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Efficient ECG Abnormalities Recognition Using Neuro-Fuzzy Approach

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Abstract— **This paper deals with improved ECG abnormalities recognition using Wavelet Transform techniques for feature extraction and Arrhythmia detection based on Neuro-Fuzzy approach. This improvement is based on suitable choice of features in evaluating and predicting life threatening Arrhythmia. Analyzing electrocardiographic signals (ECG) includes not only inspection of P, QRS and T waves, but also the causal relations they have and the temporal sequences they build within long observation periods. Wavelet-transform is used for effective feature extraction and Adaptive Neuro-Fuzzy Inference System (ANFIS) is considered for the classifier model. In a first step, QRS complexes are detected. Then, each QRS is delineated by detecting and identifying the peaks of the individual waves, as well as the complex onset and end. Finally, the determination of P and T wave peaks, onsets and ends is performed. We evaluated the algorithm on several manually annotated databases, such as MIT-BIH Arrhythmia Database (MITDB), Creighton University Ventricular Tachyarrhythmia Database (CUDB), MITBIH Supraventricular Arrhythmia Database (SVDB), developed for validation purposes. The features are extracted in WT domain and used as inputs to the classifiers. The performance of the ANFIS model is evaluated in terms of training performance and classification accuracies and the results confirmed that the proposed ANFIS model has potential in classifying the ECG signals. Cross validation is used to measure the classifier performance. A testing classification accuracy of 97.93% is achieved which is a significant improvement.**

Keywords— **ECG, Wavelet, Neuro-Fuzzy, ANFIS, Cardiac Arrhythmia**

I. Introduction

The electrocardiogram (ECG) is a noninvasive and the record of variation of the biopotential signal of the human heartbeats. Electrodes are placed on the users skin to detect the bioelectric potentials given off by the heart that reach the skins surface. The ECG detection which shows the information of the heart and cardiovascular condition is essential to enhance the patient living quality and appropriate treatment. It is valuable and an important tool in diagnosing the condition of the heart diseases. Each individual heartbeat in the cardiac cycle of the recorded ECG waveform shows the time evolution of the heart's electrical activity, which is made of distinct electrical depolarization–repolarization patterns of the heart. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of an arrhythmia, which could be detected by analysis of the recorded ECG waveform. Arrhythmia can be classified into following categories: (i) Normal sinus rhythm (NSR). (ii) Pre-ventricular contraction (PVC) or ventricular premature beat (VPB) or extra systole (iii) Ventricular tachycardia (VT). (iv) Ventricular fibrillation (VF). (v) Supra ventricular tachycardia (SVT) (vi) Atrial premature contraction (APC) etc.

Premature ventricular contraction (PVC) arrhythmia, result from irritated ectopic foci in the ventricular area of the heart. These foci cause premature contractions of the ventricles that are independent of the pace set by the sinoatrial node. Many studies have shown that PVCs, when associated with myocardial infarction, can be linked to mortality. So is the case with other arrhythmias. Consequently, their immediate detection and treatment is essential for patients with heart disease. Real-time automated ECG analysis in clinical settings is of great assistance to clinicians in detecting cardiac arrhythmias, which often arise as a consequence of a cardiac disease, and may be life-threatening and require immediate therapy. However, automated classification of ECG beats is a challenging problem as the morphological and temporal characteristics of ECG signals show significant variations for different patients and under different temporal and physical conditions [1]. Many algorithms for automatic detection and classification of ECG heartbeat patterns have been presented. in the literature, including signal processing techniques such as frequency analysis[2], wavelet transform[3],[4], filter banks[5], statistical[6], heuristic approaches[7], hidden Markov models[8], support vector machines[9], artificial neural networks (ANNs)[10], and mixture-of-experts method[11]. The performance of ECG pattern classification strongly depends on the characterization power of the features extracted from the ECG data and the design of the classifier (classification model or network structure and parameters). Due to its time–frequency localization properties, the wavelet transform is an efficient tool for analyzing nonstationary ECG signals .The wavelet transform can be used to decompose an ECG signal according to scale, thus allowing separation of the relevant ECG waveform morphology descriptors from the noise, interference, baseline drift, and amplitude variation of the original signal. Several researchers have previously used the wavelet transform coefficients at the appropriate scales as morphological feature vectors rather than the original signal time series and achieved good classification performance[3][4]. Accordingly, in the current paper, the proposed feature extraction technique employs the suitable wavelet transform (Daubechies 6) in order to effectively extract the morphological and statistical information from ECG data and the extracted features are given to Adaptive Neuro-Fuzzy Inference System (ANFIS) for further classification of arrhythmia. The overview of the proposed system is shown in Fig. 1.

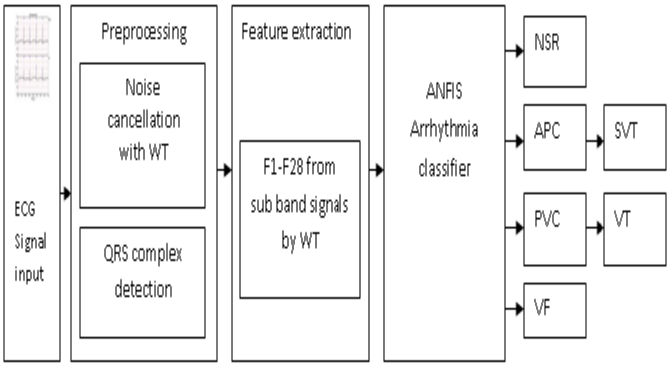

Fig. 1 Proposed System for Arrhythmia detection

The main focus of the paper is to utilize wavelet analysis method for extracting various features in wavelet Transform (WT) domain.

II. ECG DATA PROCESSING

A. ECG Data

In this study, the MIT-BIH databases are used for training and performance evaluation of the proposed ECG classifier.We used the MIT-BIH Arrhythmia Database (MITDB) [15], Creighton University Ventricular Tachyarrhythmia Database (CUDB) [16], MIT-BIH Supraventricular Arrhythmia Database(SVDB) [17] to evaluate our algorithm. The MITDB contains 48 files, 2 channels per file, each channel 1805 seconds long. The CUDB contains 35 files, 1 channel per file, each channel 508 seconds long. The SVDB database contains 78 files, 2 channels per file, each channel 1800 seconds long.

B. ECG signal components and Cardiac Arrhythmia

ECG is a graphic representation of the electrical activity of the heart’s conduction system recorded over a period of time. Under normal conditions, ECG tracings have a very predictable direction, duration, and amplitude. Because of this, the various components of the ECG tracing can be identified, assessed, and interpreted as to normal or abnormal function. The ECG is also used to monitor the heart’s response to the therapeutic interventions. Because the ECG is such a useful tool in the clinical setting, the respiratory care practitioner must have a basic and appropriate understanding of ECG analysis. The ECG, over a single cardiac cycle, has a characteristic morphology as shown in Fig.2 comprising a P wave, a QRS complex and a T wave. The normal ECG configurations are composed of waves, complexes, segments, and intervals recorded as voltage (on a vertical axis) against time (on a horizontal axis). A signal waveform begins and ends at the baseline (isoelectric line). When the waveform continues past the baseline, it changes into another waveform. Two or more waveforms together are called a complex. A flat, straight, or isoelectric line (baseline) is called a segment. A waveform, or complex, connected to a segment is called an interval. All ECG tracings above the baseline are described as positive deflections. Waveforms below the baseline are negative deflections.

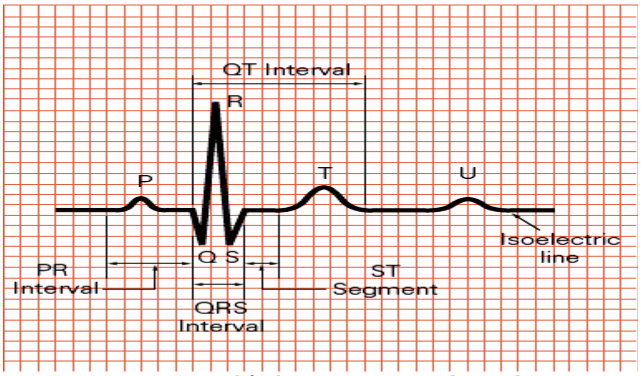

Fig. 2 ECG signal for human over one cardiac cycle

An arrhythmia is a change in the regular rhythm of heartbeat. It has two main types. If the heart beat is too slow it is considered as *bradycardia* and if the heart beat is too fast it is called *tachycardia*. In this paper we focussed on the recognition of following Arrhythmias.

1) Normal sinus rhythms (NSR) : All “p’’ waves upright, rounded and similar in size and shape. A p wave exists for every QRS complex. Each P wave is the same distance from the QRS complex less than 0.20 seconds. All ‘’QRS’’ complexes have the same size and shape and point in the same direction. Each QRS has the same distance from the T waves and the QRS duration is 0.10 seconds or less. Heart rate is varying 60-100 beats/minute and is rhythmic. Refer Fig.3.

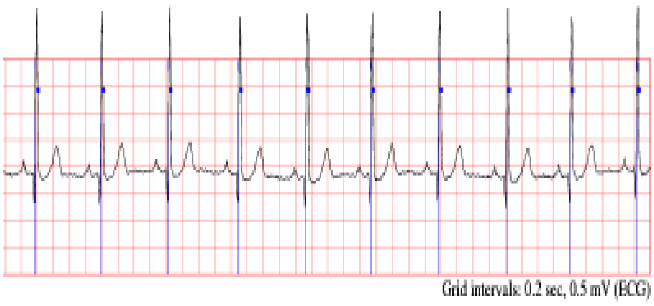

Fig. 3 Normal ECG (record 16786 of MIT-BIH Database).

2) Ventricular tachycardia (VT): Ventricular tachycardia is defined as three or more consecutive beats of ventricular origin at a rate greater than 100 beats/min. There are widened QRS complexes .The rhythm is usually regular, but on occasion it may be modestly irregular. An ECG of patient having VT is shown in Fig.4.

Fig. 4 Ventricular tachycardia (record cu13 of MITBIH Database)

3) Supra ventricular tachycardia (SVT) : Supra ventricular tachycardia (SVT), is any tachyarrhythmia that requires only atrial and/or atrioventricular (AV) nodal tissue for its initiation and maintenance. It is usually a narrow-complex tachycardia that has a regular, rapid rhythm; exceptions include atrial fibrillation and multifocal atrial tachycardia. Aberrant conduction during SVT results in a wide complex tachycardia. SVT occurs in persons of all age groups. This arrhythmia has such a fast rate that the P waves are frequently buried in preceding T waves and difficult to see. An ECG of patient having SVT is shown in Fig.5

Fig. 5 Supra ventricular tachycardia (record 800 of MIT-BIH Database)

4) Premature ventricular contraction (PVC) :PVCs result from an irritable ventricular focus. It may be uniform (same form) or multiform (different forms).Usually PVC is followed by a full compensatory pause because the sinus node timing is not interrupted. Normally the sinus rate produces the next sinus impulse on time. In contrast, PVC may be followed by a noncompensatory pause if the PVC enters the sinus node and resets its timing; this enables the following sinus P wave to appear earlier than expected. P waves are not associated with PVC and QRS is wide (>0.1 Sec). An ECG of patient having PVC is shown in Fig. 6.

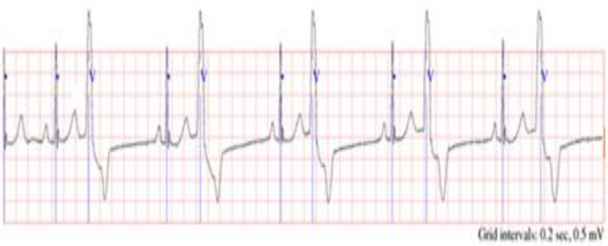

Fig. 6 premature ventricular contraction shown by V (record 119 of MIT-BIH database)

5) Atrial premature contraction (APC): A single contraction occurs earlier than the next expected sinus contraction. After the APC, sinus rhythm usually resumes. Rhythm is irregular whenever APC occurs. P Waves may have a different shape. PR Interval normally **v**aries otherwise have a normal range (0.12–0.20 sec). QRS interval is Normal (0.06–0.10 sec). An ECG of patient having APC is shown in Fig. 7.

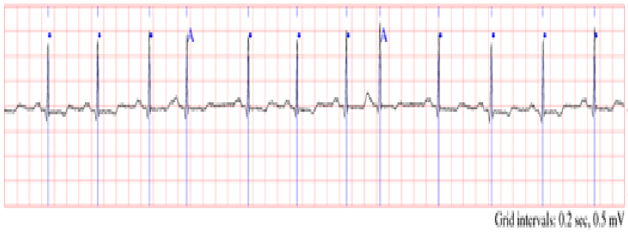

Fig. 7 Atrial premature contraction shown by A (record 100 of MIT-BIH database)

6) Ventricular fibrillation (VF) :Chaotic electrical activity occurs with no ventricular depolarization or contraction. The amplitude and frequency of the fibrillatory activity can be used to define the type of fibrillation as coarse, medium, or fine. Small baseline undulations are considered fine; large ones are coarse. No P waves, No QRS interval and no PR interval. An ECG of patient having VF is shown in Fig. 8.

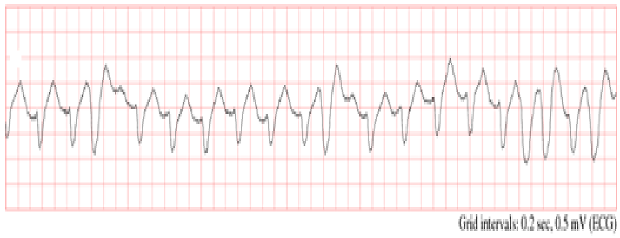

Fig.8 Ventricular fibrillation (record 418 of MIT-BIH database)

C. Wavelet Technique

In contrast to conventional techniques, the wavelet transform (WT) provides a new dimension to signal processing and event detection. Due to its time-frequency localization properties, the wavelet transform is an efficient tool for analyzing non-stationary ECG signals. The wavelet transform provides a description of a signal in a timescale domain, analogous to a time-frequency domain, allowing 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. In its continuous form, the WT of a signal $x(t) \in L^2R$ is defined as

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

where $\psi(t)$ is the prototype (or mother) wavelet ($\psi \in L^2(R)$) , a the scale factor ($a \in R^+$), b the translation factor ($b \in R$) , CWT the continuous wavelet transform operator and * the complex conjugate operator. The wavelet transform in (1), can be rewritten as a convolution product between the signal and the scaled wavelets and can also be interpreted as a filtering of the signal by bandpass filters whose center frequencies and bandwidths depend on the scaling factor. High scales translate into long, slow wavelets equivalent to narrow, low-frequency filters, while lower scales produce shorter, faster wavelets equivalent to wider, higher-frequency filters. With these properties, WT achieves an ideal balance of time and frequency resolution: slow trends are represented with a high frequency resolution and a low time resolution, while fast components are well defined in time but less in frequency. Such inherent multiresolution capabilities make WTs very effective at detecting and representing singularities, and WTs have been applied in many occasions to ECG analysis. The ECG signals are considered as representative signals of cardiac physiology, useful in diagnosing cardiac disorders. The most complete way to display this information is to perform spectral analysis. The ECG signal, consisting of many data points, can be compressed into a few parameters by Wavelet Transform (WT). These parameters characterize the behaviour of the ECG signal and they can be used for recognition and diagnostic purposes. The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The procedure of multiresolution decomposition of a signal x[n] is carried out by applying the Discrete Wavelet Transform (DWT) which is schematically shown in Fig. 9. Each stage of this scheme consists of two digital filters and two down samplers by 2. The first filter, g[.] is the discrete mother wavelet, highpass in nature, and the second, h[.] is its mirror version, low-pass in nature. The downsampled outputs of first high-pass and low-pass filters provide the detail cd1, and the approximation ca1, respectively. The first approximation, ca1 is further decomposed and this process is continued as shown in Fig. 9.Noise cancellation is done by removing baseline drift with the help of median filter [18].

III. FEATURE EXTRACTION AND BEAT DETECTION

The performance evaluation for different wavelets has been analysed on the MIT-BIH arrhythmia database. The performance of different wavelets to detect QRS complexes is critical. The ability of dyadic WT to extract electrocardiogram (ECG) features has been verified by several researchers [4][12][13].Furthermore, different wavelet and different decomposition levels were examined for their ability to classify the ECG beat. It is concluded that the Daubechies wavelet and the spline wavelet provide the best performance. Twenty eight features from ECG signals are selected in Wavelet Transform domain based on morphology and statistical parameters of the signal. These features are labeled in Table 1. All features are extracted for each individual beat in the database.

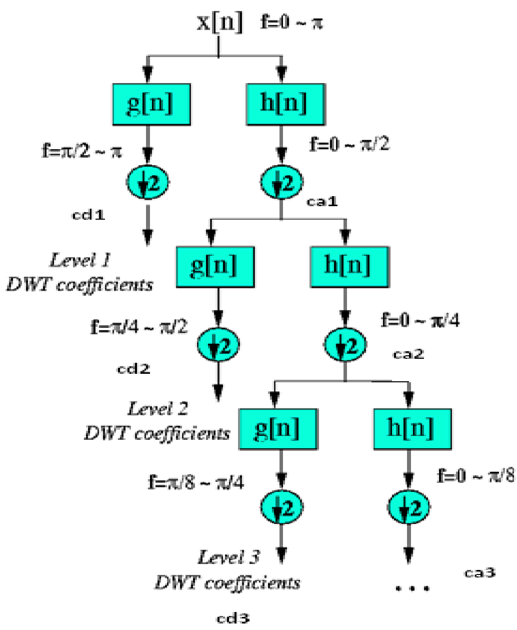

Fig. 9 Sub band decomposition of discrete wavelet transform implementation; g[n] is the high pass filter and h[n] is the low pass filter.

TABLE I
DIFFERENT FEATURES IN WAVELET TRANSFORM (WT) DOMAIN

Sr.No	Type of Features	Wavelet Transform (WT) domain
1	Morphological	Max(3,4,5), Min(3,4,5), Difference between Max and Min(3,4,5), Distance(in samples) between Max and Min(3,4), Power(2,3,4,5), Power ratio(3-2,4-3,5-4).
2	Statistical	Mean(3,4),Standard Deviation(3,4),Skewness(3,4)

There are some typical ECG signals where most of the methods fail to detect QRS complexes. Due to morphological variability in ECGs, QRS detection methods based on amplitude, threshold, squaring, slope etc. criterion fails. In pattern recognition based QRS detection, the ECG signal is first reduced into set of elementary patterns like peaks, durations, slopes and interwave segments. Thereafter the signal is represented using rule based grammer. These patterns are then used to detect QRS complexes in the ECG signals. But such methods are time consuming and require inference grammer in each step of execution. The performance of five different wavelets is evaluated on MIT-BIH database. Most of the energy of the QRS complex is related to frequency range 3-40 Hz. It is found that most of the energy of the QRS complex lies between scales of 2^3 and 2^4 and the energy decreases if the scale is larger than 2^4. The performance of different wavelets to detect QRS complexes is different as detail signals are affected by base wander and low-frequency noise. There are also large number of modulus maxima lines which makes the problem more critical. The Daubechies (db6) at level three is found more suitable for R peak detection. The Discrete wavelet decomposition of sample signal for first five scales using db6 and rbio6.8 wavelet are shown in Fig. 10 and 11 respectively.

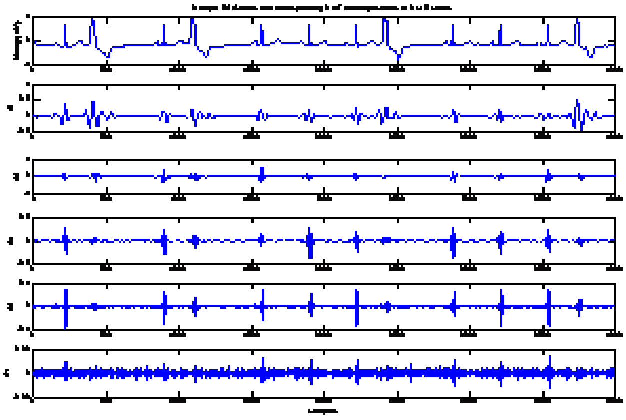

Fig. 10 ECG signal and its five level wavelet decomposition using db6

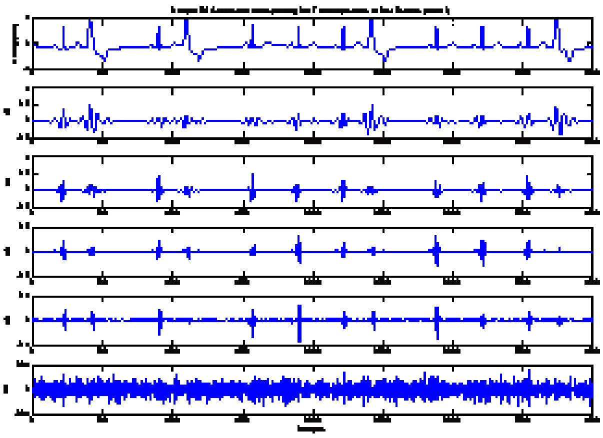

Fig.11 ECG signal and its five level wavelet decomposition using rbio6.8

For QRS detection, the signal is analysed over consecutive blocks of 252 samples. In the detection process, wavelet transform of ECG signal is calculated over 5 scales. The DWT decompositions of different ECG waveforms in the MIT-BIH database is performed according to the distance between samples, power spectra, power ratio, mean, standard deviation, skewness etc. at different scales of the signal.

IV. NEURO-FUZZY APPROACH FOR ARRHYTHMIA CLASSIFICATION

For classifying the arrhythmias like NSR, PVC, VT, VF, SVT, APC etc the Neuro-fuzzy approach is employed.Neuro-fuzzy systems are fuzzy systems which use neural networks theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and neural networks, by utilizing the mathematical properties of neural networks in tuning rule-based fuzzy systems that approximate the way man processes information.

In this work we present the ANFIS approach (adaptive neuro fuzzy inference system) which is a neuro-fuzzy hybrid method proposed by Jang [14] and it is the most widely used of neuro-fuzzy techniques and the best one to solve problems of classification and Pattern Recognition. The ANFIS is a fuzzy inference system based on the model of Takagi-Sugeno and uses five layers. In ANFIS classifiers decision making is performed in two stages:

1) Feature extraction- discrete wavelet transform (DWT) is used to extract the relevant information from the ECG input data. (like QRS complexes, P and T wave peaks, onsets and ends)

2) Classification by the ANFIS trained with the Rule-Based Decision Tree (RBDT) method. (like membership function, rules etc.).

There are several learning algorithms for a neuro-fuzzy model . Jang proposed a learning method called "hybrid algorithm". This algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS.

V. RESULTS AND CONCLUSION

In this paper, we proposed wavelet based method to detect the cardiac arrhythmias by a neuro-fuzzy approach using ANFIS. Efficient formation of morphological and statistical features from ECG data using wavelet transform is key features of the proposed scheme. Twenty eight features from ECG signals are selected based on wavelet coefficients. The features are extracted for each individual beat in the database using wavelet decomposition. We evaluated the algorithm on several manually annotated databases, such as MIT-BIH Arrhythmia Database (MITDB), Creighton University Ventricular Tachyarrhythmia Database (CUDB), MITBIH Supraventricular Arrhythmia Database (SVDB), developed for validation purposes. A testing classification accuracy of 97.93% is achieved which is a promising result. All the necessary algorithms are implemented in Matlab with necessary wavelet functions. Table 2 shows recognition Results on the selected files of MITBIH Arrhythmia database. Real time and economic implementation of this work along with optimization (PSO or ACO) into embedded or PDA system and checking real time performance of such system can be a future scope of this research work.

TABLE II

RECOGNITION RESULTS ON THE SELECTED FILES OF MITBIH DATABASE

Record Number	Total beats tested	Beats correctly recognized	Recognition accuracy in %	Recognition time in seconds
100	2271	2231	98.24	81.526727
101	1866	1852	99.25	65.058209
103	2087	2079	99.62	73.523010
113	1793	1766	98.49	63.209119
115	1956	1950	99.69	69.260953

116	2357	2319	98.39	83.644785
123	1517	1509	99.47	52.773334
202	2139	2012	94.06	75.735331
220	2061	1958	95.00	70.920176
221	2440	2369	97.09	86.735838
234	2758	2701	97.93	97.774988
Total	23245	22746	1077.23	820.362470
Average	2113.18	2067.82	97.93	74.578406

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