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Layered Approach for ECG beat classification utilizing Neural Network

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ABSTRACT

An Electrocardiogram (ECG) is a bio-electric signal which record heart electrical activity versus time. It is an important diagnostic tool for heart functioning. The interpretation of ECG signal is an application of pattern recognition. The technique used in this pattern recognition comprise: Signal Pre-processing, feature Extraction, training of neural network for classification. In this proposed methodology, Empirical Mode Decomposition (EMD) and neural network toolbox will be used from MATLAB environment. The processed signal is used from Physionet's' database which were developed for research in Cardio Electrophsiology.The system can classify different types of arrhythmia (Abnormal beats). The excellent performance of the algorithm is confirmed by a sensitivity of 99.89 % and a overall accuracy of 99.95% against the MIT-BIH arrhythmia database.

***Keywords* – ECG signal, Empirical Mode Decomposition (IMFs), MATLAB, neural network.**

I. INTRODUCTION

An electrocardiograph (ECG) is a Cartesian representation of the electrical potential generated by the heart. Since its invention in 1887, it has been an invaluable diagnostic tool for the clinician. Traditionally, the ECG is recorded in a hospital setting, or by an ambulatory device and the analysis is done offline by trained clinical personnel. However recent applications demand analysis online, where no skilled persons are available, or without any manual intervention. An elementary understanding of the ECG and the physiological process it represents is necessary in order to appreciate the motives for ECG analysis and the processes involved. The heart comprises four chambers, the two upper chambers are called the auricles and lower two the ventricles. The walls of each chamber consist of myocardial muscles, which themselves comprise cells called myocytes. Normally, the interior of the cell has a potential of about -70mV with respect to the extra cellular fluids surrounding the cell. Thus, there exists an electrical potential across the cell membrane. A cell in such a state is said to be polarized [1]. A cell with a trans-membrane potential of zero (or slightly positive) is said to be depolarized. Ions passing through the cell membrane can alter the potential difference. Similarly, particular ranges of membrane potential are favorable for the passage of the ions of particular molecules. This inter-relationship between ion channels and the membrane potential is complex but in normal healthy subjects, the result is a regular, periodic change in trans-membrane potential versus time. The sinus node is said to be the primary "pacemaker" of the heart. Under normal conditions it spontaneously produces an action potential, to which the rest of the myocardial muscles sympathetically respond.

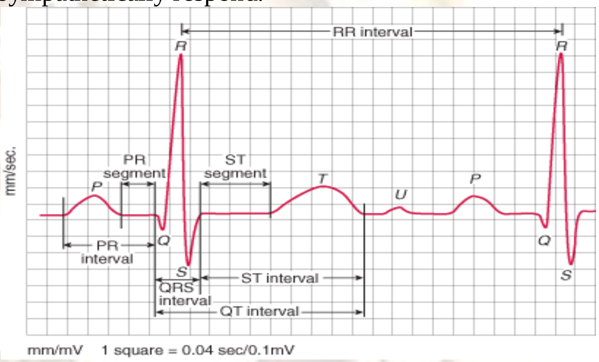


Figure-1 ECG intervals and waveform

A unique property of myocytes is their ability to propagate the trans-membrane potential from one cell to an adjacent cell. Hence, in normal healthy tissue, a wave of depolarization may be observed moving across the heart. Another property is that sudden depolarization causes the myocardium to contract [1]. These two properties result in a wave of contraction, starting from the sinus node, spreading across the heart in the inferior direction. In general, the myocardial polarization is a deterministic, periodic process and this gives rise to the regular heartbeat and ECG signal as illustrated in fig.1

1.1 Problem Statement

Technological innovation has progressed at such an accelerated pace that it is has permeated almost every facet of our lives. This is especially true in the field of medicine and delivery of health care services. As a result, AI technologies attached to the biomedical experiments with better investing of more advanced technologies for best monitoring of patient. In India, cardiac disorders are common among the people but technology has not improved with cardiac signal diagnosis technologies. Still

Bioinformatics technologies and Artificial Intelligence are rarely used for ECG signal diagnosis. So Personnel Intelligent ECG Analyzing System is timely required with computerized world to quick and accurate predictions which could be help to cardiologist to prevent death amount by cardiac problems. This paper contributes to an idea for making ECG beat classification by using SignalProcessing, Feature extraction, Neural Networking.

The algorithms in the relevant references adapt a range of different approaches to yield a procedure leading to the identification of the waves under consideration. These approaches are mainly based on use of fuzzy hybrid neural network [2] automated beat classifier depending on morphology and heartbeat interval [3].wavelet Denoising for multi-lead high resolution [4]. Extreme Learning Machines (ELM) Technique [5]. These are the few but yet promising and pioneering contribution in medical field.

The fundamental part of the Hilbert–Huang transform (HHT) is the empirical mode decomposition (EMD) method [6]. Using the EMD method, any complicated data set can be decomposed into a finite and often small number of components, which is a collection of intrinsic mode functions (IMF). An IMF represents a generally simple oscillatory mode as a counterpart to the simple harmonic function. By definition, an IMF is any function with the same number of extrema and zero crossings, with its envelopes being symmetric with respect to zero. The definition of an IMF guarantees a well-behaved Hilbert transform of the IMF. This decomposition method operating in the time domain is adaptive and highly efficient. Since the decomposition is based on the local characteristic time scale of the data, it can be applied to nonlinear and nonstationary processes.

The major advantage of the EMD is that the basis functions are derived from the signal itself. Hence, the analysis is adaptive, in contrast to the wavelet method where the basis functions are fixed. In this paper, a detection method based on the EMD approach is proposed.

The proposed algorithm is evaluated by using the ECG MIT–BIH database [7].

II. Empirical Mode Decomposition (EMD)

EMD is a method of breaking down a signal without leaving the time domain. It can be compared to other analysis methods like Fourier Transforms and wavelet decomposition. The process is useful for analyzing natural signals, which are most often non-linear and non-stationary. EMD filters out functions which form a complete and nearly orthogonal basis for the original signal. Completeness is based on the method of the EMD; the way it is decomposed implies completeness. The functions, known as Intrinsic Mode Functions (IMFs), are therefore sufficient to describe the signal, even though they are not necessarily orthogonal. The reasons are described in Huang et al., publication. The real meaning here applies only locally. For some special data, the neighboring components could certainly have sections of data carrying the same frequency at different time durations. But locally, any two components should be orthogonal for all practical purposes. The fact that the functions into which a signal is decomposed are all in the time-domain and of the same length as the original signal allows for varying frequency in time to be preserved. Obtaining IMFs from real world signals is important because natural processes often have multiple causes, and each of these causes may happen at specific time intervals. This type of data is evident in an EMD analysis, but quite hidden in the Fourier domain or in wavelet coefficients.

An Intrinsic mode function (IMF) is function that satisfies the following two conditions namely:

i. In the whole data set, the number of extrema and the number of zero crossing must either equal or differ at most by one and,

ii. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The name "Intrinsic mode function" is adopted because it represents the oscillation mode imbedded in the data. With this definition, the IMF in each cycle, defined by the zero crossing involves only one mode of oscillation, no complex riding waves are allowed. With this definition, an IMF is not restricted to a narrow band signal, and it can be both amplitude and frequency modulated. In fact, it can be non-stationary. As both imply finding modes with zero Local mean that the components all satisfy the condition imposed on them.

Here we define a algorithm/process to extract the IMFs commonly called as sifting process.

III. Empirical Mode Decomposition Algorithm

1. Identify the local maxima *e*max and minima *e*min i.e the extrema of the data: do(t)= X(t).

2. Generate/Interpolate between the maxima and connect it with a cubic spline curve, the applies to the minima, in order to obtain envelope which are the upper *e*u(t) and the lower *e*i(t).

3. Obtain the local mean *m*1(t) by averaging the envelopes:

$$m1(t) = \frac{eu(t)+ei(t)}{2} \qquad (1)$$

4. Since IMF should have zero local mean , subtract out the mean from the data i.e:

$h1(t) = X(t).- m1(t)$ (2)

which ia an extract of details

5. Check the properties h1(t) is an IMF if, it is found that h1(t) is not an IMF component, iterate the procedure from step 1 to step 4

6. If h1(t) is an IMF, then set residue:

$r = X(t) - h1(t)$ and then $h1(t)=C1$ (3)

The procedure from step 1 to step 6 is repeated by sifting the residual signal. The sifting processing ends with the residue *r*.

As described above, the process is indeed like sifting to separate the finest local mode from the data first based only on the characteristic time scale. The sifting process, however, has two effects to eliminate riding waves and to
Smooth uneven amplitudes.

7. The residue now contains information about longer periods resift to find additional components:

$r1 - c2 = r2, \ldots\ldots rn-1 - cn = rn$ (4)

8. From the principle of superposition of the components reconstruct the data:

$$X(t) = \sum_{i=1}^{n} Ci + rn \quad (5)$$

9. The sifting process should be applied with care, for carrying the process to an extreme could make the resulting IMF a pure frequency modulated signal of constant amplitude.

10. To guarantee that the IMF components retain enough physical sense of both amplitude and frequency modulations, we have to determine a criterion for the sifting process to stop. This can be accomplished by limiting the size of the Standard Deviation SD, computed from the two consecutive sifting results as:

$$SD = \frac{\sum_{i=0}^{T} |h1(k-1)(t) - h1k(t)|^2}{h1^2(k-1)(t)} \quad (6)$$

11. A typical value for the SD can be set between 0.2 and 0.3, which is a rigorous limitation for the difference between the sifting.

IV. Methodology

The block diagram in fig.2 depicts the overall methodology for the arrhythmia classification used in this work. The complete schematic includes steps like Data acquisition, ECG pre-processing stage, feature extraction (IMFs) and training of neural network. Finally performance evaluation of the classifier using statistical parameters in terms of sensitivity, specificity, and overall accuracy.

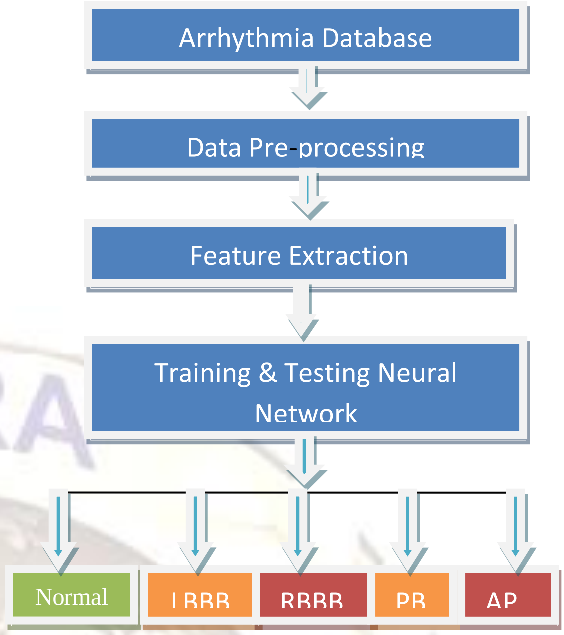


Figure-2 Schematic of the proposed algorithm..

A. ECG Data Acquisition

MIT – BIH arrhythmia database was used in this work for training, validation and testing of designed classifier model. This is a standard database containing 48 half-hour excerpts of two channel ambulatory ECG recording, obtained from 47 subjects from 1975 and 1979 containing 360 samples per second per channel with 11 bit resolution over a 10mV range.

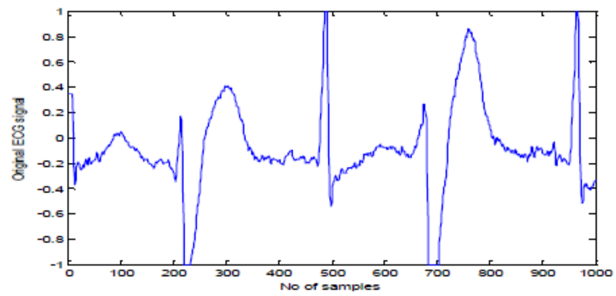
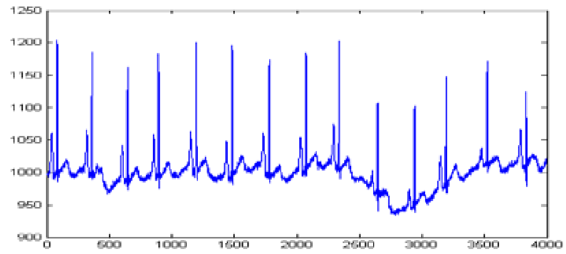


Figure-3 ECG signals from MIT-BIH database.

B. Data Pre-processing.

The digitized ECG signal contains many types of high frequency contaminations like interspersions and muscle noise. And also some of un-wanted signal those arising from the skin surface. Hence they require pre-processing before actual feature extraction process. For this a low pass filter with cut-off frequency from 30 to 100Hz was used. The base line wandering was removed by subtracting the signal from a low order polynomial.

(a)



(b)

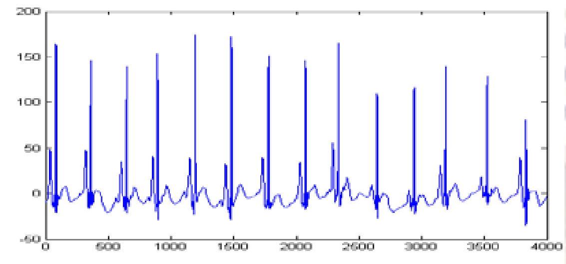


Figure-4 (a) Original ECG signals containing noisy components (MIT-BIH database); (b) Out of the Pre-processing filter block.

C. Feature Extraction.

The process of feature extraction is nothing but decomposing the ECG into IMFs [6]. The EMD is applied on the data X (t) and the individual IMF's are obtained to locate the fiducial points on the ECG signal. The EMD of X (t) (equation 5) is obtained. Where C1 is obtained IMF and rn is the residue.

D. RR Peak Detection.

Since R-wave is the most distinct component available in the ECG signal, which is normally detected by the lower order IMF's. Normally this type of R-wave also contain high frequency component but, using EMD noisy ECG can filter out the complex QRS and its associated uneven waves/patterns. These patterns can be denoted as IMF1, IMF2, and IMF3 and so on [8].

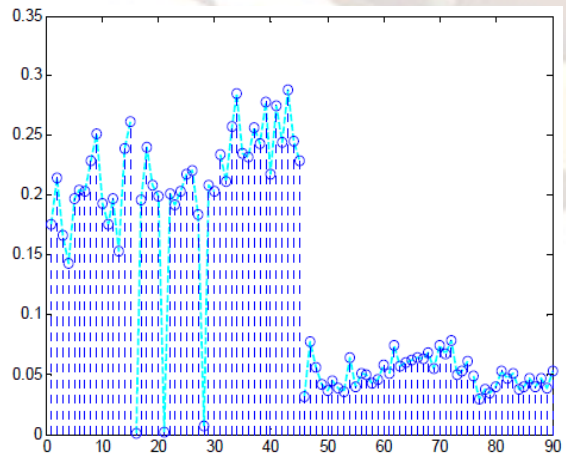


Figure-5 R peak detection of ECG records used For classification

V. Neural Network Training (NN) Classifier

The Neural Network (NN) has to apply, the structure of discreet propagation known as "feed forward propagation" is used in the training stage of the NNs [9-10]. In this paper, we are interested in the classification of the arrhythmias presenting some anomalies. All the ECG data, used from the MIT-BIH Arrhythmia Database which was digitized at a sampling rate of 360 Hz

Neural Network is biologically inspired network that are suitable for classification of biomedical data. A combination of EMD and NNs is proposed to classify cardiac arrhythmias. The precision of classification results of the anomalies depends on the number of parameters selected; the number of neurons of input layer is equals to the numbers of parameters used for classification. The parameters extracted are used to train the NN. Typically, for classification, the configuration usually used is the layered approach of feed forward neural networks with Log-sigmoid activation function that using the generalized back propagation for training which minimize the errors between the desired outputs and the actual outputs of the NNs. The desired output is being a real number in the interval (0 & 1).

The classification steps of the signals are depicted in Fig.2 which distinguishes the various stage from Data acquisition, its pre-processing, extraction of features, training the neural network. The architecture of the NN contains: five inputs neurons, two hidden layer with eight neurons and one output neurons as depicted in fig.6. The training of the neural network ends if the sum of the square errors for all segments is less than 0.01. The number of data set used for training and testing of the NNs classifier and the results obtained are tabulated in table.1. The parameters extracted normal wave, LBBB, RBBB, PB and AP are used as inputs vector to NNs classification. The output of the classifier is a shown in fig. 7.

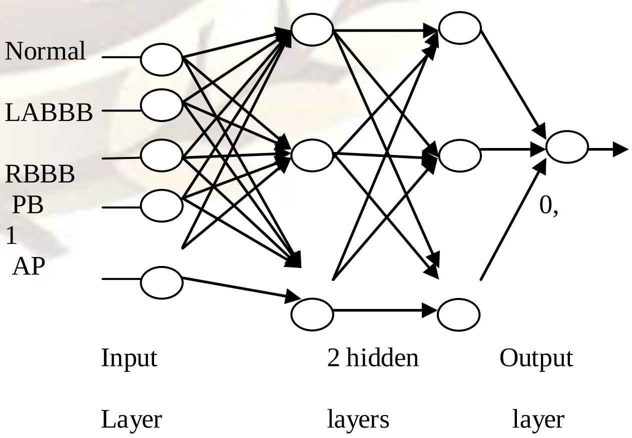


Figure-6 Three layered feed-forward classifier.

VI. Simulation & Results.

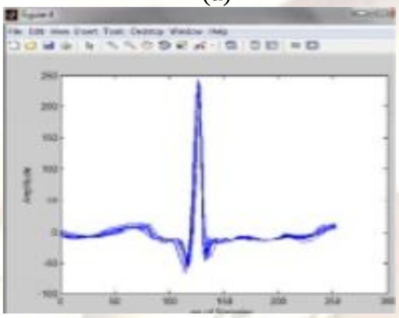
To evaluate the performance of the classifier; three criteria are required that needs to be considered as below:

$$\text{Sensitivity (\%)} = \frac{TP}{TP+FN} \times 100 \qquad (7)$$

$$\text{Specificity (\%)} = \frac{TN}{TN+FP} \times 100 \qquad (8)$$

$$\text{Overall (\%) Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \times 100 \qquad (9)$$

(a)



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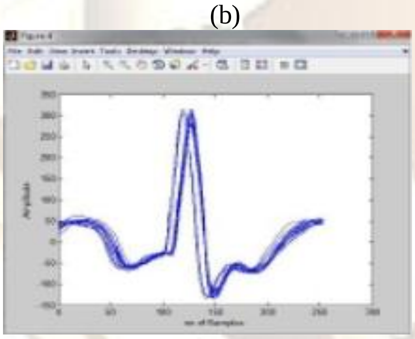

(c)

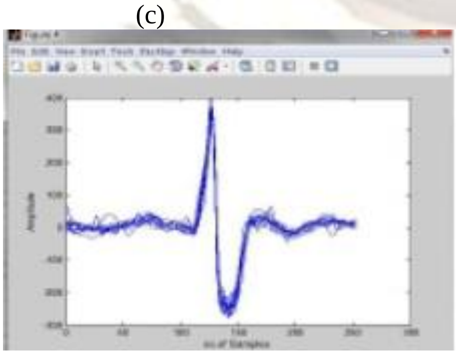

Figure-7 Beat Sample; (a) Normal; (b) LBBB; (c) RBBB.

The results of classification using the partition neural classifier are summarized in Table-1. In this case, the accuracy and sensitivity are higher and the rate of false classification is weaker.

Table-1 Statistical Analysis

Arrhythmia class	Sensitivity %	Specificity %	Accuracy %
Normal	100	98.78	100
LBBB	97.50	100	98.75
RBBB	100	98.55	100
PB	98.50	99.76	98
APB	97.00	100	98
Overall Accuracy (%) 99.95			

The performance of the combination of Empirical Mode Decomposition and neural network for classification are considered to be acceptable comparatively with the manual diagnostic. These approaches can constituent a tool for the diagnostic and the classification of the normal and abnormal cardiac beats. The patterns used in the three sets normal beat, Left bundle branch block beat(LBBB) ,Right bundle branch block beat (RBBB) were distinct. The records no. 100, 101,104, 105, 106, 107, 108, 109, 111, 112, 113, 203, 207, 212, 214, 231 were used for training, testing and validation.

We extracted characteristic parameters of the ECG signals for various pathologies. These decomposition modes constitute a data base for the learning NNs. The neural network used in this study is a three-layer feed-forward propagation type of structure. In order to overcome the difficulty of intensive computational time taken using NN classifier, attempt has been made to reduce the numbers of input data parameters which is beneficial for ECG signal decomposition.

VII. CONCLUSION

P and QRS waves can be used as reliable indicators of heart diseases. In this paper, both EMD and Neural Network classifier are presented as diagnostic tools to aid the physician in the analysis of heart diseases. Three types of ECG samples were selected from MIT - BIH arrhythmia database for experiments. The aim of using an Neural Networks (NN) is to decrease the error by obtained training parameters are extracted using EMD (IMFs). The NN has been presented and developed to classify electrocardiography signals. The technique used is obtained by incorporating the NNs, IMF's and significant parameters; extracted from the ECG records, combining their advantages. The Statistical analysis of the results listed in Table-1 show it is evident that the classifiers presented are effective for classification of cardiac arrhythmia with an overall accuracy of 99.95%. The accuracy of the tools depends on several factors, such as the size of database and the quality of the training set and, the parameters chosen to represent the input of the classifier. The single output neuron, allowing to easily classification according the abnormalities ECG signal, is used. The results conclude that it is possible to classify the cardiac arrhythmia with the help of neural networks. The advantage of the NNs classifier is its simplicity and ease in use. Thus a new beat classification algorithm using EMD has been proposed. Empirical mode decomposition (EMD) method has found a powerful method for nonlinear non-stationary data analysis.

VIII. ACKNOWLEDGEMENT

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