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"Automatic Classification of Cardiac Arrhythmias using MLP and RBF Neural Network Classifiers"

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Abstract—*World Health Organization statistics shows that 31% of all global deaths are due to cardiac disorders. If no initiative is taken to check this most predictable and preventable among all chronic diseases world will have to suffer with millions of heart patients. Due to large variation in the morphologies of Heart patient's ECG signal it is difficult to identify the type of cardiac disorder by the clinical doctors. The main objective of this work is to enable the clinical doctors to treat the patient according to CPR guidelines before sending him to cardiologist to diagnose cardiac arrhythmia. Processing of ECG signal and identifying the cardiac disorders is a challenging task. Cardiac arrhythmias such as Sudden Cardiac Arrest (SCA), Ventricular Tachycardia(VT), Atrial Fibrillation(AF) and Cardiac Ischemia(CI) ECG data is taken from MIT database. A significant work has been done in the past for arrhythmia identification. Time and Frequency domain analysis of ECG of any patient is not enough to detect possibility of cardiac arrhythmia as ECG is non stationary signal. This paper presents an algorithm based on the wavelet decomposition on ECG signal to extract its features and these are fed to MLP and RBF neural network classifiers to recognize different types of cardiac arrhythmias. Automatic recognition of cardiac arrhythmias is important for diagnosis of heart disorder to give proper treatment. The accuracy of both RBF and MLP classifiers is observed as 98.55%. It is proved that RBF computation time and RMSE are very less compared to MLP algorithm. The ECG data is collected from MIT-BIH database.*

1. INTRODUCTION

Electrocardiogram (ECG) is an important bio-signal representing the electrical activity of the heart. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. Fig. 1 shows a normal ECG signal. The majority of the clinically useful information in the ECG is available in the intervals and amplitudes. Automatic ECG feature extraction is important, particularly for identification of cardiac diseases. Earlier based on time domain method, the ECG feature extraction system provided features such as amplitudes and intervals. Recently, a number of techniques such as spectral and bi-spectral analysis have been proposed to detect ECG features. But they are not always adequate to know automatic detection of the disease. Ischemia (CI) is caused by a temporary lack of oxygen rich blood to the heart and it is a heart disease that covers heart tissues caused by narrowing of the arteries which makes less oxygenated blood to reach the heart muscle. Sudden Cardiac Arrest (SCA) is also a major health problem and is responsible for almost half of all heart disease deaths. It occurs when oxygenated blood doesn't reach the brain. Ventricular tachycardia (VT) is a type of abnormal heart rhythm. It causes heart to beat too fast, usually over 100 beats per minute. It's caused by faulty electrical signals in heart. Atrial fibrillation occurs when the electric current in the heart is generated from all over the atria at a very high speed, above 300 impulses a minute. This does not allow the atria to contract in a synchronized fashion. Because of the high number of impulses generated by the heart, and their location, the atria begin to quiver. Analysis of such heart patients ECG is difficult. Sometimes even many experienced doctors are unable to detect the abnormalities of the heart.

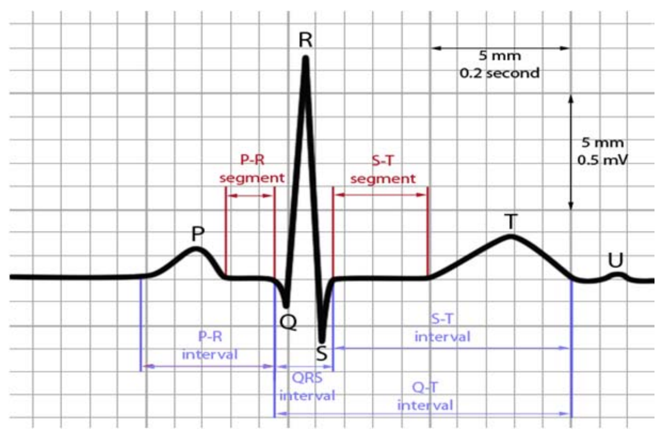

Fig. 1: Normal ECG signal

This work presents an algorithm based on the wavelet decomposition on ECG signal to extract its features and recognize different types of cardiac arrhythmia using artificial neural networks. In pre-processing stage is noise is removed. Baseline drift (2Hz) may be caused in the chest-lead ECG signals by coughing or breathing with large movement of the chest, or when an arm or leg is moved in case of limb-lead ECG acquisition. This is removed through mean correction technique. The statistical mean of the signal vector is computed and subtracted from each sample so that the distribution of the samples is along the axis and so that DC noise will be removed. One minute ECG data of various diseases is taken and sampled at a frequency of 250Hz. Wavelet transform technique is used to extract the ECG features. These features are fed to the MLP and Radial Basis Function neural network classifier.

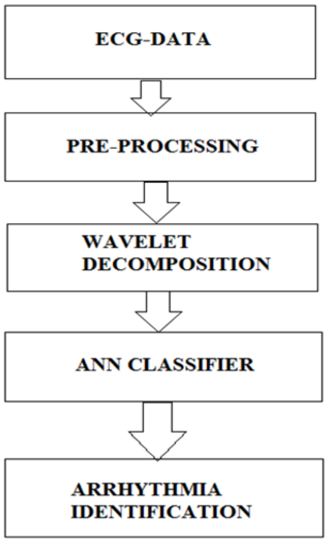

Fig. 2. Algorithm to identify cardiac disorder

2. PROCESSING STEPS TO IDENTIFY CARDIAC DISORDER

2.1. Wavelet Decomposition

Generally, the wavelet transform can be expressed by the following equation:

$X(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} \varphi^{*}\left(\frac{t-b}{a}\right) x(t)dt$, where 'a' is scaling and ' b' is time.

There are three types of wavelet transforms; continuous wavelet transforms (CWT), discrete wavelet transforms (DWT) and multi resolution based discrete wavelet transforms. Discrete wavelet transforms are widely used for feature extraction and data compression. The DWT is also used for de-noising the signals. The ECG is a non-stationary signal whose frequency components vary with time. Hence, use of wavelet transform is very efficient in the qualitative extraction of the features from the ECG signal. DWT decomposes the ECG signal to get important features. In one dimensional DWT, at each decomposition level, the HPF associated with scaling function produces detail information which is related to high-frequency components, while the LPF associated with scaling function produces coarse approximations, which are related to low frequency components of the signal. The approximation part can be iteratively decomposed. This process for two-level decomposition is depicted in Fig. 3. A signal is broken down into many lower resolution components. This operation is called the wavelet decomposition tree.

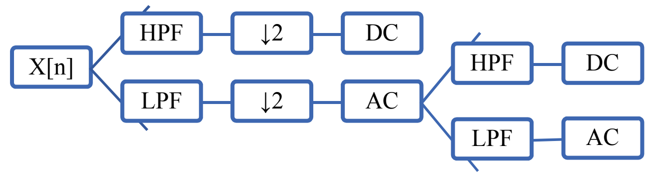

Fig. 3 Two-level Wavelet decomposition

The wavelet representation of a discrete signal X consisting of N samples can be computed by convolving X with the Low-Pass Filters (LPF) and High-Pass Filters (HPF) and down-sampling the output signal by 2, so that the two frequency bands each contains N/2 samples. This technique is based on the use of wavelets as the basis functions for representing other functions. These basis functions have a finite support in time and frequency domain. Multi resolution analysis is achieved by using the mother wavelet, and a family of wavelets generated by translations and dilations of it. Decompose a signal into low frequency approximation coefficients (AC) and high frequency detailed coefficients (DC).Take the low frequency component, and perform the same processing on that keep going on processing the required number of 6-levels.The features of the ECG signal extracted from the above mentioned technique serves as a training set of data for further classification of various diseases.

2.2 Statistical features

The statistical features extracted using signal processing techniques are mentioned below which has given an optimised and accurate results in training artificial neural networks.

X(i) represents the value of the i^{th} sample of the raw ECG discrete data signal i=1,…….,N.

- Median

  The middle value of a set of ordered data

  $M_{dn}=\{(n+1) \div 2\}^{th}$ value

  n is the number of values in the set of data
- Standard deviation of the raw signal

  $$\sigma_{x}=\left(\frac{1}{N-1}\sum_{i=1}^{i=N}(X(i)-\mu_x)^2\right)^{1/2}$$
- Energy of the raw signal

$$E_x = \sum_{i=-\infty}^{i=\infty} |X(i)|^2$$

- The Mean of the absolute values of the first differences of the raw signal

$$\delta_x = \frac{1}{N-1} \sum_{i=1}^{i=N-1} |X(i+1) - X(i)|$$

- The Mean of the absolute values of the second differences of the raw signal

$$\gamma_x = \frac{1}{N-2} \sum_{i=1}^{i=N-2} |X(i+2) - X(i)|$$

- The Means of the absolute values of the first differences of the normalized signal

$$\delta_x^n = \frac{1}{N} \sum_{i=1}^{i=N-1} |X^b(i+1) - X^b(i)|$$

$$X^b = \frac{X(i) - \mu_x}{\sigma_x}$$

Where μ_x and σ_x are the mean and standard eviations of X.

3. ARTIFICIAL NEURAL NETWORKS

A classification scheme is developed in which a feed forward neural network is used as a classification tool depending on the distinctive frequency bands of each arrhythmia. The Multilayer perceptron (MLP) algorithm allows experiential acquisition of input/output mapping knowledge within multilayer networks. MLP performs the gradient descent search to reduce the mean square error between the actual output of the network and the desired output through the adjustment of the weights. It is highly accurate for most classification problems because of the property of the generalized data rule. In the traditional MLP training, the weights are adapted using a recursive algorithm starting at the output nodes and working back to the first hidden layer. The Radial basis function neural network (RBFNN) has high speed learning algorithm due to this it is broadly used neural in the field of Pattern classification. It is a non-linear hybrid network which is physically including neurons of distinct hidden layer.

3.1 Multilayer perceptron

Multilayer Perceptron networks (MLP) are having sigmoid activation function which is a continuous differentiable function. This works with a powerful and computationally efficient method of error back propagation. This method involves finding the derivatives of an error function with respect to the weights and biases in the network.

The network with multiple layers containing differentiable activation functions like sigmoid, then the output of these functions are differentiable with both the input variables and with the weights and biases. If we define an error function, such as the squares of the sum of squares error which is differentiable function of the networks outputs, then this error itself is a differentiable function of weights. We can therefore evaluate the derivatives of the error with respect to the weights, and these derivatives can then be used to find weight values which minimise the error function, by using gradient descent, one of the more powerful optimization methods.

$$Y_k = \sum_{j=1}^{n} w_{kj} x_j$$

Y_k is output of activation function, where w_{kj} is synoptic weight from j^{th} neuron to k^{th} neuron and x^j is input to the j^{th} neuron

$$E^p = 1/2 \sum (t_0 - y_0)^2$$

E^p is error function calculated from t_0 true value and y_0 value from activation function

$$\frac{\partial E}{\partial w_{0i}} = -(t_0 - y_0) x_i$$

Which represents a gradient descent error function and the updated new weight vector is calculated as:

$$\Delta w_{0i} = \gamma (t_0 - y_0) x_i$$

γ is learning rate

woi (new) woi (old) + Δw_{0i}

3.2 Radial Basis Function

Radial basis function (RBF) provides an important property in which the activation of the hidden unit is determined by the distance between the input vector and a prototype vector. In this technique we use Gaussian function as our activation function.

The procedure in training the RBF is faster than that we use in MLP. This can be given by internal representation formed by the hidden units, and leads to a two stage training procedure. In first stage the parameters governing the basis function are determined using relatively fast, unsupervised learning methods. The second stage of training then involves the determination of the final layer weights, which requires the solution of a linear problem, and which is therefore also faster.

$$Y_K(X) = \sum_{j=1}^{M} w_{kj} \emptyset_j(X) + w_{k0}$$

$Y_k(X)$ is the output of the activation function.

$$\emptyset_j(X) = \exp\left(\frac{-\left\|X - \mu_j\right\|^2}{2\sigma_j^{\,2}}\right)$$

$\emptyset_j(X)$ is the Gaussian activation function).

Where X is d-dimensional input vector with elements x_i, and μ_j is the vector defining the centre of the basis function.

4. RESULTS

The features extracted are relevant for a particular type of disease. There are two types of features-Morphological features, gives the characteristic morphology details that include coefficients from wavelet decomposition, their maxima and minima etc. Statistical features completes the feature set, includes mean, variance, and standard deviation. In order to find the above features the ECG signal is decomposed to 6-levels using Daubechies4(db4) as the mother wavelet as shown in fig.8 then the maximum and minimum values of detailed and approximation coefficients, mean, median, variance, standard deviation and energy are found. All these features are concatenated into a single feature vector. 18 features are extracted for each single beat. These features are given as the input to the ANN classifier. These extracted features are acting as the variables for training the neural networks for classification. Classification performance is analyzed and obtained from neural network solutions through which TP, TN, FP, FN, Accuracy, precision, sensitivity and selectivity calculated by the confusion matrix as shown in Table1.

Table 1: Confusion matrix

MLP/RBF	**TP**	**FP**	**FN**	**TN**	**S**	**SP**	**PP**
CI	23	1	0	45	100	97.8	95.8
VT	15	0	0	54	100	100	100
AF	15	0	1	53	93.7	100	100
SCA	15	0	0	54	100	100	100

Notations:

S-Sensitivity, TP-True positive ,TN-True Negative, FP-False positive , FN-False Negative ,SP-Specificity, PP-Positive Predictivity

5. CONCLUSION

The experimental result illustrated the high level of accuracy using Radial Basis Function neural network for arrhythmias classification. This paper proposed the classification of heart diseases into four classes: Atrial fibrillation, Cardiac Ischemia, Sudden Cardiac Arrest and Ventricular Tachycardia. The 68 records of one minute ECG data of four different diseases collected from MIT-BIH database. The overall system classification accuracy obtained using MLP and RBF algorithms is 98.55% and the computational speed of RBF is more than that of MLP with very less MSE. Hence, this paper concludes that arrhythmias identification using RBFNN is highly efficient than MLPNN.

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