two methods in updating parameters. In order to fine-tune premise parameters that define membership functions, ANFIS exploits gradient. For consequent parameters that define the coefficients of each output equations, ANFIS employs the least-squares method to identify them. This method is thus called hybrid learning method since it combines gradient descent and the least-squares method. Other optimization methods are the Gauss-Newton or Levenberg-Marquardt methods [10].

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RESULTS AND DISCUSSIONS

The dataset was divided into two groups; training and testing (1600 vectors in each group). Changes of the final (after training) membership functions with respect to the initial (before training) membership functions of the input parameters were examined. Membership function of each input parameter was divided into three regions, namely, small, medium, and large. The examination of initial and final membership functions indicates that there are considerable changes in the final membership function.

After training, 1600 testing data were used to validate the accuracy of the ANFIS model for the detection of epileptic seizure. In classification, the aim is to assign the input patterns to one of the two classes, usually represented by outputs restricted to lie in the range from 0 to 1, so that they represent the probability of class membership. Generally speaking, while the classification is carried out, a specific pattern is assigned to a specific class according to the characteristic features selected for it.

In this application, there were two classes: epileptic or normal. The classification results of the ANFIS model were displayed by a confusion matrix defined by labelling the desired classification on the rows and the actual network outputs on the columns. As mentioned, epileptic spikes information consists of delta range (less than 4 HZ). Thus, the sub-bands that contain epileptic information are CA3 and CD3. ANFIS was fed by statistical features extracted from CA3, CD3 for 100 epochs Table 1 shows the confusion matrix of ANFIS fed by STD feature CA3 and CD3. Figure 2 represents initial membership function and final membership function of ANFIS. Error convergence of trained ANFIS is presented in Figure 3.

Table 1:Confusion matrix STD feature CA3 and CD3

Desired / Output	Epileptic	Normal
Epileptic	793	7
Normal	33	767

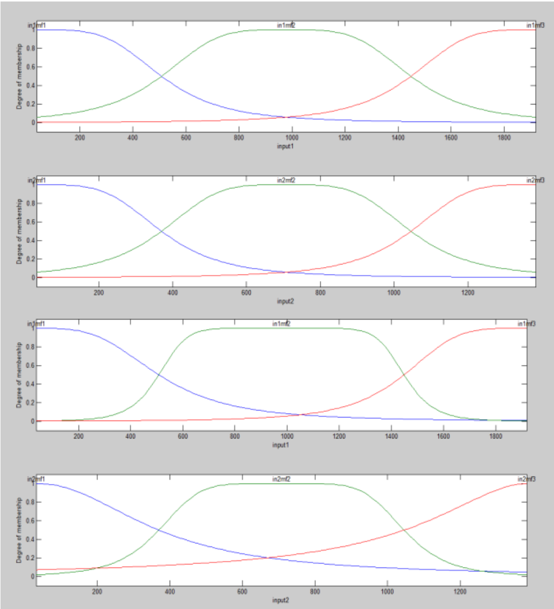

Fig. 2: Initial membership function (top), after training membership function (bottom) for STD feature CA3 and CD3

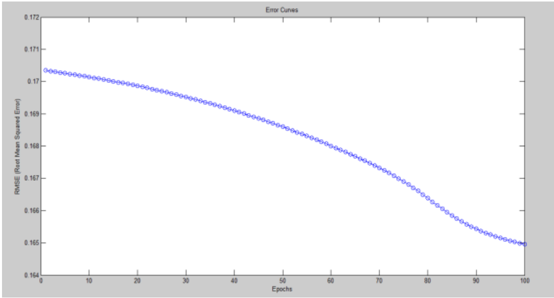

Fig. 3: Network error convergence of ANFIS for STD feature CA3 and CD3

Choosing the number of epochs, a few points were taken into account. The meaning of final membership function was maintained while minimizing training errors and excluding over fitting. In this relation, different numbers of epochs for each step were examined to select those epochs which were more compatible with the afore-mentioned criteria.

The highest accuracy was obtained by feeding ANFIS with STD of CA3 and CD3, which exceeded the accuracy of [24] proposed system with less input dimension and implementation of standalone neural network [25] (Table 2).

Specificity: number of correctly classified normal subjects/number of total normal subjects.
Sensitivity: number of correctly classified epileptic patients/number of total epileptic patients.
Total classification accuracy: number of correctly classified subjects/number of total subjects.

Table 2:Comparison of different methods for EEG classification

Classifier type	Total accuracy (%)	Specificity (%)	Sensitivity (%)
MLPNN [25]	92	91.90	92
ANFIS [24]	94	93.70	94.30
Proposed ANFIS fed by STD CA3 & CD3 (Db4)	97.50	95.90	99.13

As it is seen in Table 2, the proposed ANFIS model in this study classified normal subjects and epileptic patients with the accuracy of 95.9% and 99.13%, respectively. The classification accuracy of ANFIS [24] was 93.7% for normal subjects and 94.3% for epileptics. The correct classification rates of the stand-alone neural network (MLPNN) were 91.9% for normal subjects and 92% for epileptic patients. The total classification accuracy of the stand-alone neural network and ANFIS [24, 25] were 92% and 94% respectively. Thus, the accuracy rates of the ANFIS model presented for this application were found to be higher (97.5%) than that of the stand-alone neural network model and ANFIS [24]. These results indicate that the proposed ANFIS model has some potential in epileptic seizure detection.

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CONCLUSIONS

In this study, the problems of epileptic spike detection such as similarity with some artifacts like eye blinking and time consuming process of visual inspection were addressed. After filtering and removing artifacts via DWT by using Bior3.3 on origin EEG signals, segmentation was done. 200 EEG signals, each with duration of 23.6 s and 4097 sample points were used (100 signals from healthy subjects and 100 from epileptic subjects). Each signal was windowed into 16 segments. Finally, there were 3200 segments (1600 segments from each group).Feature sets based on DWT of Db4 of segmented EEG signals for 3 levels were obtained and decomposed each segment to 4 sub-bands.

The system showed improvements, compared with the similar previous works, both in total accuracy and sensitivity while using Db4 as a mother wavelet and STD as a statistical feature to reduce dimension for third approximation and detail coefficients.

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