Selective Feature Coding for Cardiac Arrhythmia Detection through ECG Signal Analysis

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Abstract

Detection of abnormalities in the ECG signal to achieve an automatic diagnosis of several heart related diseases has become an increased research aspect. This paper focused to develop an automatic detection system to detect abnormalities in ECG. These abnormalities results in different cardiac arrhythmias. Towards the detection of different cardiac arrhythmias, this paper analyzed the ECG signal through Dual Tree Complex Wavelet Transform (DTCWT) as a feature extraction technique and further proposed a new selective band coding technique to extract only the informative features from the sub bands obtained from DTCWT. The novelty of this proposed system is to remove the redundant information, thereby achieving a fast and accurate detection results. Multi-Class Support Vector Machine (MC-SVM) is used for classification purpose. Extensive simulations are carried out for the MIT-BIH database and the performance is measured through the performance metrics such as Accuracy, Precision, Recall, False Positive Rate, F-Measure and overall computational time. The proposed method is also compared with conventional approaches to alleviate the performance enhancement in the detection of Cardiac Arrhythmias (CAs) with less time span.

Keywords : Accuracy, Cardiac Arrhythmia, Detection Rate, DTCWT, ECG, MC-SVM, SA

I. Introduction

In recent years, cardiovascular diseases (CVDs) have become a common reason for most of the global deaths. In 2012, it was observed that the overall deaths due to the CVDs are around 17.5 million people, which is 31% of global deaths [XX]. Due to the different types of CVDs, most of the deaths are happening within fraction of hours. To avoid these deaths and sufferings, a proper and continuous monitoring is necessary over the cardiac activity. An electrocardiogram (ECG) is a signal that
expresses the myocardium electrical activity on the surface of body and provides the significant information about the status of cardiac activity [XL]. The accurate detection of heart beat detection through the ECG signal plays a vital role in the diagnosis of different CVDs [XIII]. Since the ECG signal is a graphical form through which an easy analysis can be done and the abnormal cardiac activity can be easily detected there by recognizing the abnormalities in the shape of the ECG signal. However, a lengthy monitoring is required to record and analyze the ECG signals since the symptoms of some types of CVDs are generally not irregular. Hence the research related to the automatic ECG signal processing approaches has been actively conducted from several decades.

An ECG signal with no abnormalities is considered as rhythm and if any abnormalities are observed, then it can be simply termed as an arrhythmia. Since the shape of an ECG signal generally reflects the cardiac activity of a heart, ECG signal is considered to represent the cardiac physiology, useful in the diagnosis of disorders in the cardiac activity and also in the detection of cardiac arrhythmia [XXXVI],[XXXVII]. An arrhythmia can be defined as an irregular electrical activity of the heart and can cause the heartbeat to be fast or slow. It can occur even in a healthy heart and to be a minimal consequence, but they may cause a serious problem to the heart and also may lead to the stroke or sudden cardiac death. Since the ECG signal is a non-stationary signal, the arrhythmia can occur at a random time-scale, i.e., the symptoms of arrhythmia may not show up at regular intervals and happen only at irregular intervals during the day. Hence, to achieve an effective diagnosis results, the ECG signal variability have to be observed for several hours. For this reason, and also due to the voluminous ECG signal data, the study of ECG signal analysis is tedious and time consuming. Thus, an automatic and computer-aided detection and classification of cardiac arrhythmia has become an essential for clinical cardiology applications, particularly to the treat the patients in the intensive care unit (ICU) [XXXVII].

Some of the methods have been developed in past years to achieve effective results in the detection and classification of different cardiac arrhythmias. Among those approaches, most of the methods were focused to achieve 100% results in the classification and detection. But they didn’t much focus on the time complexity. As itself the main aim of Computer aided diagnosis is to reduce the time complexity, the sufficient work towards this achievement is not carried out. Further the extraction of only important features which provides a proper discrimination between different arrhythmias and also reduces the computational time is required. Considering this as a main objective, this paper aims to develop an automatic cardiac arrhythmia detection system based on the variations in the characteristics of ECG signal and supervised learning. A novel feature extraction technique is proposed in this paper to extract only a limited set of features for every type of arrhythmia. Furthermore, novel supervised machine learning is also used to perform the classification and detection based on the characteristics of extracted feature set. Extensive simulations are carried out over the developed system to check the robustness through standard ECG databases.

Rest of the paper is organized as follows: the details of literature survey are discussed in section II. Section III discusses the details of ECG signal and its characteristics and also discussed different types of arrhythmias. Section IV discusses
II. Literature Survey

In the recent years, several methods have been developed in the literatures for detection and classification of ECG arrhythmias. So many methods are proposed by considering the both time domain and frequency domain characteristics to deeply analyze the ECG signal and making the detection system most effective in the detection of all possible cardiac arrhythmias. Generally, the arrhythmia beat classification involves three phase, namely, feature extraction, feature selection, and construction of classifier. As a premise of classification, the feature extraction is very important and also the preliminary step since a robust and reliable classification system depends on the effective features. Generally the features are essentially extracted to reduce the redundant information from voluminous ECG data and to extract only the effective features through which the more discrimination can be provided between the different arrhythmias. Generally the feature extraction is used in two domains, time domain to extract the morphological features and frequency domain to observe the changes in the power spectrum of ECG signal and time-frequency domain to exhibit simultaneous morphological and spectral features.

In [XI], an automatic beat classification system was developed to classify the beats namely, Normal (N), Premature Ventricular Contraction (PVC), Premature Atrial Contraction (PAC), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB). This method assumed that the ECG signal is cyclostationary and tried to extract the hidden features based on the spectral correlation as a non-linear statistical transformation inspecting the periodicity of correlation. Principal Component Analysis (PCA) for feature reduction and Support Vector Machine (SVM) for classification were used.

Fatin, A.E.et.al., [II] investigated on the representation ability of linear and non-linear features and proposed a combined mechanism to improve the ECG data classification. Totally five types of beats are tested here, namely, Non-ectopic beats (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), fusion betas (F), and unclassifiable and paced beats (U). This method combines the linear feature analysis techniques namely, PCA of wavelet transform (WT) coefficients with non-linear feature reduction methods like Independent Component Analysis (ICA) [XVII] and SVM is used for classification purpose.

Compared to the WT, dual tree complete wavelet transform (DTCWT) has more effective representation of linearly dependent features. Considering this as advantage, Thomas, et.al., [IX] developed a new method for automatic classification of cardiac arrhythmias. Along with decomposed sub-bands through DWT, four extra features namely, Kurtosis, Skewness, AC power, and timing information are extracted for an ECG signal. An extended Kalman filter for feature extraction and Bayesian networks for ECG signal beat classification was developed in [IX]. In this method, a new polargram (polar representation of the signal) was constructed based on the Bayesian state of variables.
Lin et al., [X] developed a simple and reliable heartbeat determination algorithm based on the PCA. Further the fuzzy logic and fisher’s Linear Discriminant Analysis (FLDA) was used for determination. Combining the timing interval based features with morphological features, a new PVC detection method is to recognize the PVC from normal beats and other heart diseases. This method used the most popular stationary wavelet transform [XXXII] to denoise the signal before processing for feature extraction. Different supervised learning classifiers such as RBFNN, SVM and MLPNN are used and also compared with respect to the performance metrics. Bagged Decision Tree (BDT) combined with time-domain feature extraction method in [XII] to classify the arrhythmia beats in the ECG signal. The main feature considered here is RR interval followed by four second order linear predictive coding coefficients.

Zhu et al., [XIII] proposed a new method called as Location, Width, and Magnitude (LWM) for feature extraction from the ECG signal. The P wave, T wave and QRS wave are obtained through the Gaussian Function and further the P-Q interval and S-T interval are obtained through the streaming of Gaussian function. Two types of arrhythmias, namely, PVC and PAC are detected through this method. A parallel general regression neural network (GRNN) is accomplished by Li. P.F. et al., [XIV] to perform personalized automatic classification of heart beats form long-term ECG signals.

A multi-level feature based automatic ECG classification system was developed by Kutlu, et al., [XV] combining a diverse set of features including, morphological features, higher order statistics, wavelet package coefficients, and Fourier transform coefficients. The complete methodology is accomplished in three phase, first stage classifies total beats into five types and the second stage further classifies into sub groups. Finally the third stage processes the beats that are labeled as unclassified beats in the first two classification stages. In all stages, the classifiers are based on the $k$-nearest neighbor algorithm.

A perturbation method combined with SVM for the classification of ECG beats in [XVI]. The perturbation method is used to reduce the dimensionality of feature space. If there exists any redundant information in the training stage, it can be discarded by analyzing the total disturbance of the SVM output corresponding to the perturbed inputs. A higher order spectral analysis (HOS) based feature extraction technique is proposed in [XVIII] to classify the ECG signals to detect the heart rate variability (HRV). Further SVM is used at the classification phase.

A new approach based on MC-SVM and error correcting output codes is developed by Ubeyli. E. D [XIX] to classify the ECG beats. Initially the signals are decomposed through DWT and then processed for classification through MC-SVM. Totally this method focused on four types of beats (normal, congestive heart failure beat, ventricular tachyarrhythmia beat, atrial fibrillation beat).

An adaptive feature selection method followed by modified support vector machine algorithm was developed by Shen, C.P. et al., [XX] to perform automatic cardiac arrhythmia detection. Initially wavelet transformed coefficients are enumerated and then only few selected features are selected as main features through...
adaptive feature selection. A new classifier, combining the one-against SVMs, k-means clustering and majority voting machine (MVM) is developed here.

Further the method proposed by Acir, N [XXI] is based on the fast least square SVM (LSSVM). A multi-feature analysis based on VF and VT detection method is proposed in [XXII] considering the spectral, temporal and complexity features. Totally 13 features are extracted here. Further, a filter type feature selection mechanism was proposed to analyze the relevance of computed parameters. In [XXIII], a novel feature extraction followed by feature selection method was developed to classify totally five types ECG beats based on the Discrete Cosine Transform and PCA [XXV],[XXVI]. Three classifiers namely, FFNN, LSSVM and PNN are used for classification. An automatic heartbeat recognition based on HOS of wavelet packet decomposition (WPD) coefficients was proposed by Kutlu, et.al., [XXIV]. Finally the HOS features of WPD coefficients are processed for classification through k-NN classifier.

Four different feature extraction techniques, namely, Principal Components of DWT, Independent Components of DWT [XXIX], Principal components of DCT and Independent Components of DCT and three different classification techniques, KNN, Decision Tree (DT), and ANN were combined by Martis, R. J. et.al., [XXVII] to detect the normal, AF and AFL automatically. In [XXVIII], a new and efficient methodology was proposed using Hilbert Haung Transform (HHT) which includes a set of essential features such as kolmogorov complexity, weighted mean frequency, and some other statistical measures such as kurtosis, median skewness, standard deviation and central moment are used in this method. An EMD, approximate entropy and wavelet packet entropy based feature extraction method is proposed in [XXX] combined with SVM and PNN for the detection of ECG beats. Further this method also used particle swarm optimization (PSO) to optimize the parameters of SVM and PNN.

III. ECG Signal and Arrhythmias

Since the ECG is a more important signal to analyze the cardiovascular diseases, the knowledge about the ECG is required. Further a clear knowledge about the terminology, intervals, segments present in the ECG is also needed. This section gives the details of ECG and its characteristics. Further, the characteristics of different types of arrhythmias considered in this paper for detection are also illustrated more clearly.

Electrocardiogram

An ECG is a main object through which the status of heart can be analyzed, i.e., whether the heart is working properly or not. An ECG signal is a composite form of several beats and every ECG signal contains QRS complex, P wave and several intervals like QT, ST, QRS, RR and PR and different segments like PR and ST. For a normal ECG signal (captured for healthy person), all these aspects have normal characteristics like normal amplitude and normal time intervals. For an abnormal ECG signal, captured from a person with some heart problem, the characteristics of ECG signal will be different. So to analyze the condition of a patient through ECG,
the analysis of ECG characteristics is required. Fig.1 shows the features of one
cardiac cycle and the normal characteristics of ECG signal are depicted in Table 1.

![Fig. 1 Normal ECG waveform](image)

**Table 1:** ECG features and their normal duration

| Feature     | Description                                                                 | Duration   |
|-------------|-----------------------------------------------------------------------------|------------|
| P Wave      | Initial upward movement and it is a small and smooth wave                   | 80ms       |
| PR Interval | Interval measured from the starting of P wave to starting of QRS complex    | 120-200ms  |
| PR Segment  | Measured from the end of P-wave to the starting of QRS complex              | 50-120ms   |
| QRS Complex | Generally starts from the downward deflection of Q, then a large upward deflection R and ends with a downward S wave | 80-120ms   |
| RR Interval | Measured between two R-peaks                                               | 0.6-1.2s   |
| ST Segment  | Starts from the J-point to the starting T-Wave                              | 80-120ms   |
| ST Interval | Starts from the J-point to the End of T-Wave                                | 320ms      |
| QT Interval | Starts from the onset of Q and ends at the offset of the T-Wave             | < 440ms    |
| T Wave      | Second upward movement and it is a smooth wave                              | 160ms      |
| U Wave      | Low amplitude upward movement                                              | -          |

**Cardiac Arrhythmias**

A deviation in the shape of ECG signal is termed as arrhythmia. Based on
different types of deviations, approximately there are sixteen types of arrhythmias.
This paper only considered five types of arrhythmias because most of the heart
related diseases are based on them only. The five cardiac arrhythmias are namely,
Normal Sinus Rhythm (N), Premature Ventricular Contraction (PVC), Premature Atrial Contraction (PAC), Left Bundle Branch Block (LBBB) and Right Bundle Branch Block (RBBB).

**Normal Sinus Rhythm (N):** This is the default rhythm of heart beat and the rhythm is at the range of 60-100 bpm. In this rhythm, each QRS complex is preceded by P wave. Consisting normal P wave and the PR interval remains constant. QRS complexes are less than 100ms wide.

**Premature Ventricular Contraction (PVC):** PVCs are premature, they occur earlier than expected if measured against previous R-R intervals. PVCs widens the QRS complexes from normal interval. Approximately the width of widened QRS complex is greater than 0.12s. The PVC replaces the sinus beat and induces a delay to the next sinus beat (the RR interval is increases after PVC).

**Premature Atrial Contraction (PAC):** PACs are also premature and an abnormal (non-sinus) P wave is followed by QRS complex. The abnormal P wave may be hidden in the preceding T wave, producing a peaked or camel hump appearance. PACs produces an inverted P wave with a relatively short interval greater than or equal to 120ms. Unlike PVCs, the PACs narrows the QRS complex.

**Left Bundle Branch Block (LBBB):** LBBB is the consequence of anatomical or functional dysfunction in the left bundle branch, causing the impulse to be blocked. The duration of QRS complex is greater than or equal to 120ms. The R peak time is greater than 60ms. ST and T waves are usually opposite in direction to QRS. Deep and broad S-wave and broad clumsy R wave are the main characteristics of ECG signal with LBBB.

**Right Bundle Branch Block (RBBB):** RBBB is the consequence of anatomical or functional dysfunction in the right bundle branch, causing the electrical impulse to be blocked. The hallmark of the RBBB is QRS duration, greater than 120ms, large R wave and broad and deep S wave. The duration of S-wave is greater than R wave. Further the RBBB ECG signal also having down sloping ST segments and inverted T wave.

**IV. Proposed Detection Method**

In the proposed detection mechanism, initially the ECG signal is segmented into beats of time span 0.7s based on the locations of R-peaks provided according to the MIT-BIH database [XXXVI]. Further, each 0.7s segment is decomposed into sub bands through DTCWT. Further the obtained sub bands are processed for redundant information reduction through an effective sub band adaptive filtering (SAF). Finally, the obtained sub bands with only significant information are processed for training through SVM model. Finally a cross validation is carried out to check the obtained results about the classification of different arrhythmias. The flow chart of proposed mechanism is represented in fig. 4.

**DTCWT**

Generally wavelet transform is applied over an image/signal to decomposes it into fine frequency sub bands thereby the clear analysis can be done through its spectral characteristics. Discrete Wavelet Transform (DWT) is one of the famous
transform in the spectral decomposition techniques and used to capture the variation at the global level. DWT is one of the most well known transformation techniques, in which the signal is decomposed into different frequency sub-bands, viz., approximations and details. However, the lack of shift-invariance property of DWT makes it not robust to variations of shifts in the signal, i.e., the variations in the amplitudes of wavelet coefficients will be observed if there is a shift in the original input signal and the main reason is due to the down sampling operation held before the decomposition. A simple solution to overcome this problem is the accomplishment of an undecimated form of the dyadic filter, but this constitutes an unnecessary computational complexity over the system and also develops a high redundancy in the obtained frequency sub bands.

DTCWT is derived from the wavelet family and it robust to the shift variations and also can solve the problem of shift-invariance of DWT. The redundancy factor of DTCWT is of order $2^1$ for a one-dimensional (1-D) signal, which is less that of undecimated DWT. The complete architecture of DTCWT is accomplished through two trees of real filters (Filter A and Filter B), as represented in figure 2. The two trees represent the real and complex part of CWT. The two important properties such as the directional selectivity and shift invariance make this transform useful in the recognition of cardiac arrhythmias with different patterns. According to the fig. 2, the accomplishment of DTCWT over a signal $x(n)$ is realized with the parallel deployment of two DWTs over the signal $x(n)$. Since the DTCWT derives $2N$ DWT coefficients for an $N$ point input signal, it is a two time expansive [XXVII]. The filters in the both upper and lower trees are designed in such a manner that the output obtained through the upper DWT part is considered as real part and output obtained through the lower DWT part is considered as the complex part of CWT. This design makes the DTCWT shift invariant and hence this paper considered for preprocessing of ECG signal before processing them to the detection unit.

![Fig. 2 Architecture of 3-level DTCWT](image)

**Selective Band Coding**

Compared to the original input signal, the signal decomposed into sub bands will reveal much significant information regarding the inner characteristics of signal.
But, the redundancy is also a factor which needs to consider which has a linear relation with the number of sub bands. As the higher redundancy is observed in the sub bands, the processing overhead also arises and makes the system much slower. Hence there is a need to incorporate a Subband Adaptive Filtering (SAF) mechanism between the decomposition unit and its further processing units. SAF helps in the removal of redundant information and only extracts the informative coefficients from every sub band. In earlier, Kong Aik et. al., [XVII] developed SAF theory in the signal processing for generalized purpose. With reference to the [XVII], this work focused to accomplish the mechanism of SAF theory over the sub bands obtained after the deployment of DTCWT over ECG signal. To do so, initially the ECG signal is decomposed into various sub bands through DTCWT and then they are processed through SAF to extract only informative sub bands from the overall sub bands. The detailed mechanism is illustrated in the following:

The main working criterion based on which the SAF works is LMS-type adaptive filter. Here the main objective is such type of filters is to converge the objective function based on the updating of adaptive weights in iterative manner. Here the LMS filter is converged upon the minimum value of error between the desired value and original value. A basic version of SAF is proposed in [XVII] but observed a high convergence time. To reduce this time and to make it faster, an improved version of SAF, called as normalized SAF (NSAF) is proposed in [XXI]. In this method, the convergence speed is enhanced while keeping the steady state error as it is of the SAF. Further this approach suffered from high complexity for a system with long and unknown parameters. To overcome this issue, a dynamic selection based NASF (DS-NASF) scheme is proposed in [XXIII]. This method obtains a set of optimal sub band adaptive filters which shows a great contribution towards the convergence speed optimization and also used in the updating of adaptive filter weights. This approach works based on the minimization of mean square deviations (MSDs) between successive sub bands based on the selection of dynamic sub and filters in an iterative manner. With the help of critical sampling, this approach achieves a greater improvement in the reduction of computational complexity while maintaining its performance on the weights selection. The operational detail of DS-NSAF is outlined as follows;

In the SAF system, the desired band $d(n)$ that generates from its lowering band is formulated as,

$$d(n) = u(n)W^0 + v(n)$$  \hspace{1cm} (1)

Where $W^0$ is an unknown column vector to be evaluated with the help of an adaptive filter, $v(n)$ is the variance $\sigma_v^2$ for every band, and $u(n)$ defines a row input vector of length $M$ and formulated as;

$$u(n) = [u(n)u(n-1)\ldots u(n-M+1)]^T$$  \hspace{1cm} (2)

Initially, the ECG signal is decomposed into $N$ sub bands through DTCWT. The obtained sub band signals are then critically decimated to a lower sampling rate with respect to their demanded bandwidth. Here the proposed SAF main objective is to reduce the redundant information from the decimated sub bands. For this purpose, the decimated sub bands are processed for the SAF.
The original signal $d(n)$ is decimated to $k$ signals and the decimated filter output at each sub band is defined as:

$$y_{iD}(k) = u_i(k)w(k)$$  \hspace{1cm} (3)

Where, $u_i(k)$ is a $1 \times M$ row such that,

$$u_i(k) = [u_i(kN), u_i(kN - 1), ..., u_i(kN - M + 1)]$$

and

$$w(k) = [w_0(k), w_1(k), ..., w_{M-1}(k)]^T$$

denotes the estimated weight value and the decimated band error is then defined by,

$$e_{iD}(k) = d_{iD}(k) - y_{iD}(k) = d_{iD}(k) - u_i(k)w(k)$$  \hspace{1cm} (4)

Where $d_{iD}(k) = d_i(kN)$ is the reference information at each band. In the process of NASF the weight optimization is defined as,

$$w(k + 1) = w(k) + \mu \sum_{i=0}^{M-1} \frac{u_i^T(k)}{||u_i(k)||^2} e_{iD}(k)$$  \hspace{1cm} (5)

Where $\mu$ is the step size. Here this weight utilized for the optimization of band selection process. However the computational time of this approach is observed to be larger which effects on the convergence optimization. To overcome this problem, a MSD based weight optimization is proposed here. This approach also considers the largest decrease of MSDs between the sub bands in successive iterations. Hence the weight error vector is then defined as, $\hat{w} = w^* - w(k)$. The weight optimization is then defined as,

$$\hat{w}(k + 1) = \hat{w}(k) + \mu \sum_{i=0}^{M-1} \frac{u_i^T(k)}{||u_i(k)||^2} e_{iD}(k)$$  \hspace{1cm} (6)

using this weight vector and taking the expectation a MSD is computed which satisfies the absolute expectation as,

$$E||\hat{w}(k + 1)||^2 = E||\hat{w}(k)||^2 + \mu^2E \left[ \sum_{i=0}^{N-1} \frac{e_{iD}^T(k)}{||u_i(k)||^2} \right] - 2\mu E \left[ \sum_{i=0}^{N-1} \frac{u_i^T(k)e_{iD}(k)}{||u_i(k)||^2} \right]$$  \hspace{1cm} (7)

Where

$$\Delta = \mu \sum_{i=0}^{N-1} \left( 2E \left[ \frac{u_i(k)e_{iD}(k)}{||u_i(k)||^2} \right] - \mu E \left[ \frac{e_{iD}^2(k)}{||u_i(k)||^2} \right] \right)$$  \hspace{1cm} (8)

represents the difference of MSDs between two successive bands. The bands with minimum MSD will be chosen to have a selective band which will be further processed. Instead of processing overall bands to the further process, this approach extracts only a few set of informative bands and reduces the redundant information.

**Multi-Class SVM**

Since the proposed system considered more than two arrhythmias, Multi-class classification is required. SVM is one of the most prominent machine learning algorithm, and used in various applications to perform multiple attacks classification.
SVM has an ability to classify only two classes in a single instance. To detect multiple attacks, the SVM needs to be accomplished multiple times, resulting in multi-class SVM. In the SVM based multi-class classification, ‘Binary tree’, ‘One-against-one’ and ‘One-against-all’ [VIII],[XXXII] are the three possible approaches. The second approach i.e., ‘One-against-one’ SVM classification method needs a \( k(k-1)/2 \) two-class SVM classifiers where each one is trained on data for two classes. Next, the third method, i.e., one-against-all SVM needs ‘k’ two-class SVM classifiers to accomplish the attack detection. Finally the Binary tree SVM method needs only ‘k-1’ two-class SVM classifiers to detect k number of classes. Hence, this approach also considered Binary tree SVM classifier to perform intrusion detection.

In the initial phase, the SVM classifies only one class from remaining classes, for instance the N is detected from remaining arrhythmias (LBBB, RBBB, PAC and PVC). In the next phase, the SVM separates the LBBB from the remaining (RBBB, PAC and PVC). At the third phase, the RBBB is separated from the remaining (PAC and PVC) and finally the PAC and PVC are classified in the last phase. A simplified architecture of MC-SVM is represented in fig. 3.

The above fig.4 depicts the flow details of proposed detection mechanism. Since the main objective of this system is to detect the type of arrhythmia carrying by an ECG signal, the ECG signal with particular arrhythmia is given as input. For a given input ECG signal, initially it is decomposed into beats and then every beat is subjected to DTCWT to obtain sub bands with different frequencies. The main novelty of this approach is the proposed selective band coding through which the unnecessary information is removed from every sub band. Here the selective band coding assumes the linear relations between the original signal and the derived sub bands to filter out it. The sample at which there linear relation does not exist between the successive features, they are removed and remaining features are kept as it is. This mechanism removes only the unnecessary features but not information representing by those features. Hence the proposed approach is able to find all the possible arrhythmias carrying by ECG signals.

**Fig. 3 Cardiac Arrhythmias detection based on Binary Tree MC-SVM**

**Fig. 4 Flow chart of proposed method**

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*Gopisetty Ramesh et al.*

255
V Simulation Results

This section describes the details of experimental evaluation carried out over the developed detection system. The experimental evaluation is carried out in the personal computer with 1TB hard disk and 8GB RAM.

Dataset

To evaluate the developed system, the standard database MIT-BIH database is used which comprises of 48 ECG records and each record contains a 30-minute ECG signal. The original signals in this database are sampled at 360Hz with 11bit resolution over a 10mV range and band pass filtered at 0.1-100Hz. The ECG records from this database includes the signals with acceptable quality, small R-peak amplitudes, baseline drift, irregular heart rhythms, wider R waves, sudden changes in the morphology of beats, muscle noise, sharp and tall P and T waves, negative R waves, long pauses and multiform V beats. Totally there are 16 types of arrhythmias. In this study, only five types of arrhythmias (N, LBBB, RBBB, PAC and PVC) are used since these beats occupy the majority of database. The number of beats considered for training and testing are shown in the Table 2.

According to the Table 2, the total number of beats trained is 46050 and the total number of beats tested is 7021. All these beats are extracted from the MIT-BIH database records, namely 100, 102, 103, 109, 111, 113, 118, 208, 217, 221, 231 and 233.

| Arrhythmia | N   | LBBB | RBBB | PVC  | PAC  | Total |
|------------|-----|------|------|------|------|-------|
| Training   | 23564 | 7321 | 6428 | 6417 | 2320 | 46050 |
| Testing    | 4523  | 807  | 725  | 712  | 254  | 7021  |

Results

In this paper, the accuracy, precision, recall, False Positive Ratio (FPR) and F-Measure are considered to evaluate the performance of proposed approach. The basis for these metric evaluations is confusion matrix and represented in Table 3.

| Actual     | Predicted |       |       |       |       |       |
|------------|-----------|-------|-------|-------|-------|-------|
|            | Normal    | TP    | FN    |       |       |       |
|            | Abnormal  | FP    | TN    |       |       |       |

Based on the obtained TP, TN, FP and FN values from the confusion matrix, performance metrics are evaluated and the respective mathematical representation is given as;

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]
Where

\[ \text{TP} = \text{True Positives} \]
\[ \text{TN} = \text{True Negatives} \]
\[ \text{FP} = \text{False Positives} \]
\[ \text{FN} = \text{False Negatives} \]

After testing the test beats specified in Table 2, the obtained results are represented through the confusion matrix shown in Table 4.

**Table 4: Confusion Matrix**

| Arrhythmia | N   | LBBB | RBBB | PAC | PVC | Total |
|------------|-----|------|------|-----|-----|-------|
| N          | 4496| 07   | 08   | 08  | 04  | 4523  |
| LBBB       | 05  | 790  | 04   | 07  | 01  | 807   |
| RBBB       | 02  | 07   | 711  | 02  | 03  | 725   |
| PAC        | 03  | 02   | 02   | 698 | 07  | 712   |
| PVC        | 02  | 02   | 02   | 245 | 07  | 254   |

**Table 5: Performance metrics of proposed approach**

| Arrhythmia | Precision (%) | Recall (%) | F-Measure (%) | FPR (%) | Accuracy (%) |
|------------|---------------|------------|---------------|---------|--------------|
| N          | 99.7338       | 99.4030    | 99.5681       | 0.0048  | 99.4445      |
| LBBB       | 97.7722       | 97.8934    | 97.8327       | 0.0029  | 99.5014      |
| RBBB       | 97.6648       | 98.0689    | 97.8664       | 0.0027  | 99.5584      |
| PAC        | 97.3500       | 98.0337    | 97.6906       | 0.0030  | 99.5299      |
| PVC        | 94.2307       | 96.4566    | 95.3306       | 0.0022  | 99.5157      |

**Table 6: Comparative analysis**

| Metric     | Zhu et al., [13] | Homaieinezhad, M. R. et al., [33] | Li et al., [17] | Proposed |
|------------|------------------|-----------------------------------|-----------------|----------|
| Precision (%) | 94.2354          | 96.3352                           | 96.6032         | 97.3503  |
| Recall (%)   | 92.8223          | 97.5223                           | 97.5230         | 97.9711  |
| F-Measure (%)| 93.5234          | 96.9632                           | 96.8201         | 97.6576  |
| FPR (%)      | 0.9523           | 0.8541                            | 0.6234          | 0.00312  |
| Accuracy (%) | 92.8523          | 95.0654                           | 96.8032         | 99.5099  |

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Gopisetty Ramesh et al.
According to the details represented in the above Table 4, the detected results are described as follows; out of the total 4523 test beats of normal sinus rhythm class, totally 4496 are detected as normal sinus rhythms. Next, out of the 807 test beats of LBBB class, totally 790 are detected as LBBB. Next, the total numbers of beats recognized as RBBB are 711 out of 725 input test beats. Similarly the detected results for PAC and PVC are 698 and 245 out of 712 and 254 respectively. Based on the values represented in Table 4, the performance evaluation is measured through the performance metrics and is represented in Table 5. Further the proposed approach is compared with conventional approaches with respect to the performance metrics and is represented in Table 6. As it can be seen from the Table 6, the proposed method attained an improved performance in the detection of all possible arrhythmias compared to the conventional approaches, Zhu.et.al., [XIII], Homaeinezhad, M. R. et al., [XXXIII] and Li.et.al., [XVII].The method described in the [XIII] is based on the morphological features of ECG beats. The P wave, T wave and QRS wave are obtained through the Gaussian Function and further the P-Q interval and S-T interval are obtained through the streaming of Gaussian function. Two types of arrhythmias, namely, PVC and PAC are detected through this method. Considering only the Gaussian functionality is not sufficient to represent the discrimination between different types of arrhythmias.

Next, the method proposed in [XVII] considered DWT for feature extraction. As it is already discussed that the DWT based feature extraction results in the non-robustness of shift invariances occurred in the amplitudes of ECG signal. Further this method used SVM for classification. In the conventional approach [XXXIII], the geometrical features are considered as features and this method is utilizes three classifiers namely, k-NN, SVM and BPNN which increases an extra complexity.

To further alleviate the performance, the proposed approach is simulated over the same dataset with noise factor. All the test signals are subjected to noise addition and then they are processed for testing. The simple Additive White Gaussian Noise (AWGN) with zero mean and a variance of $\sigma^2$ is considered. Here the SNR is considered as a statistic for the noise. The SNR is varied from 20dB to 40dB and at every test case, the performance is measured through the performance metrics. The obtained performance metrics such as precision, detection rate (recall), accuracy, false positive rate are depicted in fig.5. In the case of noise presence, the signal characteristics will change and this change will effect on the recognition performance. The discrimination of a signal becomes more critical to differentiate it from the noise samples. In such scenario, the performance will be less when compared to the performance obtained with pure signals. Under this simulation, initially the noise contaminated ECG signal is processed for noise filtering through the method proposed by Gopisetty Ramesh et.al. [XL]. Signals classified after classification are represented through the confusion matrix, as shown in Table 7.
Table 7: Confusion Matrix in the presence of noise

| Arrhythmia | N   | LBBB | RBBB | PAC  | PVC  | Total |
|------------|-----|------|------|------|------|-------|
| N          | 4486| 09   | 10   | 12   | 06   | 4523  |
| LBBB       | 06  | 785  | 06   | 08   | 02   | 807   |
| RBBB       | 04  | 12   | 699  | 04   | 06   | 725   |
| PAC        | 04  | 03   | 03   | 693  | 09   | 712   |
| PVC        | 05  | 02   | 04   | 04   | 239  | 254   |

Table 8: Performance metrics of proposed approach in the case of noise addition

| Arrhythmia | Precision (%) | Recall (%) | F-Measure (%) | FPR (%) | Accuracy (%) |
|------------|---------------|------------|---------------|---------|--------------|
| N          | 99.5782       | 99.1819    | 99.3796       | 0.0076  | 99.2024      |
| LBBB       | 96.7940       | 97.2738    | 97.0333       | 0.0041  | 99.3590      |
| RBBB       | 96.8144       | 96.4137    | 96.6136       | 0.0036  | 99.3020      |
| PAC        | 96.1165       | 97.3314    | 96.7201       | 0.0044  | 99.3305      |
| PVC        | 91.2213       | 94.0944    | 92.6555       | 0.0034  | 99.4587      |

Table 9: Comparative analysis in the case of noise addition

| Metric         | Zhu et al., [13] | Homaieinzhad, M. R. et al., [33] | Li et al., [17] | Proposed |
|----------------|------------------|----------------------------------|-----------------|----------|
| Precision (%)  | 92.3345          | 94.2355                          | 95.3578         | 96.1048  |
| Recall (%)     | 90.9894          | 93.6341                          | 96.4109         | 96.8590  |
| F-Measure (%)  | 91.5231          | 94.5897                          | 95.6389         | 96.4764  |
| FPR (%)        | 1.2253           | 1.0023                           | 0.8364          | 0.00462  |
| Accuracy (%)   | 91.9973          | 94.2079                          | 95.5119         | 99.3305  |
Fig. 5 Comparative Analysis in case of varying noise conditions (a) Accuracy (b) Detection Rate (Recall) (c) Precision (d) False Positive Rate

Table 10: Average time for training and testing processes

| Time (Sec) | Approach | Time (Sec) |
|------------|----------|------------|
| Training Time | Zhu.et.al., [13] | 115.4435 |
| | Homaieinezhad, M. R. et al. [33] | 120.2247 |
| | Li.et.al., [17] | 98.3417 |
| | Proposed | 85.5563 |
| Testing Time | Zhu.et.al., [13] | 105.5417 |
| | Homaieinezhad, M. R. et al. [33] | 110.8746 |
| | Li.et.al., [17] | 85.4789 |
| | Proposed | 72.3547 |

Uniqueness of the proposed approach of this paper is the accomplishment of selective band coding that extracts features representing more important information about the arrhythmia. Compared to the morphological features, the transformed features are more informative and hence this approach also used the transform technique, DTCWT to transform the ECG beat into spectral domain. Finally the performance evaluation is measured through performance metrics in the presence of noise is represented in Table 8 and the proposed approach is compared with conventional approaches with respect to the performance metrics in case of noise addition is represented in Table 9. The reduced time complexity due to the accomplishment of selective band coding is represented in Table 10.

Further the proposed approach developed a new feature selection technique which reduces the unnecessary redundant information from the decomposed sub bands and only preserves the features those are significant. This novelty of developed system reduces the maximum time taken for training and testing. As the
number of bands or features is reduced, the total time taken for training followed by testing also decreases substantially. Fig.6 represents the graphs of total computational time occurred for proposed and conventional approaches.

![Fig. 6 Computational Time comparison](image)

The observed training and testing time details for the data simulated in this paper are represented in Table8. It can be observed that the proposed system attained a very less computational time compared to the conventional approaches. This feature is very interesting and it is very helpful in the diagnosis of ECG signal within less time span when there is a voluminous ECG data.

VI. Conclusions

This paper developed a new Automatic Cardiac Arrhythmia Detection system based on the spectral features of ECG signal. DTCWT is used at sub band decomposition and a novel subband adaptive filtering is applied to extract the significant and informative sub bands. Further the MC-SVM is used at classification phase. Since the proposed approach used a novel selective band coding technique to remove the redundant information from the obtained sub bands, the computational time is observed to be very less. The achieved novelty in the reduction of overall computational time is illustrated in the simulation results section. Furthermore, the obtained final set of features after selective band coding are also more informative and are succeeded in the achievement of an enhanced performance. The obtained simulation results, i.e., the accuracy, detection rate, precision and FPR are also observed to be optimal when compared to the conventional approaches and hence it can be concluded that the proposed automatic detection mechanism is more effective in the diagnosis of ECG signal when there is a huge crowd.

On an average, the proposed approach obtained an increment in the accuracy is of 3.8186(%)\(^{[13]}\), 5.1126(%)\(^{[14]}\), and 7.3332(%)\(^{[16]}\) from the conventional approaches, Li.et.al.,\(^{[17]}\), Homaeinezhad, M. R. et al.,\(^{[22]}\), and Zhu.et.al.,\(^{[19]}\) respectively. Further the proposed approach obtained a greater decrement in the reduction of computational time and it is of 63.0742(sec), 73.1883(sec), and 25.909(sec) from Zhu.et.al.,\(^{[19]}\), Homaeinezhad, M. R. et al.,\(^{[22]}\), and Li.et.al.,\(^{[17]}\) respectively.
To further enhance the performance of automatic Cardiac Arrhythmia detection system, it can be extended by proposing a new redundant information reducing technique considering the power spectral properties of ECG signals. As the number of decomposition levels increases, the number of sub bands also increases and if the entire bands are considered for processing, the complexity will be increased. Hence to reduce the complexity, the total number of bands needs to reduced and to do this, a new technique can be designed as a future work of this paper.

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