Classification of Cardiac Arrhythmias based on Dual Tree Complex Wavelet Transform

Manu Thomas*, Manab Kr Das *Student Member, IEEE* and Samit Ari, *Member, IEEE*

***Abstract*—The electrocardiogram (ECG) is a standard diagnostic tool to distinguish the different types of arrhythmias. This paper develops a novel framework for feature extraction technique based on dual tree complex wavelet transform (DTCWT). The feature set comprises of complex wavelet coefficients extracted from the 4th and 5th scale of DTCWT decomposition and four other features (AC power, kurtosis, skewness and timing information). This feature set is classified using feed forward neural network. In this work, five types of ECG beats (Normal, Paced, Right Bundle Branch Block, Left Bundle Branch Block and Premature Ventricular Contraction) are classified from the MIT-BIH arrhythmia database. The performance of the proposed method is compared with statistical features extracted using discrete wavelet transform (DWT). The experimental result shows that the proposed method classifies ECG beats with an overall sensitivity of 97.80%.**

Index Terms*—*Artificial neural network (ANN), Discrete wavelet transform (DWT), Dual tree complex wavelet transform (DTCWT), Electrocardiogram (ECG).

I. INTRODUCTION

ECG offers cardiologists with useful information about the rhythm and functioning of the heart. Therefore, its analysis represents an efficient way to detect and treat different kinds of cardiac diseases. The small changes in amplitude and duration of ECG cannot be determined precisely by the naked eye and ECG patterns may have to be observed over several hours, hence there is a need for computer aided diagnosis system.

Numerous techniques are applied to analyze and classify ECG beats. In [1], the authors classified PVC beats from normal and other abnormal beats by using wavelet transformed ECG waves with timing information 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 tool for the classification of five types of ECG beats (N, LBBB, RBBB, PVC and APC). A comparative 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 achieved using the approximation wavelet coefficient of ECG signal in conjunction with three timing information as feature and RBF Neural network as a classifier. Here, classification was performed on five types of ECG beats (N, LBBB, RBBB, PVC and APC). In [4], the authors have used particle swarm optimization and radial basis function neural network (RBFNN) for classifying six types of ECG beats. In [5], an experimental pilot study is performed to investigate the effects of pulsed electromagnetic field (PEMF) at extremely low frequency (ELF) in response to photoplethysmographic (PPG), electrocardiographic (ECG), electroencephalographic (EEG) activity using discrete wavelet transform. In [6], the author has proposed Electroencephalography (EEG) seizure detection using the DTCWT-Fourier features and neural network as a classifier. These features achieve perfect classification rates (100%) for the EEG database from the University of Bonn. In [7], the authors have classified five types of ECG beats recommended by Association for the Advancement of Medical Instrumentation (AAMI) standard, i.e. normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB), fusion of normal and VEB, unknown beat using ECG morphology, heart beat intervals and RR intervals as feature and classifier model based on linear discriminants. In [8], the authors have shown the generalization capability of the Extreme Learning Machine (ELM) over the support vector machine (SVM) approach in the automatic classification of ECG beats. In [9], wavelet transform and probabilistic neural network is used to classify six types of ECG beats. This technique has shown high classification accuracy but the experiment is limited to very small sets of data. In [10], a combination of independent features and compressed ECG data is used as input to the multilayered perceptron network. An accuracy of 88.3% is reported over 10 files of MIT-BIH database.

In this paper, we have proposed a novel technique for classifying ECG beats using complex wavelet coefficients of 4th and 5th scale DTCWT decomposition in conjunction with four features extracted from the QRS complex of each cardiac cycle. Fourier transform (FT) of a signal provides poor time frequency localization of the signal and short time Fourier transform (STFT) analyses every spectral component equally [11]. Wavelet analyses the non-stationary signal with varying window size thereby ensuring good time frequency localization of the signal. The DTCWT provides approximate

Manu Thomas is with the Department of Electronics and Communication Engineering, National Institute of Technology, Rourkela, India.(email: thomas.manu83@gmail.com).

Manab Kumar Das is with the Department of Electronics and Communication Engineering, National Institute of Technology, Rourkela, India. (email: manabkrdas@gmail.com).

Samit Ari is with the Department of Electronics and Communication Engineering, National Institute of Technology, Rourkela, India. (email: samit.ari@gmail.com).

shift invariance and directionally selective filters (properties lacking in the traditional wavelet transform) while preserving the usual properties of perfect reconstruction and computational efficiency. The ability of DTCWT to provide shift invariance indicates the ability of its coefficient to distinguish between input signal shifts. ANN trained by the back propagation algorithm, classifies ECG beats to appropriate classes. A comparative study is performed on two sets of features, and experimental results indicate that DTCWT based features perform better than the DWT features.

The rest of the paper is organized as follows: Section II presents the ECG database used in our experimental study. Section III explains the basic concepts of DWT and DTCWT. The proposed technique is described in section IV. Experimental results and discussions are presented in section V. The conclusion of this paper is reported in section VI.

II. ECG DATA

ECG data of MIT-BIH arrhythmia database is used to evaluate the performance of the proposed technique. The database was created in 1980 as a reference standard for arrhythmia detectors. The database comprises of 48 files, each containing 30 minutes of ECG segment selected from 24 hour recordings of 48 different patients. These records were sampled at 360 Hz and band pass filtered at 0.1-100 Hz [12]. In this paper, Normal beats (N) and four types of abnormal beats are used for evaluating the performance. The four types of abnormal beats are Left bundle branch block (LBBB), Right bundle branch block (RBBB), Premature ventricular contraction (PVC) and Paced beats (P).

III. BACKGROUND THEORY

A. Discrete Wavelet Transform: The wavelet transform (WT) of a signal allows the representation of temporal features at multiple resolutions. This is achieved by the decomposition of the signal over dilated (scale) and translated (time) versions of a prototype wavelet. The WT of a signal $x(t)$ is given by

$$WT_a x(b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-b}{a} \right) dt \tag{1}$$

Where $\psi(t)$, $a(a \in R^+)$ and $b(b \in R)$ are the prototype wavelet, scaling factor and translation factor respectively. The wavelet transform of a signal can be interpreted as a filtering of the signal by band pass filters whose center frequencies and bandwidths depend on the scaling factor. For analyzing discrete signals discrete wavelet transform is used, and it can be easily implemented by cascading a pair of low pass and high pass finite impulse response filters corresponding to the wavelet followed by decimation by 2 step [1]. The time invariance property of continuous WT is lost due to dyadic sampling of the translation parameter, hence the dyadic sampling is limited to scaling factor only [11]. The prototype wavelet used in our experimental study is daubechies wavelet of order 2 (Db2) due to its morphological similarity to the QRS complex of the ECG signal.

B. Dual Tree Complex Wavelet Transform: Kingsbury in 2001 introduced the DTCWT. The major drawback of DWT based technique in analyzing 1D signal is the lack of shift invariance property i.e. the amplitude of the wavelet coefficient varies significantly as the input signal is shifted slightly. This occurs due to down sampling operation at each level. A well known way of providing shift invariance is to use the undecimated form of the dyadic filter tree but this suffers from increased computation requirements and high redundancy in the output. The DTCWT overcomes this problem with a redundancy factor of 2^1 for 1D signal, which is substantially lower than the undecimated DWT. In [13], Kingsbury has explained the shift invariance property of DTCWT in detail. The DTCWT employs two trees of real filters (Tree A and Tree B) as shown in Fig. 1. The two trees correspond to the real and complex part of the complex wavelet transform. Shift invariant and directionally selective properties make this transform useful in pattern recognition and signal analysis application [6]. The DTCWT of a signal *x(n)* is implemented using two critically sampled DWTs in parallel to the same data, as shown in the Fig. 1. The transform is 2 times expansive because for an N point signal it gives 2N DWT coefficients [13]. The filters are designed in a specific way such that the sub band signals of the upper DWT can be interpreted as the real part of a complex wavelet transform and sub band signals of the lower DWT can be interpreted as the imaginary part. When designed in this way, the dual tree complex DWT is nearly shift invariant, in contrast with the critically sampled DWT. The Filters used in each stage are of length 10 [14]. The sets of coefficient used in first level are shown in Table I and the remaining levels are shown in Table II.

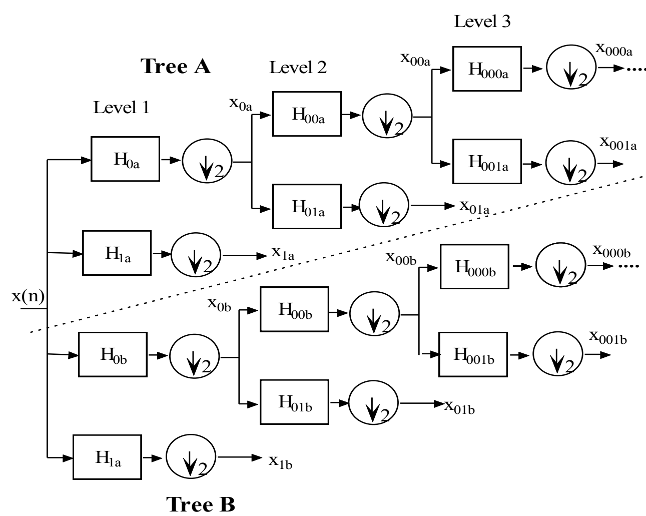

Fig. 1. Dual tree CWT corresponding to 3 levels

TABLE I
FILTER COEFFICIENTS USED IN FIRST LEVEL

TREE A		TREE B	
H0a	H1a	H0b	H1b
0.00000000	0.00000000	0.01122679	0.00000000
-0.08838834	-0.01122679	0.01122679	0.00000000
0.08838834	0.01122679	-0.08838834	-0.08838834
0.69587998	0.08838834	0.08838834	-0.08838834
0.69587998	0.08838834	0.69587998	0.69587998
0.08838834	-0.69587998	0.69587998	-0.69587998
-0.08838834	0.69587998	0.08838834	0.08838834
0.01122679	-0.08838834	-0.08838834	0.08838834
0.01122679	-0.08838834	0.00000000	0.01122679
0.00000000	0.00000000	0.00000000	-0.01122679

TABLE II
FILTER COEFFICIENTS USED IN REMAINING LEVELS

TREE A		TREE B	
H00a	H01a	H00b	H01b
0.035163840	0.000000000	0.000000000	0.035163840
0.000000000	0.000000000	0.000000000	0.000000000
-0.088329420	-0.114301840	-0.114301840	0.088388340
0.233890320	0.000000000	0.000000000	0.233890320
0.760272370	0.587518300	0.587518300	-0.760272370
0.587518300	-0.760272370	0.760272370	0.587518300
0.000000000	0.223890320	0.233890320	0.000000000
-0.114301840	-0.088388340	-0.088329420	-0.114301840
0.000000000	0.000000000	0.000000000	0.000000000
0.000000000	-0.035163840	0.035163840	0.000000000

The reconstruction filters can be obtained by reversing the alternate coefficients of analysis filters.

IV. PROPOSED METHOD

The entire methodology can be classified into three steps such as (i) Pre-processing (ii) Feature extraction and (iii) Classification. The pre-processing step includes the filtering of ECG signals using a band pass filter (3-20 Hz) in order to remove embedded noise such as motion artefacts, power line interference and baseline wandering. The filtered ECG signals are normalized to a mean of zero and standard deviation of unity. This eliminates the amplitude variance from file to file. In this work, we have focused on classification only and used the annotation file from MIT BIH database in order to locate the R peaks of the ECG signals.

A. Feature Extraction

Feature extraction is the technique of extracting significant information from a signal. It is the most important step in pattern recognition application since each feature represents the given signal in lower dimension, thereby reducing the computational complexity and overcoming the problem of over fitting of the training samples resulting in good generalization to new samples. The choice of feature extraction techniques is very important since a good classifier may fail to classify the beats, if the features selected are not proper [5]. Two types of features are extracted across the QRS complex of each cardiac cycle: (i) Discrete wavelet transform (DWT) based features (ii) Dual tree complex wavelet transform (DTCWT) based features

1) *DWT based features:* The first step is to extract the QRS complex signal by choosing 256 samples around the R-peak. The choice of decomposition levels completely depends upon the maximum frequency component of the ECG signal. The obtained signal is decomposed to five levels beyond which baseline wander becomes predominant. The decomposition levels correspond to the detail coefficient D1 to D5 and approximation coefficient A5. The following statistical features are computed from each sub band:

(i) Maximum of the wavelet coefficient in each sub band.
(ii) Minimum of the wavelet coefficient in each sub band.
(iii) Mean of the wavelet coefficient in each sub band.
(iv) Standard deviation of the wavelet coefficient in each sub band.

Total 24 features are extracted by the aforementioned technique, and these features are given as input to the ANN classifier.

2) *DTCWT based features:* The DTCWT has multi 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:

(i) 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 1D 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) RR-interval ratio (IR) reflecting the deviation from a constant beat rate given by

$$\frac{T_i - T_{i-1}}{T_{i+1} - T_i} \qquad (2)$$

Where, T_i represent the time at which R-wave for beat i occurs. The local RR-interval ratio provides a convenient differentiation between normal beats (IR_i ~1) and PVC beats ($IR_i < 1$) [1]. Total 28 features are extracted by the DTCWT based technique and these features are also classified using ANN classifier.

B. Classifier

The Artificial neural network used in our experimental study is a three layered, feed forward network, which employs the back propagation training algorithm with adaptive learning rate [15]. The size of input layer depends on the size of feature vector, and the size of output layer depends on the number of classes into which we are classifying the ECG beats. Hence, there will be 28 neurons in the input layer for DTCWT based features and 24 neurons for DWT based features. The number of neurons in the output layer is 5. The number of neurons in the hidden layer is 43, which is chosen empirically based on experimental results. The activation function used is tansigmoid function. The back propagation algorithm with adaptive learning rate minimizes the mean square error between the actual output and the desired output. Initially, the learning rate parameter is set to 0.5 and momentum constant to 0.9.

V. RESULTS AND DISCUSSION

In this paper, 12 files from MIT-BIH database are used for evaluating the performance of the proposed method. The beats are selected from the following files: 100, 102, 103, 109, 111, 113, 118, 208, 217, 221, 231 and 233. The network is trained using 2235 beats (1041 from N, 344 from P, 300 from LBBB, 301 from RBBB and 249 from PVC) and tested over the remaining data which corresponds to 24,245 beats (11464 from N, 3222 from P, 4311 from LBBB, 3115 from RBBB and 2133 from PVC). The classification results of ANN classifier using two feature sets are shown in Table III. The diagonal elements indicate the correctly classified beats corresponding to their respective classes. From the table, it is clear that 24 N beats, 31 P beats, 373 LBBB beats, 57 RBBB beats and 48 PVC beats are misclassified using DTCWT technique whereas 86 N beats, 41 P beats, 351 LBBB beats, 332 RBBB beats and 523 PVC beats are misclassified by DWT based technique. In clinical diagnosis, PVC beat has higher risk of sudden death compared to all other beats used in our experimental study [9]. Therefore it is important to classify PVC beats accurately. Classification performance is evaluated using four common metrics as found in literature [16].

$$\text{Accuracy (Acc)} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (3)$$

$$\text{Sensitivity (Sen)} = \frac{TP}{TP + FN} \qquad (4)$$

$$\text{Specificity (Spe)} = \frac{TN}{TN + FP} \qquad (5)$$

$$\text{Positive predictivity (Ppe)} = \frac{TP}{TP + FP} \qquad (6)$$

Where, TP, TN, FP and FN denotes true positive, true negative, false positive and false negative respectively. Accuracy is the measure of overall system performance over all the available classes, Sensitivity is the fraction of real events that are correctly detected among all real events, Specificity is the fraction of non-events that has been correctly rejected and Positive predictivity is the fraction of real events in all detected events. The detection sensitivity of PVC beats using DWT is 75.48% whereas the proposed method gives a detection sensitivity of 97.74%. The proposed method has also shown a significant improvement in detection sensitivity of RBBB beats by 8.83% when compared to DWT technique. The overall detection sensitivity of DTCWT based feature is high compared to the DWT based feature due to the efficient classification of N, P, RBBB and PVC beats.

Classification performance of the two feature sets are shown in Table IV. The proposed method gives the highest classification sensitivity with average accuracy of 99.06%, sensitivity of 97.31%, specificity of 95.75% and positive predictivity of 95.32%. The relationship between sensitivity and specificity is illustrated by the Receiver operating characteristics (ROC) curve. An ROC curve is a graph that plots false positive rate (FPR) versus true positive rate (TPR). For ideal classification the value of TPR=1.0 and FPR=0.0 which corresponds to the upper left corner of ROC curve. From the ROC curve shown in Fig. 2 the proposed method has higher TPR and lower FPR than the DWT method.

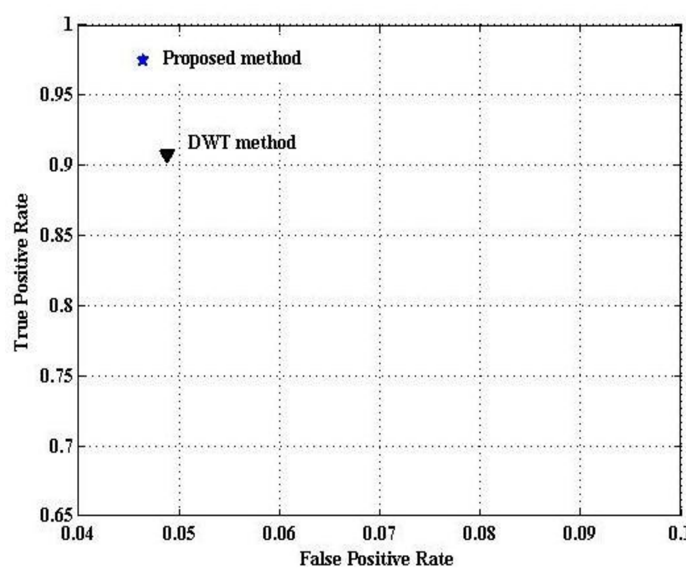

Fig. 2. Comparison of TPR and FPR for proposed and DWT based technique.

TABLE III
CLASSIFICATION RESULTS OF 12 FILES SELECTED FROM MIT-BIH ARRHYTHMIA DATABASE

CLASS	CONFUSION MATRIX [DWT]					CLASS	CONFUSION MATRIX [DTCWT]				
	N	P	LBBB	RBBB	PVC		N	P	LBBB	RBBB	PVC
N	11378	27	21	17	21	N	11440	2	7	6	9
P	13	3181	5	10	13	P	0	3191	23	0	8
LBBB	199	119	3960	5	28	LBBB	17	54	3938	15	287
RBBB	319	1	10	2783	2	RBBB	3	1	35	3058	18
PVC	81	125	248	69	1610	PVC	9	2	30	7	2085

TABLE IV
CLASSIFICATION PERFORMANCE OF DWT AND DTCWT BASED TECHNIQUE

METHOD	CLASS	PERFORMANCE MATRIX			
		Acc (%)	*Sen* (%)	*Spe* (%)	*Ppr* (%)
DWT	N	97.12	99.24	95.21	94.89
	P	98.70	98.72	98.70	92.12
	LBBB	97.38	91.85	82.23	93.30
	RBBB	98.21	89.34	99.84	96.49
	PVC	97.57	75.48	99.71	96.17
DTCWT	N	99.78	99.79	99.77	99.74
	P	99.62	99.03	99.71	98.18
	LBBB	98.06	91.34	83.10	97.64
	RBBB	99.64	98.17	99.90	99.09
	PVC	98.47	97.74	98.54	86.62

VI. CONCLUSION

In this paper, a new technique is proposed for classifying ECG beats using DTCWT based feature set. Four features (AC power, kurtosis, skewness and RR interval ratio) extracted from QRS complex of each cardiac cycle concatenated with the features extracted from the 4th and 5th decomposition levels of DTCWT, is used as total feature set. The performance of the proposed method is compared with DWT based statistical features. The proposed method has shown a promising sensitivity of 97.80% which indicates that this technique is an excellent model for computer aided diagnosis of cardiac arrhythmias. The proposed methodology can be used in tele-medicine applications, arrhythmia monitoring systems, cardiac pacemakers, remote patient monitoring systems.

ACKNOWLEDGMENT

The work is supported by the Department of Science and Technology (DST), India, under sanctioned order no. SR/FTP/ETA-76/2010.

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