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COMPLEX WAVELET TRANSFORM BASED CARDIAC ARRHYTHMIA CLASSIFICATION

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Abstract- **ElectroCardioGram (ECG) wave reveals the electrical activity of the cardiac system. The small changes in amplitude and duration of ECG signal cannot be described precisely by the human eyehence there is a need for computer aided diagnosis system. In this proposed method, dual tree complex wavelet transform based feature extraction approach is used for a classification of cardiac arrhythmias. The feature set consist of complex wavelet coefficients extracted from the fourth and fifth scale of DTCWT decomposition of a QRS complex signal in association with four other features like AC power, kurtosis, skewness and energy extracted from the QRS complex signal.Support Vector Machine (SVM) is used to classify the ElectroCardioGram (ECG) beats. The empirical results reveal that the DWT and DTCWT established feature extraction technique classifies ECG beats of MIT-BIH Arrhythmia database.**

Index Terms- Discrete Wavelet Transform(DWT), Dual Tree Complex Wavelet Transform(DTCWT), Electro Cardio Gram(ECG), Support Vector Machine(SVM).

I .INTRODUCTION

The analysis of ECG has been extensively used for diagnosing many cardiac diseases. Arrhythmias commonly occur due to abnormal heart beat. These cardiac disease can be noninvasively diagnosed using ECG signal. Computer-aided heart arrhythmia identification and classification can play a significant role in the management of cardiovascular diseases. An important step toward detection of arrhythmia is the classification of heartbeats. The rhythm of the ECG signal can then be decisive by knowing the classification of consecutive heartbeats in the signal. Hence, there is a need for computer aided diagnosis system which can accomplish higher recognition accuracy. Numerous techniques are applied to analyse and classify ECG beats.

In [1], the biographer classified PVC beats from normal and other abnormal beats by using wavelet transformed ECG waves with timing data as feature and ANN as a classifier. An overall accuracy of 95.16% is achieved by using this technique. In [2], PCA is used as a gadget for the classification of five types of ECG beats (N, LBBB, RBBB, PVC and APC). A relative study is performed on three methodologies of feature extraction (principal component of segmented ECG beats, principal component of error signals of linear prediction model, principal components of DWT coefficients). In [3], an accuracy of 94.64% is accomplished using the approximation wavelet coefficient of ECG signal in conjunction with three timing data as feature and RBF Neural network as a classifier. Here, classification was performed on five types of cardiac beats (N, LBBB, RBBB, PVC and APC). In [4], the biographer have used particle swarm optimization and radial basis function neural network (RBFNN) used for classifying six types of ECG beats. In [5], an experimental pilot study is performed to examine the property of pulsed electromagnetic field (PEMF) at extremely low frequency(ELF) in response to photo plethysmographic (PPG), electrocardiograph (ECG), and Electro Encephalo Graph (EEG) activity using discrete wavelet transform. In [6], the biographer has proposed Electroencephalography (EEG) seizure detection using the DTCWT-Fourier features and neural network as a classifier. These features accomplish perfect classification rates (100%) for the EEG database from the University of Bonn. In [7], the biographer have classified five types of ECG beats recommended by Association for Advancement of the Medical Instrumentation (AAMI) standard, i.e. normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB),fusion of normal and VEB, exotic beat using ECG morphology, heart beat intervals and RR intervals as feature and classifier based on linear discriminates. In [8], the authors have shown the generalization capability of the Extreme Learning Machine (ELM) up the support vector machine (SVM) approach in the automatic classification of cardiac beats. In [9], wavelet transform and probabilistic neural network is used to classify six types of ECG beats. This technique has displayed high classification accuracy but the experiment is limited to very small sets of data. In [10], a combo of independent features and compressed ECG data is used as input to the multi-layered perceptron network. An accuracy of 88.3% is reported up 10 files of MIT -BIH database. In this paper, we have proposed a novel technique for classifying cardiac beats using complex wavelet coefficients of 4th and 5th scale DTCWT decomposition in association with four features extracted from the QRS complex signal of each cardiac cycle. Fourier transform (FT) of a signal provides destitute time frequency localization of the signal and short time Fourier transform

(STFT) analyses every spectral component uniformly .Wavelet analyses the non-stationary signal with varying window size thereby assure good time frequency localization of ECG signal. The dual tree complex wavelet transform add approximate shift invariance and directionally selective filters while conserving the usual properties of perfect reconstruction and computational capability. The ability of dual tree complex wavelet transform to allow shift invariance indicates the ability of its coefficient to differentiate the shifting of input signals. Artificial neural network trained by the back propagation algorithm for classifying ECG beats to appropriate classes. A parallel study is performed on two sets of features, and experimental results indicate that DTCWT based features accomplish better than the DWT features.

II. ECG DATA

Data from the MIT-BIH arrhythmia database were used in this paper which includes recordings of many common and aggressive arrhythmias along with examples of normal sinus rhythm. The database contains 48 recordings, each containing two 30-min ECG lead signals. These records were sampled at 360 Hz and band pass filtered at 0.1-100 Hz [10].

III. PROPOSED FRAMEWORK

The suggested technique consists of three main stages: (i) pre-processing, (ii) feature extraction and (iii) classification. The pre-processing level contains amplitude normalization and filtering of ECG signals. The ECG signals are normalized to a mean of zero and standard deviation of unity, hence decreasing the amplitude variance from file to file. The embedded noises in ECG signals are eliminated using a band pass filter with a cut off frequency of 4–22 Hz. The pre-processed ECG signal is used in next level for extracting significant features. The features extracted using DTCWT technique is applied as input to an SVM classifier which maps the feature vectors to the respective class labels. The proposed block diagram as shown in Fig I.

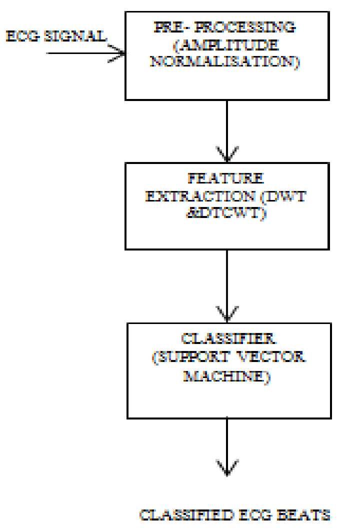

Fig.I.Block diagram of the proposed technique.

IV. WAVELETS

A. Introduction

The wavelet transform has rise recent years as a powerful time frequency analysis. Both short period, high frequency and longer period, lower frequency information can be seize simultaneously using wavelets. Hence the method is particularly useful for the search of transients, aperiodicity and other non-stationary signal features where, through the interrogation of the transform, small changes in signal morphology may be highlighted over the scales of interest. Another key merit of wavelet techniques is the variety of wavelet functions available, thus allowing the most appropriate to be chosen for the signal under investigation.

B. Feature extraction using discrete wavelet transform

The analysis of the ECG signals was performed using the DWT .The selection of appropriate wavelet and the number of decomposition levels is essential in analysis of signals using the wavelet transform. The number of decomposition levels is chosen based on the frequency components of the signal. The levels are chosen such that those parts of the signal that associate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In this project, the number of decomposition levels was chosen to be 5. Thus, the ECG signals were decomposed into the detail co-efficient *D*1–*D*4 and one final approximation co-efficient *A*4. The smoothing feature of the Daubechies wavelet of order 2(db2) made it more sufficient to detect changes of the signals. Therefore, the wavelet coefficients were computed using the db2. The frequency bands corresponding to different levels of decomposition for Daubechies wavelet of order 2 (db2) with a sampling frequency of 256 Hz .The discrete wavelet coefficients were computed using the MATLAB software. The feature selection is an important component of designing the pattern classification .since even the best classifier will perform badly if the features used as inputs are not selected well. The computed discrete wavelet coefficients provide a solid representation that shows the energy distribution of the signal in time and frequency. In spite of reducing the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients was used. From each sub-band four statistical parameters are computed i.e. maximum, minimum, mean and standard deviation of the wavelet coefficient. Thethree level sub-band decomposition using DWT technique as shown in Fig II.

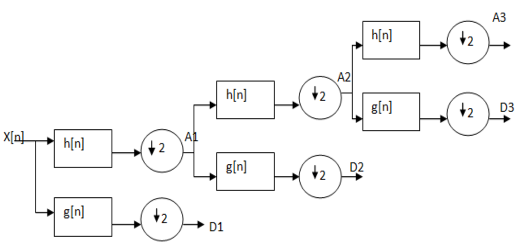

Fig.II. Three level sub-band decomposition using DWT technique

C. Feature extraction using dual tree complex wavelet transform

The dual tree complex wavelet transform has multiple resolution representation, just like the DWT. Two sets of real filters are used for generating the real part (TREE A) and the imaginary part (TREE B) of the complex wavelet transform. The feature extraction technique can be summarized as follows: Extract the QRS complex by taking 256 samples around the R-peak. (ii) Decompose the QRS complex signal to five resolution scales by using 1D DTCWT.(iii) Choose the features of DTCWT from 4th and 5th scale and compute the absolute value of the real and imaginary coefficients (detail coefficients) from each scale.(iv) Perform ID FFT on the selected features and take the logarithm of the Fourier spectrum. The shift invariant property of DTCWT and FFT helps in classifying the ECG beats efficiently. In addition to the complex wavelet based features, four other features are extracted from the QRS complex of each cardiac cycle.(i) AC power of the QRS complex signal.(ii) Kurtosis of the QRS complex signal.(iii) Skewness of the QRS complex signal. (iv) Energy of the QRS complex signal. These features are also classified using SVM classifier. Dual tree CWT corresponding to three levels as shown in Fig III.

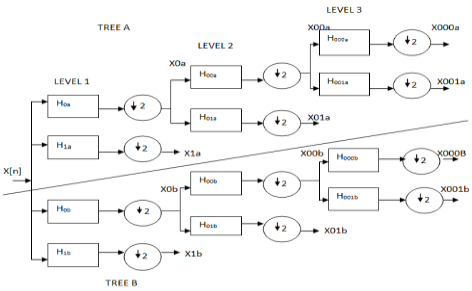

Fig.III.Dual tree CWT corresponding to three levels

The ECG signals of MIT-BIH database are sampled at a frequency of 360 samples per second, hence the frequency component in ECG range between 0 and 180 Hz. In our work, the wavelet coefficients are computed across the QRS complex is maximum in the frequency range of 8-20Hz.The number of decomposition levels is limited to 5 beyond which baseline.

V. SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) was introduced by Vapnik. Support Vector Machines (SVM) is a relatively new learning method used for binary classification. The basic idea is to find a hyperplane which separates the d-dimensional data perfectly into its two classes. SVM is a supervised classification method. Here, a set of known objects is called training set. Each object of the training set consists of a feature vector and a belonging class value. Based on the training data, the learning algorithm extracts a decision function to classify the unknown input data. The architecture of SVM shown in Fig V. For examples (xi, yi) i = 1 ... l, where each example has d inputs ($x_i \in R^d$), and a class label with one of two values (yi∈(-1,1)) .

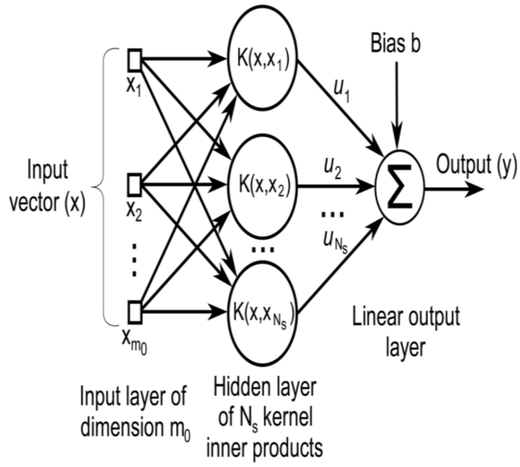

Fig V Architecture of SVM

Now, all hyper planes in R^d are parameterized by a vector (w), and a constant (b), expressed in the equation

$$w.x+b=0$$

w is the vector orthogonal to the hyperplane. Given such a hyperplane (w, b) that separates the data, this gives the function.

$$f(x) = sign(w.x + b)$$

Which correctly classifies the training data However, a given hyperplane represented by (w, b) is equally expressed by all pairs $(\lambda w, \lambda b)$ for $\lambda \epsilon R^+$ .The canonical hyperplane is defined to be that which separates the data from the hyperplane by a distance of at least1. That is, we consider those that satisfy

$$y_i(x_i.w+b) \geq 1 foralli$$

To obtain the geometric distance from the hyperplane to a data point, we must normalize by the magnitude of w. This distance is given by

$$d((w,b),x_i = \frac{yi(xi.w+b)}{\parallel w \parallel} \geq \frac{1}{\parallel w \parallel}$$

The hyperplane that maximizes the geometric distance to the closest data points is needed. This is accomplished by minimizing$\parallel w \parallel$.

The vectors closest to the boundaries are called support vectors and the distance between the support vectors and hyper plane is called margin. In order to detect the arrhythmias and to reduce false positives, the feature vector is analysed by a classifier. SVMs are a useful technique for data classification. In addition, SVMs are supervised learning models with associated learning algorithms that analyse data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts two possible classes for each given input. A brief strategy for ECGclassification is as follows:

1. Select input data patterns

2. Embed input data into a multi-dimensional feature space by computing inner products of data patterns by using a kernel function

3. Seek for linear relations among the data patterns in the feature space by trying to find a separating hyperplane with maximum support vector margins.

VI. RESULTS

Classifier is evaluated using the parameters sensitivity,and accuracy.

Sensitivity = (TP/TP+FN)*100

Accuracy= (TP+TN)/(TP+TN+FP+FN)*100

Where TP stands for true positive, TN for true negative, FP forfalse positive and FN for false negative. The performance of classification shown in table I.

Table I Classification performance

Accuracy	71.7391
Specificity	50

VII. CONCLUSION

This paper, a technique is proposed for classifying ECGbeats using DTCWT based feature set. Four features AC power,kurtosis, skewness and energy extracted from QRS complex of each cardiac cycle concatenated with the features extractedfrom the fourth and fifth decomposition levels of DTCWT, are usedas total feature set. In this paper, the SVM is used as a classifier because it has ability to learn and generalize, smaller training set requirements, fast operation, and ease of implementation. The major advantage of this network is that it finds the nonlinear surfaces separating the underlying patterns which is generally considered as an improvement on conventional methods and the complex class distributed features can be easily mapped by classifier. The proposed method has shown a promising sensitivity of 50% which indicates that this technique is an excellent model for computer aided diagnosis of cardiacarrhythmias. The performance of the proposed method is comparedwith DWT based statistical features and it is seen that the proposedfeature set achieves higher recognition accuracy than DWT basedfeature. The proposed methodology can be used in telemedicine applications, arrhythmia monitoring systems, cardiac pacemakers, remote patient monitoring andin intensive care units.

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