International Journal of Computational Intelligence and Informatics, Vol. 4: No. 2, July - September 2014

Evaluation of Wavelets and Classifiers in Classifying Cardiovascular Disorders using Wavelet Transform

R Harikumar
Bannari Amman Institute of Technology
Sathyamangalam
India-638 401

S N Shivappriya
Kumaraguru College of Technology
Coimbatore
India-641 049

R Janani
Kumaraguru College of Technology
Coimbatore
India-641 049

***Abstract*-The cardiac abnormalities are to be detected and treated earlier in order to avoid its adverse effects. The PQRST properties from the recorded ECG are used to analyze the type of arrhythmia. Noise removal has to be done effectively for further processing of the ECG signals. In this paper, twelve different ECG samples from MIT BIH Arrhythmia database are analyzed using six mother wavelet functions- haar, db8, sym5, coif5, bior4.4 and rbio4.4. And cardiac disorders like Myocardial Infarction, Premature Ventricular Contraction (PVC), Ventricular Tachycardia, Supra ventricular arrhythmias, ST deviation, Ventricular Fibrillation (VF) are classified using Naive Bayes (NB) classifier and Support Vector Machine (SVM) classifier. The databases are extracted from MIT-BIH, EURO, VFDB, SVDB, MIT-ST Change, CUVTDB databases. Wavelet transform algorithm is used for extracting the features. The wavelets are evaluated using three different performance measures such as Peak Signal to Noise Ratio, Mean Squared Error and Mean Absolute Error. The experimental results shows that coif5 wavelet is efficient in significantly reducing the baseline wandering in the ECG signals and the samples are classified using Naive Bayes classifier and Support Vector Machine classifier which achieved 94.45% and 96.76% accuracy respectively.**

Keywords-ECG, Naive Bayes, SVM and Wavelet Transform, Baseline Wanders

I. INTRODUCTION

Electrocardiogram is a main way of gathering information from a body in order to better analyze the hearts activities. The analysis of heart beat cycles in ECG signal is very important for long-term monitoring of heart patients. Electrocardiogram (ECG) is a recording of the electric potential variation due to the cardiac activities. Electrocardiography has a profound influence on the practice of medicine [1]. ECG is characterized by a recurrent sequence of a five principal waves, denoted by P,Q,R,S and T each one showing some beat by beat variability [2][3]. This paper deals with the detection of QRS Complexes using wavelet transform based algorithm.

The ECG ranges from a few micro volts to about 1V in magnitude. Whereas the characteristic waves of an ECG have a maximal magnitude of only few mill volts, a wandering baseline in the ECG due to variations in electrode-skin impedance may reach 1V. Some noises can corrupt ECG signal significantly. Considerable ECG noises are power-line noise, Electro Myo Gram (EMG) noise and baseline noise [1]. These noises can mask some important features of the ECG signal hence it is desirable to remove them for proper analysis and display of the ECG signal. Power-line noise consists of interference in the ECG by nearby AC power supplies and power lines. This affects the ECG as sinusoidal waves which are of the same frequency as the base and harmonic frequencies of 50 or 60 Hz of the power supply. EMG noise is caused by the contraction of other muscles besides the heart. When other muscles contract, they generate depolarization and depolarization waves that can also be detected by the ECG.

Various approaches for Classification were reported which involves heuristic approach Expert systems and Markov models [5], [6], [7]. Naive Bayesian classifier is a simple Bayesian network that assumes all features are conditionally independent given the class variable [8]. Since no structure learning is required, it is very easy to construct and implement NB in practice. Despite its simplicity, the naïve Bayes has been found to be competitive with other more advanced and sophisticated classifiers.

Support Vector Machine based classification methods represents a major development in pattern recognition research. Two innovations of SVMs are responsible for the success of these methods, namely, the ability to find a hyper plane that divides samples in to two classes with the widest margin between them, and the extension of this concept to a higher dimensional setting using kernel function to represent a similarity measure on that setting [9]. Both innovations can be formulated in a quadratic programming framework whose optimum solution is obtained in a computation time of a polynomial order. This makes SVMs a practical and effective solution for many pattern recognition and classification problems in bioinformatics. In our study, the Wavelet algorithm and

NB and SVM are used to detect and classify Myocardial infarction, Premature Ventricular Contraction, ventricular Tachycardia, Supra Ventricular Arrhythmia, ST deviation, Ventricular Fibrillation.

II. PROBLEM FORMULATION

A. Cardiovascular Diseases

The cause of CVD is due to heart attacks, strokes heart valve problems and arrhythmia. Myocardial Infarction, Premature Ventricular Contraction, Ventricular Tachycardia, Supra Ventricular arrhythmias are the life threatening cardiac disorders [10]. The classification of ECG into these different cardiac diseases is a complex task. Therefore the characteristic shapes of ECG have to be found for the successful classification. By using the magnitude, area and duration typical heart beats are analyzed by using ECG and the PQRST wave properties [11]. Therefore ECG abnormality detection should be reliable in an ECG monitoring system or a defibrillator, if not the patient will lose the chance of treatment. Therefore for this analysis Wavelet transform algorithm is efficient rather than Discrete Fourier Transform (DFT). The ECG signals were pre- processed by filtering it to remove the baseline wander, the power line interference, and the high frequency noise, hence enhancing the signal quality, and omitting the equipment and the environmental effects. As for pre-processing of the ECG signal, noise cancellation requires different strategies for different noise sources. The noise reduction using an adaptive filter with constant or unity reference input was performed, which was used to cancel baseline wander. However, this filter is not reliable for applications that require diagnostic ECG analysis. The baseline wandering and the power-line interference are the most substantial noises and can strongly affect the ECG signal analysis [12].

Low frequency artifacts and baseline drift may be caused in the chest lead ECG signals by coughing or breathing, with large movements of the chest, or when an arm or leg is moved during the ECG data acquisition. Also, a large baseline drift may cause the positive or negative parts in the ECG to be clipped or badly detected by the analog to digital converter or the other hardware. The baseline wander is an extraneous, low-frequency activity in the ECG which may interfere with the signal analysis, making the clinical interpretation inaccurate. When baseline wander takes place, ECG measurements related to the isoelectric line cannot be computed since it is not well-defined. Baseline wander is often exercise-induced and may have its origin in a variety of sources, including perspiration, respiration, body movements and poor electrode contact

There are hundreds of different types of cardiac arrhythmias like Atrial Flutter, Atrial Fibrillation, Ventricular Flutter, Ventricular Fibrillation etc. There are many databases out there for personal use that make project like this possible. So finding the quality ECG signal, which does not require filtering and relatively clean signals are desired. The signals are then analyzed using Naive Bayes classifier and Support Vector Machine (SVM).

Using an ECG is a non-invasive technique that is simple to analyze. A patient is attached to few leads and then every single beat is analyzed by the equipment that makes up the ECG. To understand better about ECG, knowledge about the signal outputted by the leads that are analyzing the heart are to be known. Each heart beat signal is analyzed by the ECG. Certain properties help us to determine which cardiac arrhythmias, if any is occurring in the heart. For the arrhythmias in this paper most of them can be analyzed due to differences in the QRS part of the signal. The difference in the heart is determined by the width and height.

III. ANALYIS OF BASIC MOTHER WAVELETS AND ITS TYPES

Wavelet families vary in terms of several important properties like support of the wavelet in time and frequency and rate of decay, symmetry or ant symmetry of the wavelet, the accompanying perfect reconstruction filters have linear phase, number of vanishing moments, wavelets with increasing numbers of vanishing moments result in sparse representations for a large class of signals and images, regularity of the wavelet, smoother wavelets provide sharper frequency resolution, additionally, iterative algorithms for wavelet construction converge faster and the Existence of a scaling function [13].

Following are the basic types of mother wavelets:

1. Crude wavelets – Gaussian, Morlet, Mexican hat.
2. Infinitely irregular wavelets – Meyer, Dmeyer.
3. Orthogonal and Compactly supported wavelets – Daubechies, Symlet, Coiflets.
4. Biorthogonal and Compactly supported wavelet pairs – Biorthogonal , Reverse biorthogonal.
5. Complex wavelets – Complex Gaussian, Complex Morlet, Complex Shannon, Complex frequency B-spline.

Properties of the wavelets are as follows:

- Haar

Compactly supported orthogonal, symmetry, existence of scaling function, orthogonal analysis, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm and explicit expression.

- Daubechies

Arbitrary regularity compactly supported orthogonal, asymmetry, arbitrary number of vanishing moments, existence of scaling function, orthogonal analysis, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm.

- Coiflets

Arbitrary regularity, compactly supported orthogonal, near symmetry, number of vanishing moments, vanishing moments for scaling function, existence of scaling function, orthogonal analysis, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm.

- Biorthogonal

Arbitrary regularity, compactly supported biorthogonal, symmetry, arbitrary number of vanishing moments, existence of scaling function, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform.

- Reverse Biorthogonal

Arbitrary regularity, compactly supported biorthogonal, symmetry, arbitrary number of vanishing moments, existence of scaling function, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm

IV. MATERIALS AND METHODS

A. Materials

1. MIT-BIH arrhythmia database

In this paper, ECG database from MIT-BIH and EURO [14] database were used. MIT-BIH database is comprised of 48 files, each containing 30-min ECG segments selected from 24-hour.recordings of 47 different patients. The database is annotated both in timing information and beat classification. [16].

2. Euro Database

This database consists of 90 annotated excerpts of ambulatory ECG signals from 79 patients. Each record is two hours in duration and sampled at 250 samples per second [17].

3. Malignant Ventricular Arrhythmia Database

This database includes 22 half –hour recordings of subjects who experienced episodes of Ventricular Tachycardia, Ventricular Fibrillation and Ventricular Flutter [18].

4. Supra ventricular Database

This database includes the 78 half-hour recordings of the ECG signals [19].

5. ST Change Data

ST change (ST) database includes beat annotation but currently no ST annotations. The recordings are primarily from exercise stress test and exhibits transient ST changes.

6. Crieghton University Ventricular Tachyarrhythmia Database

This database includes 35 eight-minute ECG recordings of human subjects who experienced episodes of sustained Ventricular Fibrillation.

B. Methods

1) Feature extraction

Wavelet transform algorithm [20] is the decomposition of the signal, which is the combination of a set of basis function obtained by Dilation and Translation.

$$\omega_a x(b) = \frac{1}{a^{0.5}} \int_{-\infty}^{\infty} x(t)\varphi((t-b)/a)dt, a > 0 \quad (1)$$

The ECG wave has to be detected for extracting the features.

The WT algorithm is applied to the digitized ECG signal, without pre-filtering. Then the ECG signal is pre processed in order to remove noise. The following steps describe the significant peak detection of ECG waves.

1. QRS Complex Detection

From the digitized ECG signal, the noise is removed. Then the Stationary wavelet transform (SWT which is a translation invariant) is applied to the noise removed ECG signal. Then the maximum amplitude signal in the ECG wave have to be selected, therefore R wave is selected, which is having the maximum amplitude. From the detected R peak the onset and offset points are detected by setting the search window before and after the R peak, this is to avoid the effect of Baseline drift.

2. QRS delineation

In the delineation process the WT algorithm starts from the detectors position, $n_{qrs.}$ The morphology depends on the number of significant maxima; the delineation looks before n_{pre} and after n_{post} within the QRS complex, to do this the samples of first and last peaks in the QRS complexes are identified.

3. T Wave Detection

The T wave is detected by fixing the search window ($W_{2^4}X[n]$) after the offset of QRS complex. The threshold is fixed and the maximum value exceeding the threshold is the T wave peak.

4. T Wave Delineation

T wave is found at the scale 2^4. The maximum of the search window greater than the given threshold are the significant slope of T wave.

5. P Wave Detection

Fixing the search window before the offset of the QRS complex the T peak is detected and finding the maxima of ($W_{2^4}X[n]$)in that window and the value which exceeds the threshold value are considered to be the P peak.

6. P Wave Delineation

P wave delineation is done similar to that of P wave delineation.

In this paper, Wavelet algorithm is used for feature extraction, 16 sets of input features such as QRS interval ,T wave interval P wave interval, R amplitude, S amplitude, QRS delineation interval, T wave delineation interval, P wave delineation interval, Slope of ST interval, Mean, Variance, Skewness , Kurtosis [21], Standard Deviation, Spectral Entropy were extracted from 90 samples are taken from MIT-BIH, Arrhythmia, EURO, Malignant Ventricular Arrhythmia, Supra Ventricular Database, ST Change Database and Creighton University Ventricular Tachyarrhythmia Database.

MATLAB is used for the detection, analysis and for the classification of the ECG signals.

1) Classifier Module

a) ECG Classification Flow

This stage consists of the Segmentation, Extraction and classification process. The heart beat begins from the P wave and finishes at the next P wave of the following heart beat. After this process feature extraction was done for extracting the significant features of ECG (16 features) mentioned above was extracted, after which the classification was done using the Naive Bayes classifier and Support Vector Machine. The classification algorithms check for any abnormalities in the heart beat.

2.1) Classification of Arrhythmias using Naive Bayes Classifier

The naive Bayes classifier, also called simple Bayesian classifier, is a classifier built upon the Bayes' theorem. It is essentially a simple Bayesian Network (BN) and particularly suitable for the case when the dimensionality of the inputs is high. It uses the Bayes rule to compute the posterior of classification variable [22]. Posterior of classification variable C based n the feature variables Z1, Z2, …, Zn is given by

$$P(C|Z1, Z2, .., Zn) = \frac{P(C)\prod_{i=1}^{n} P(Zi|C)}{P(Z1,Z2,...,Zn)} \quad (2)$$

Assuming it as class conditional independent, it can be written as

$$P(Z1, Z2 \ldots, Zn|C) = P(Z1|C)P(Z2|C) \ldots P(Zn|C) \quad (3)$$

which means that the joint conditional probability is the product of all the marginal conditional probabilities. The second assumption is that all features Z1, Z2… Znis directly dependent on classification variable C. If the two assumptions are imposed on the general BN classifier, we can obtain the naïve Bayes classifier as

$$P(C|Z1, Z2, .., Zn) = \frac{P(C)\prod_{i=1}^{n} P(Zi|C)}{P(Z1,Z2,...Zn)} \quad (4)$$

Therefore to predict the class of each sample we derive the model as

$$C = \arg\max P(C)\prod_{i=1}^{n} P(Zi|C) \quad (5)$$

The above equation can be used to predict the class of each sample.

2.2) Classification of Arrhythmias using Support Vector Machine (SVM)

Support Vector Machine has recently found considerable attention in classification problems due to its generalization capabilities. These classifiers maximize the distance (margin) between the training examples and the decision boundaries by mapping the training examples to higher dimensional space [23, 24]. The dimension of the new space is considerably larger than that of the original data space. Then the algorithm finds the hyper plane in the new space having the largest margin of separation between the classes of the training data using an optimization technique known as the risk minimization. For a binary classification problem where there are only two classes in the training data = $\{-1, 1\}$, a hyper plane can be defined as:

$$W.x + b = 0 \quad (6)$$

Where W is the normal to the hyper plane and b / W is the shortest distance of the plane from the origin. For a good classification model, the positive and negative examples of the training data should fulfill the following two conditions:

$$(W.xi) + b > 0 \quad \text{if } Y_i = 1 \quad (7)$$

$$(W.xi) + b < 0 \quad \text{if } Y_i = -1 \quad (8)$$

These inequalities can be combined into one set of

Inequalities

$$y(W.x + b) \geq 1 \text{ for all i} \quad (9)$$

The SVM finds an optimal hyper plane responsible for the largest separation of the two classes by solving the following optimization problem subject to the condition in (9).

$$Minw, b\frac{1}{2}W^TW \quad (10)$$

The quadratic optimization problem of (9) and (10) can be solved using a Lagrangian function

$$Lp(w, b, \alpha) = \frac{1}{2}W^TW - \sum_{i=1}^{m} \alpha i(yi(Wxi + b) - 1) \quad (11)$$

Whereαi is the constant known as Lagrangian Multipliers. The solution of (11) for αi determines the parameters w and b of the optimal hyper plane. We thus obtain a decision function for the binary classification as:

$$f(x) = sgn(\sum_{i=1}^{m} yi\alpha i(x, xi) + b) \quad (12)$$

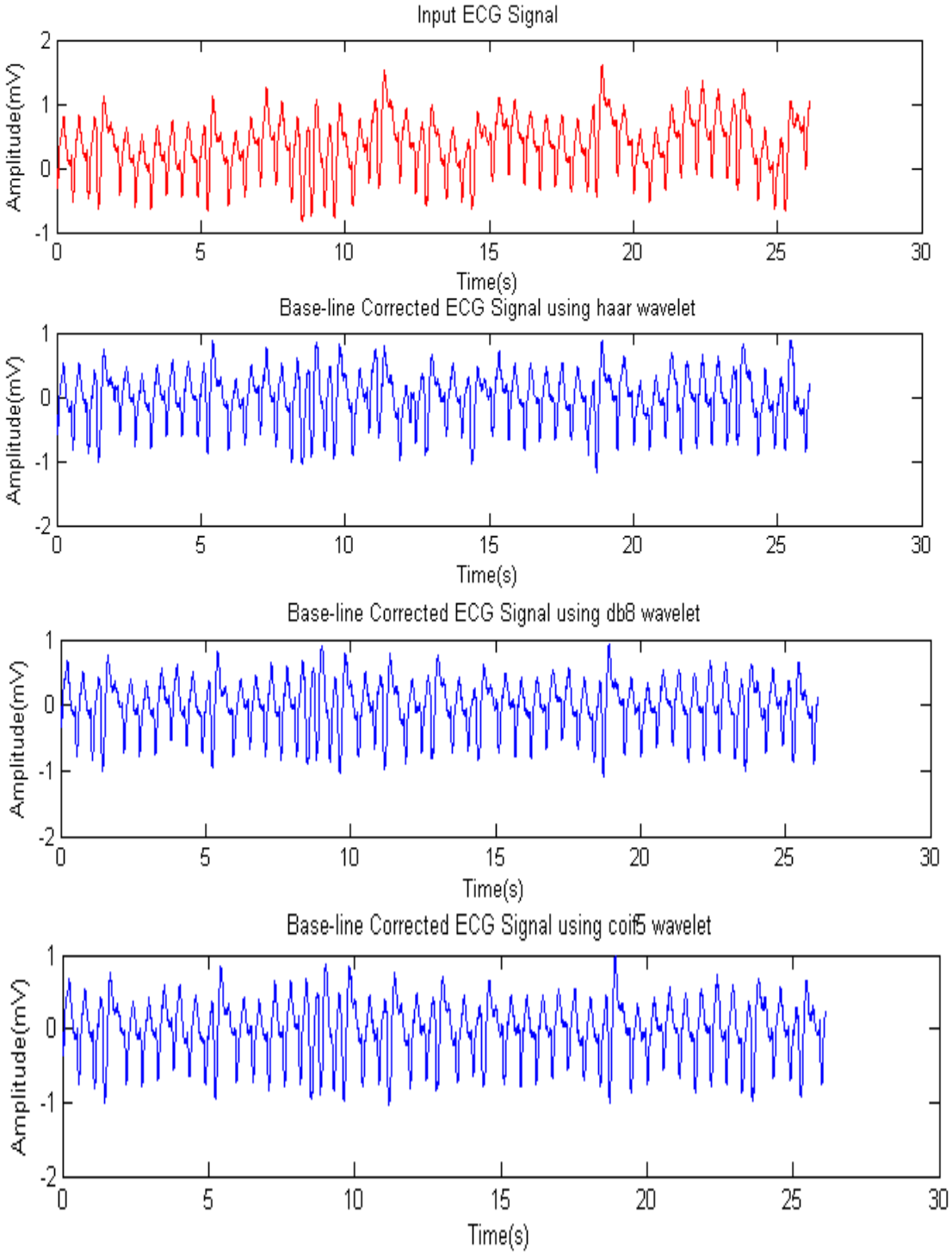
In any classification task only a few Lagrangian Multipliers αi tend to be greater than zero and the corresponding training vectors are the closest to the optimal hyper plane and are called the support vectors. In nonlinear SVM, the training samples are mapped to a higher dimensional space with the help of a kernel function K(xi ,xj) instead of the inner product <xi, xj> . Some of the famous kernel functions are the polynomial kernels, radial basis function kernels, and sigmoid kernels [25].

V. RESULTS AND DISCUSSION

In removing the baseline wander from raw ECG signal samples five different mother wavelets are analyzed. And totally 16 features such as QRS interval, T wave interval P wave interval, R amplitude, S amplitude, QRS delineation interval, T wave delineation interval, P wave delineation interval, Slope of ST interval, Mean, Variance, Skewness, Kurtosis, Standard Deviation and Spectral Entropy were extracted from each of the 90

samples and were used for classification. From the 90 samples, 15 samples were trained first and remaining were tested.

Table 1, 2, 3, 4, 5 shows the PSNR, MSE and MAE performance of the five wavelets respectively. Table 6, 7, 8 shows Sensitivity and Positive Predictivity of the detection and delineation of QRS Complex, P-Wave and T-wave. The overall sensitivity is around 100%. And overall Positive Predictivity is around 95% for detection and delineation of QRS complex, P-wave and T-wave.



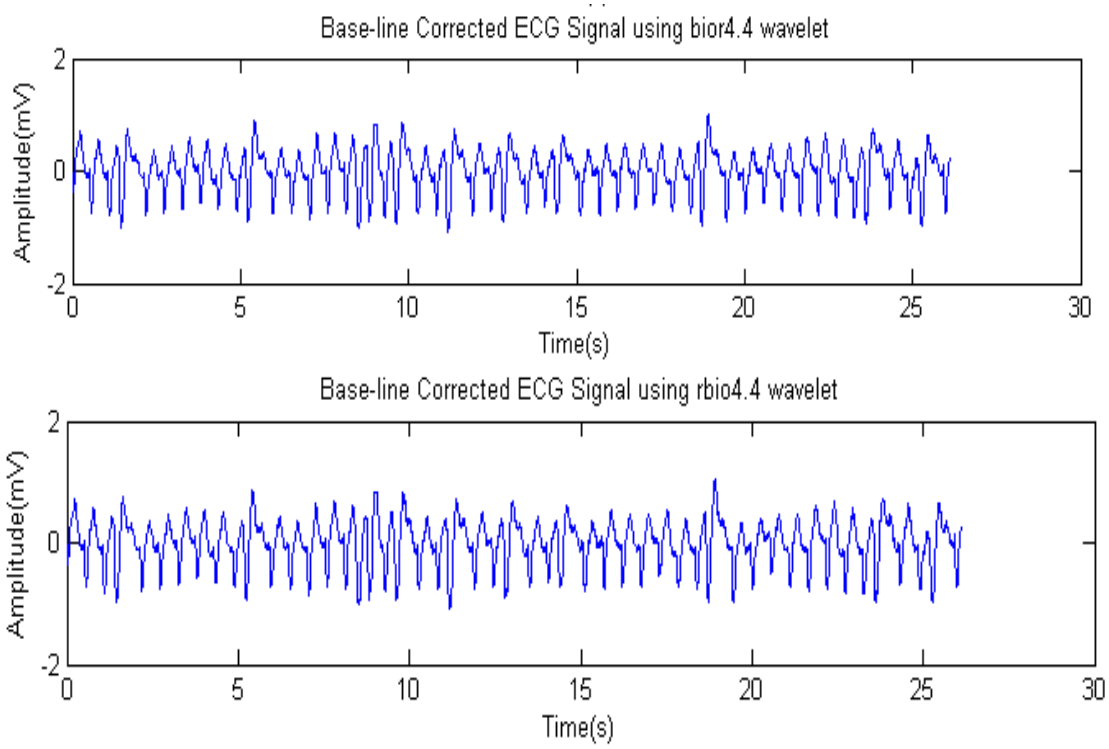


Figure 1: Raw ECG signal and the Baseline corrected ECG signals using haar, db8, coif5, bior4.4 and rbio4.4 wavelets

TABLE 1. PERFORMANCE OF HAAR WAVELET ON TWELVE SAMPLES OF ECG SIGNALS

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
haar	PSNR in dB	63.03	65.39	68.71	68.51	71.86	77.03	62.54	70.86	55.81	55.62	66.18	75.00
	MSE	0.03	0.18	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.17	0.01	0.002
	MAE	0.17	0.08	0.08	0.09	0.005	0.02	0.18	0.06	0.36	0.41	0.12	0.03

TABLE 2. PERFORMANCE OF DB8 WAVELET ON TWELVE SAMPLES OF ECG SIGNALS

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
db8	PSNR in dB	63.30	67.93	69.06	68.56	71.59	76.30	62.59	71.16	55.71	55.61	66.07	76.94
	MSE	0.03	0.01	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.17	0.01	0.001
	MAE	0.17	0.07	0.08	0.09	0.004	0.001	0.03	0.005	0.17	0.18	0.01	0.001

TABLE 3. PERFORMANCE OF COIF5 WAVELET ON TWELVE SAMPLES OF ECG SIGNALS

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
coif5	PSNR in dB	63.36	68.98	69.10	68.57	71.38	76.46	62.59	71.13	55.77	55.60	65.96	77.35
	MSE	0.03	0.008	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.18	0.01	0.001
	MAE	0.17	0.07	0.08	0.09	0.05	0.03	0.18	0.06	0.36	0.41	0.12	0.02

TABLE 4. PERFORMANCE OF BIOR4.4 WAVELET ON TWELVE SAMPLES OF ECG SIGNALS

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
bior4.4	PSNR in dB	63.25	68.18	68.99	68.57	71.45	76.76	62.60	71.14	55.81	55.51	65.92	76.39
	MSE	0.03	0.009	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.18	0.01	0.005
	MAE	0.17	0.07	0.08	0.09	0.05	0.02	0.18	0.06	0.36	0.41	0.12	0.03

TABLE 5. PERFORMANCE OF RBIO4.4 WAVELET ON TWELVE SAMPLES OF ECG SIGNALS

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
rbio4.4	PSNR in dB	63.20	67.89	69.09	68.57	71.46	76.60	62.60	71.14	55.79	55.55	65.93	77.13
	MSE	0.03	0.01	0.008	0.009	0.004	0.001	0.03	0.05	0.17	0.18	0.01	0.001
	MAE	0.17	0.07	0.08	0.09	0.05	0.03	0.18	0.06	0.36	0.41	0.12	0.02

TABLE 6. QRS COMPLEX PERFORMANCE COMPARISON ON SEVERAL DATABASES

Databases	QRS Complex					
	Detection			*Delineation*		
	Se %	*PP%*	*No. of Error Beats*	*Se%*	*PP%*	*No. of Error Beats*
ST CHANGE DB	100	100	0	100	100	0
CUVT DB	100	100	0	100	100	0
EURO DB	100	100	0	100	100	0
MVA DB	100	92.3	1	100	92.3	1
MIT-BHA DB	100	95	1	100	95	1
SUVT DB	100	95.9	2	100	95.9	2

TABLE 7. P WAVE PERFORMANCE COMPARISON ON SEVERAL DATABASES

Databases	P Wave					
	Detection			*Delineation*		
	Se %	*PP%*	*No. of Error Beats*	*Se%*	*PP%*	*No. of Error Beats*
ST CHANGE DB	100	100	0	100	100	0
CUVT DB	100	79.16	10	100	79.16	10
EURO DB	100	70.58	5	100	70.58	5
MVA DB	100	96.7	2	100	96.7	2
MIT-BHA DB	100	95	1	100	95	1
SUVT DB	100	95.9	0	100	95.9	0

TABLE 8. T WAVE PERFORMANCE COMPARISON ON SEVERAL DATABASES

Databases	T Wave					
	Detection			**Delineation**		
	Se %	*PP%*	*No. of Error Beats*	*Se%*	*PP%*	*No. of Error Beats*
MIT-BIH A DB	100	95	1	100	95	1
SUVT DB	100	97.9	1	100	93.8	3
ST CHANGE DB	100	100	0	100	100	0
CUVT DB	100	97.9	1	100	93.7	3
EURO DB	100	100	0	100	100	0
MVA DB	100	100	0	100	100	0

TABLE 9. PERFORMANCE COMPARISON OF NAÏVE BAYES CLASSIFIER AND SUPPORT VECTOR MACHINE CLASSIFIER

Performance Evolution	NBClassifier	SVM Classifier
Sensitivity	98 %	97 %
Specificity	16 %	33 %
Precision	94 %	97 %
Accuracy	94 %	97 %
F-Measure	95.9	83.9
Rate of Positive Prediction	94 %	96 %
Rate of Negative Prediction	0.02 %	0.03 %
False Negative Rate	0.05 %	0.02 %
False Positive Rate	0.16 %	0.33 %
Negative Predictive value	0.5	0.33%

VII. CONCLUSION

In this study the baseline wander removal is done for ECG using five different wavelets- haar, db8, coif5, bior4.4 and rbio4.4 and the cardiac arrhythmias such as MI, PVC, VT, ST, VF and SVT has been detected and classified using six different types of databases. Initially sixteen features were extracted from the samples and the datasets were trained and tested using two classifiers namely: Naïve Bayes classifier and Support Vector Machine classifier. Evaluating Peak Signal to Noise Ratio, Mean Square Error and Mean Absolute Error for the different wavelets coif5 wavelet is found to be efficient in removing the baseline wander from the ECG the signal. From the baseline corrected ECG signal features are extracted. On classification and evaluating the performance metrics the Support Vector Machine performs better than the Naive Bayes Classifier in terms of Sensitivity, Specificity, Precision, F-measure, Rate of Positive Prediction, Rate of Negative Prediction, False Negative Rate, False Positive Rate, Negative Predictive value and Accuracy. Similarly large number of Arrhythmias can be classified using other databases.

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