Detection and Classification of Epileptic Seizure using RBF Neural Network

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ABSTRACT

The rapid growth of the medical technologies and constant renewal of medical facilities, electrocardiography (ECG) provides an effective and easy to use means for arrhythmia classification and heart rate variability (HRV) analysis. Most of the existing ECG device has the disadvantage of poor local signal processing ability. After thorough investigation, Android platform is adopted to develop an ECG signal processing application for real time arrhythmia classification and HRV analysis. The ECG data acquired are transmitted to the Android smart phone or tablet via Bluetooth. ECG simulator is connected to signal conditional unit. The received analog signals are converted to the digital values and then passed to the microcontroller. From the microcontroller data, will be transmitted with the help of Bluetooth and it will be received from the mobiles phones. Android application for interface with ECG kit for monitoring patient health status is created. For this process, first Bluetooth connection with ECG Bluetooth device is established, once the connection is success, data from established connection is received through mobile phones.

Keyword : - *Electrocardiography, arrhythmia, ECG simulator and HRV etc….*

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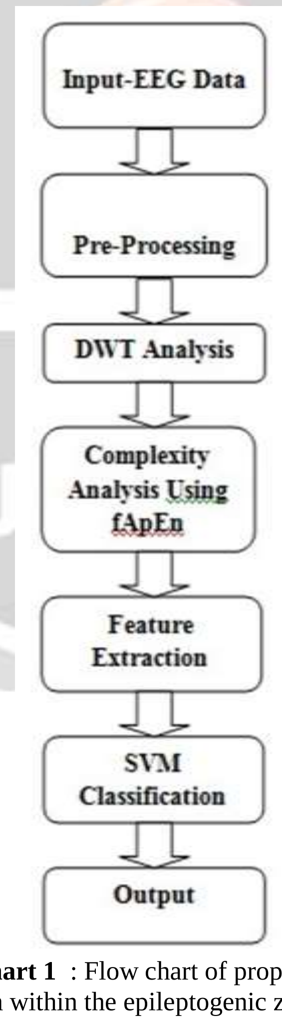
1. Introduction

Awareness (absence seizure). Diseases An epileptic seizure is a brief episode of signs or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. The outward effect can vary from uncontrolled jerking movement (tonicclonic seizure) to as subtle as a momentary loss of of the brain characterized by an enduring predisposition to generate epileptic seizures are collectively called epilepsy, but seizures can also occur in people who do not have epilepsy. Additionally, there are a number of conditions that look like epileptic seizures but are not. A first seizure generally does not require treatment unless there is a specific problem on either electroencephalogram (EEG) or brain imaging. Epilepsy is a common neurological condition which affects the central nerve system that causes people to have a seizure. A wavelet based fuzzy approximate entropy (fApEn) method is presented for the classification of EEG signals into healthy/ interracial versus ictal EEGs. Discrete wavelet transform is used to decompose the EEG signals into different sub-bands. The fuzzy approximate entropy of different sub bands is employed to measure the chaotic dynamics of the EEG signals .In this work it is observed that the quantitative value of fuzzy approximate entropy drops during the octal period which proves that the epileptic EEG signal is more ordered than the EEG signal of a normal subject. The fApEn values of different sub-bands of all the data sets are used to form feature vectors and these vectors are used as inputs to classifiers. The classification accuracies of radial basis function based support vector machine (SVMRBF) and linear basis function based support vector machine (SVML) are compared.
The main objective is to reduce the time consuming in detection of epileptic seizure being performed by a trained professional manually from the long time EEG recordings, to increase the accuracy of the result and reasonably to reduce costly procedure. In this work fuzzy approximate entropy has been employed as a complexity measure EEG signal for automatic seizure detection using support vector machine. The proposed method utilizes the observation that fApEn values are calculated to measure the regularity or predict-ability of EEG signal drops during seizure

interval. EEG signals are decomposed into different subbands through DWT to obtain the detail wavelet coefficients (D1–D5) and approximate wavelet coefficients (A5). The fApEn features are calculated by using the wavelet coefficients D1–D5 and A5 which provide the best detection rates for all cases. The 100% classification accuracies are obtained using SVMRBF for cases1 and 2.The success of the proposed method is verified by comparing the performance of classification problems as addressed by other researchers.

2. Proposed System

The proposed method is evaluated through seven stages, and obtained high classification accuracies that indicate good classifying performance of the proposed method. The paper is organized as follows. In Module 1 input from clinical data and data recording are described and given as input. In Module 2 discusses the preprocessing methodology to remove unwanted noises and to improve the image quality for processing. In Module 3 the evaluation procedure that is DWT is applied to analysis. In Module 4 Complexity Analysis Using fApEn is performed. In Module 5 feature extraction is applied. In module 6 classification based on SVM as to be carried out. In module 7 the experimental results are presented which are concluded. The data sets A and B consist of segments which are recorded from the surface of the scalp of five healthy subjects using a standardized electrode placement scheme. The subjects are asked to relax at an awake state with eyes open (A) and eyes closed(B). The data sets C,D, and E are recorded from the epileptic subjects through intracranial electrodes for interictal and ictal epileptic activities.



Flow Chart 1 : Flow chart of proposed system

All the segments of set D are recorded from within the epileptogenic zone during a seizure free interval. Segments in set C are also recorded during a seizure free interval from the hippocampal formation of the opposite hemisphere of the brain. Segments of set E are recorded during seizure activity. All the signal segments are recoded through the

128-channelamplifier system, using an average common reference. A 12 bit ADC converter is used to convert the segments which are continuously stored on the disk of a data acquisition system at a sampling rate of 173.61Hz

Pre-processing includes the steps that are necessary to bring the input data into an acceptable form for filtering and processing. Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images. The analysis of a signal through DWT, selections of two parameters are highly important.

- First, the number of decomposition levels, which are generally determined based on the dominant frequency components of the signal.
- Second, wavelet function, have pointed out that the Daubechies order-4(db4) wavelet is suitable for analyzing EEG data because of its orthogonality property and efficient filter implementation.

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information. The discrete wavelet transform has a huge number of applications in science, engineering, mathematics and computer science. Most notably, it is used for signal coding, to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. Practical applications can also be found in signal processing of accelerations for gait analysis, in digital communications and many others. It is shown that discrete wavelet transform (discrete in scale and shift, and continuous in time) is successfully implemented as analog filter bank in biomedical signal processing for design of low-power pacemakers and also in ultrawideband (UWB) wireless communications.

Many signals like EEG having the nonstationary and transient characteristics, in such condition ideally Fourier transform may not be applied directly. But time– frequency method scan be used. Wavelet transforms (WT) are extensively applied in biomedical engineering areas for explaining a variety of real-life problems. Most of the physiological signal shaving irregular patterns like impulses which are occurring at various points in the signals are generally analyzed by WT.
Complexity analysis is done by fuzzy approximate entropy (fApEn). The fApEn values are calculated from these sub-band signals to extract the features and to form feature vector thereof. This feature vector is used as input to support the vector machine for classifying the EEG into normal/ interictal versus ictal data sets .

Entropy of grayscale image

Syntax

E = entropy(I)

Description

E = entropy(I) returns E, a scalar value representing the entropy of grayscale image I. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

Entropy is defined as

-sum(p.*log2(p))

where p contains the histogram counts returned from imhist. By default, entropy uses two bins for logical arrays and 256 bins for uint8, uint16, or double arrays.
It can be a multidimensional image. If It has more than two dimensions, the entropy function treats it as a multidimensional grayscale image and not as an RGB image.
SVM (Support Vector Machine) is powerful and well known for binary classification tasks in machine learning for high dimensional feature vectors due to their accuracy and capability to deal with a large number of predictors. The SVMs attempt to find an optimal hyper-plane in the high dimensional feature space to maximize the distance between this hyper-plane and the nearest data point of each class.

In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object (white circle) falling to the right is labeled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).

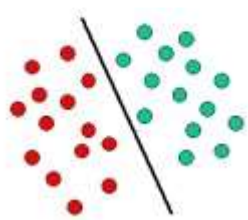


Fig 1: Linear Classifier

The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of examples that are available (train cases). This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyper plane classifiers. Support Vector Machines are particularly suited to handle such tasks. Note that in this new setting, the mapped objects (right side of the schematic) is linearly separable and, thus, instead of constructing the complex curve (left schematic), all we have to do is to find an optimal line that can separate the GREEN and the RED objects.
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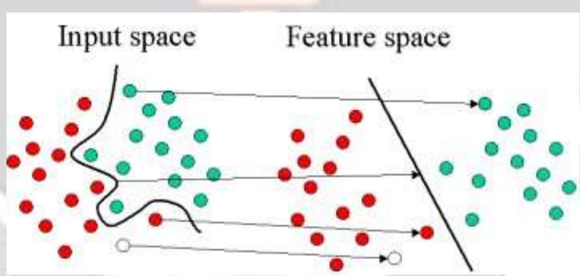

Fig 2: Classification of EEG from Nonlinear into a Linear

Support Vector Machine (SVM) is primarily a classier method that performs classification tasks by constructing hyper planes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. For categorical variables a dummy variable is created with case values as either 0 or 1. Thus, a categorical dependent variable consisting of three levels, say (A, B, C), is represented by a set of three dummy variables:
A: {1 0 0}, B: {0 1 0}, C: {0 0 1}
To construct an optimal hyper plane, SVM employs an iterative training algorithm, which is used to minimize an error function. According to the form of the error function, SVM models can be classified into four distinct groups:

- Classification SVM Type 1 (also known as C-SVM classification)
- Classification SVM Type 2 (also known as nu-SVM classification)
- Regression SVM Type 1 (also known as epsilon-SVM regression)

- Regression SVM Type 2 (also known as nu-SVM regression)

3. Cross Validation

The holdout method splits the original data set into two partitions by randomly selecting instances for a training set and a test set. Classifiers are trained using the training set and tested by the holdout test set. This method has the advantage of being simple to use. This method raises questions about the representativeness of each data set due to the poor use available data. The holdout method can be made more reliable by repeating it several times, with randomly selected training and test sets each time. The accuracy obtained on each iteration is averaged to give an overall accuracy. In order to mitigate any bias caused by a particular partition of training and test sets, repeated hold out method is used.

4. Result

All the 500 epochs of normal, interictal and epileptic (ictal) EEG data sets are decomposed into different sub-bands using DWT. The frequency ranges of these subbands are as follows: A, B, C, D, E. Approximation and detail coefficients of the sample EEG epoch taken from data sets A,B,C,D and E are plotted.

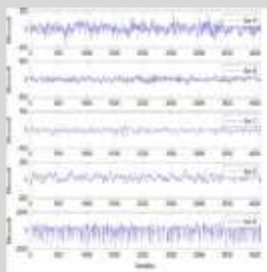

Fig3: Recordings of EEG Signal A,B,C,D and E Dataset from Top to Bottom

Let us consider only one set of data or samples as input given whose pictorial image is shown below. For Example 1: Set A is taken as input

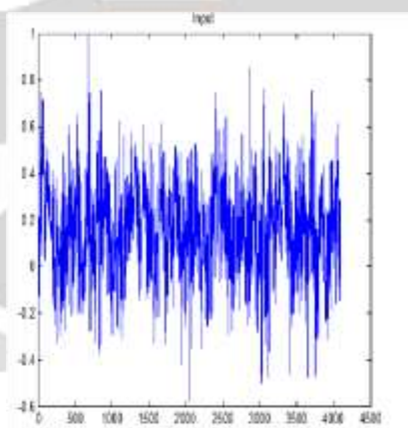

Fig4: Input of Set A

After Processing by applying DWT technique, the output image of data set A is plotted below:

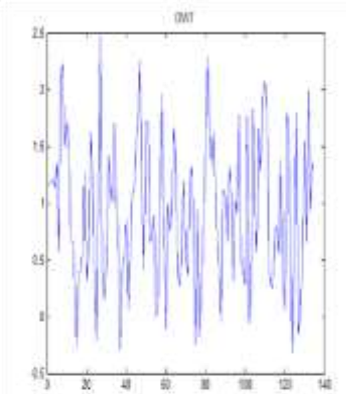

Fig5: Decomposition of DWT by using db

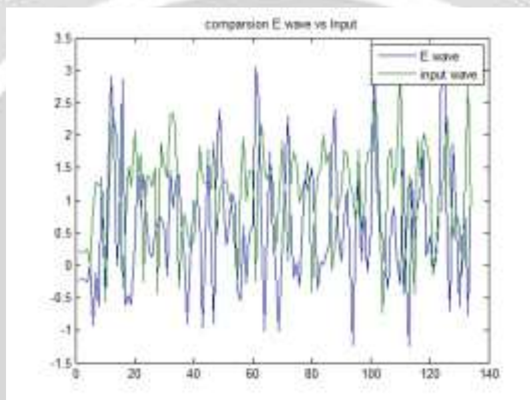

Fig6: Comparison of E wave versus input of set A

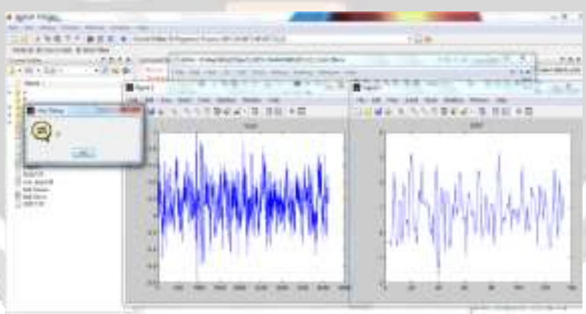

Fig7: Detection of set C through SVM

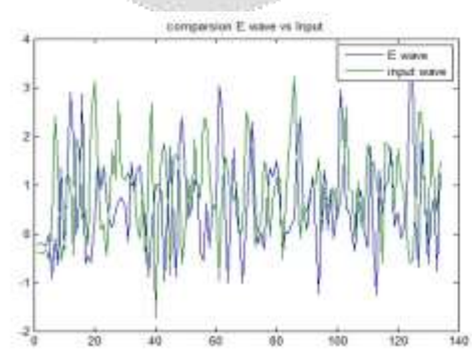

Fig8: Comparison of E wave versus input of set C

Fig9: Detection of set D through SVM is shown

Comparison of E wave versus input of set D The fApEn values are calculated from the approximation and detail coefficients of all sub-bands of the entire EEG epochs of five data sets A–E which are plotted. The fApEn values for the data sets A and B are higher than the data set E, which proves that the data set E is more ordered than the data sets A and B. Similarly the fApEn values for the data sets C and D are also higher than the data set E and less than the data sets A and B, which means that the data sets C and D are more ordered than the data sets A and B, and less regular than E. The average fApEn values for wavelet coefficients of sub-bands of data sets A, B, C, D and E . From these results it can be concluded that epileptic EEG (set E) is more regular or less complex than the normal (sets A and B) and interictal periods' data sets of EEG (sets C and D).

5. Conclusion

The detection of epileptic seizure being performed by a trained professional manually from the long time EEG recordings is a very time consuming and costly procedure. In this work fuzzy approximate entropy has been employed as a complexity measure of EEG signal for automatic seizure detection using support vector machine. The proposed method utilizes the observation that fApEn values are calculated to measure the regularity or predict-ability of EEG signal drops during seizure interval. EEG signals are decomposed into different sub-bands through DWT to obtain the detail wavelet coefficients and approximate wavelet coefficients. The fApEn features are calculated by using the wavelet coefficients and which provide the best detection rates for all cases. The 100% classification accuracies are obtained using SVMRBF for cases 1 and 2. The success of the proposed method is verified by comparing the performance of classification problems as addressed by other researchers. It can be concluded that using DWT based fApEn, more satisfactory results are achieved to discriminate the EEG signals in comparison to other methods. The presented method can be employed as a quantitative measure for monitoring the EEG and it may prove to be a useful tool in analyzing the EEG signal associated with epilepsy.

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