Classification of Cardiac Beats Using Discrete Wavelet Features

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Abstract—With the growing technology, the tools which continuously monitor the health status of the people are becoming the integral part of our lives. The detection of a cardiac disease or tracking the heart activities for ongoing cardiac conditions is now possible with portable electrocardiography (ECG) monitors. For detection and classification of ECG signals in portable devices, the robust features and efficient classification algorithms are very important. Thus, in this study, a robust feature set based on discrete wavelet transform (DWT) is proposed, and the performance of the classification tools such as artificial neural networks, support vector machines and probabilistic neural networks are compared. After preprocessing, the R peaks are located by the well-known Pan Tompkins algorithm and 200 samples are taken as equivalent R-T interval in the proposed technique. The statistical parameters such as mean, median, standard deviation, maximum, minimum, energy and entropy of DWT coefficients are used as the feature set. The proposed hybrid technique has been tested by classifying three ECG beats as normal, right bundle branch block (Rbbb) and paced beat using the signals from Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) arrhythmia database and processed using Matlab 2013 environment. The best accuracy of 99.84% has been obtained by Db4 mother wavelet with artificial neural network as classifier.

Keywords— ECG, DWT, Mobile devices, ECG Feature extraction, Pan Tompkins

1.0 Introduction

Heart is one of the most critical organs in the human body supplying blood to different parts of the body. The cardiovascular diseases (CDV) caused by the problems in the functioning of the heart remain as the dominant reason of death all over the world. According to the statistics of World Health Organization (WHO) approximately 30% of global death is caused by CDV (Murugavel, 2011). Also, according to a recently published (2014) report by Heart failure Working Group of the Turkish Society of Cardiology (TDK), there are 15 million heart-failure patients in Europe and 6 million in the United States (US), in Turkey there are 1 million patients suffering from heart failure. With another 2 million who are at serious risk of this disease and those figures will increase about two fold within 10 years

(Yuksel, 2014). Thus, it is very important to detect and diagnose as early as possible and accurately these cardiac arrhythmias since they usually cause sudden cardiac death.

One of the most powerful diagnostic tools commonly used for the assessment of the functionality of the heart is Electrocardiography (ECG) since it is a real-time non-invasive method (Guyton and Hall, 2006). However, it is tedious and time consuming to use visual inspection in ECG analysis even for an expert cardiologist. Therefore, the usage of computer software to automatically detect and classify the ECG beats using a low cost, accurate and effective system, significantly improves diagnostic accuracy and patient healing outcomes (Bruce, 1966).

In order to improve the quality of the life, the mobile healthcare systems have been growing due their importance. Thus, there is a considerable commercial interest in the wireless systems which acquire ECG signals, classify and monitor them to mobile phones or personal computers. However, extracting significant and useful features from ECG signal characteristics is a very crucial for successful implementation of these devices since they need to be fast, simple and computationally efficient.

There are several studies proposed for the analysis of the ECG beats. Gradient–based algorithm and time domain morphology was presented in (Mazomenos et al., 2012). Also, in (Chatterjee et al., 2011) statistical method of comparison between relative magnitudes of ECG samples and their time domain slope has been described. Another classifier based on ECG morphological features was reported in (Chazal et al., 2004) and (Chazal and Reilly, 2006). Wavelet transform finds application in ECG beats detection and feature extraction as reported in (Li et al., 1995), (Saxena et al., 2003) and (Martinez et al., 2004). Also, Mahesh used wavelet and Pan-Tompkins algorithm to extract time-frequency features for ECG beat detection system (Mahesh, 2014). In (Marlar and Aung, 2014) they presented classification of normal and abnormal signal using R-R interval features of ECG waveform. In (Martis et al., 2013) the principal component of 4th-levels DWT with db4 mother wavelet is used to classify normal and arrhythmic beats with accuracy of 95.60%. Finally, in (Saminu et al., 2014) a hybrid method which uses statistical parameters of discrete wavelet transform coefficients to classify three arrhythmias using artificial neural networks (ANN) is proposed.

As a contribution, in this work, same feature set based on the statistics of discrete wavelet transform coefficients are used for classification using common classifiers such as ANN, support vector machines (SVM) and probabilistic neural networks (PNN). Three ECG beats as normal, right bundle branch block (Rbbb) and paced are extracted from the signals of Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) arrhythmia database and processed using Matlab 2013 environment. Also, the effect of the selection of mother wavelet to classification performance is analyzed. This paper is an extended version of the paper presented in IEEE 6th International Conference on Adaptive Science & Technology ICAST'2014 (Saminu et.al. 2014).

After a brief introduction of the heart anatomy in the following section, ECG wave and arrhythmias considered in Section 3. The wavelets are summarized at Section 4. The acquisition, feature extraction and arrhythmia classification for the proposed method is explained in Section 5. Finally, the results of the experiments are discussed and the conclusions are drawn.

2.0 The Heart Anatomy

The heart contains four chambers that is right atrium, left atrium, right ventricle, left ventricle and several atrioventricular and sinoatrial node as shown in Figure 1. The two upper chambers are called the left and right atria, while the lower two chambers are called the left and right ventricles. The atria are attached to the ventricles by fibrous, non-conductive tissue that keeps the ventricles electrically isolated from the atria. The right atrium and the right ventricle together form a pump to circulate blood to the lungs. Oxygen-poor blood is received through large veins called the superior and inferior vena cava and flows into the right atrium. The right atrium contracts and forces blood into the right ventricle, stretching the ventricle and maximizing its pumping (contraction) efficiency. The right ventricle then pumps the blood to the lungs where the blood is oxygenated. Similarly, the left atrium and the left ventricle together form a pump to circulate oxygen-enriched blood received from the lungs (via the pulmonary veins) to the rest of the body (Acharya et al. 2012).

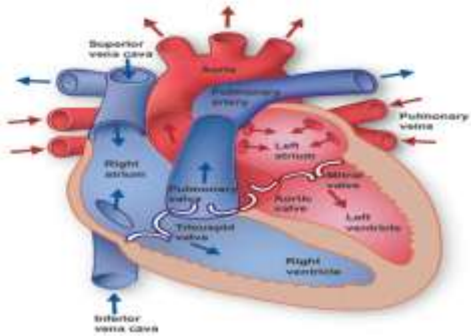


Fig. 1. A full view of Human Heart, with chambers and valves (Texas, 2012)

3.0 Electrocardiography and Arrhythmias

ECG signal is a bioelectrical signal which depicts the cardiac activity of the heart and it is a technique used primarily as a diagnostic tool for various cardiac diseases because of its simplicity. By attaching electrodes at different outer surface of the human skin, electrical cardiac signals can be recorded by an external device. These currents cause the contractions and relaxations of heart by stimulating cardiac muscle (Guyton and Hall, 2006) and travel as electrical signals through the electrodes to the ECG device, which records them as characteristic waves. Different waves and fiducial points of ECG reflect the activity of different parts of the heart which generate the respective flow of electrical currents. Figure 2 below shows a schematic representation of a normal ECG and its various waves.

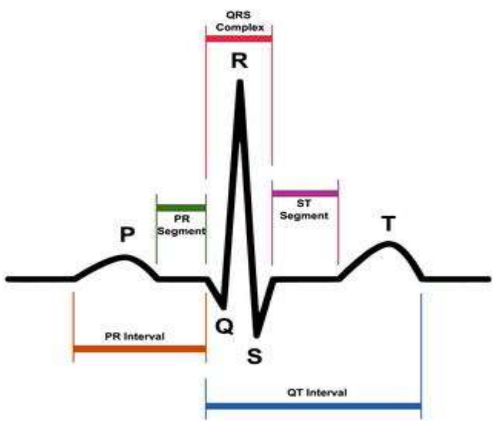


Fig. 2. Normal ECG wave (Yuksel, 2014)

The most important features include the information lying in the P,Q,R,S,and T waves of the ECG signal, ECG beats should be classified based on these features in order to detect different types of cardiovascular diseases. The length of a normal QRS wave is between 80 to 120ms (Williams and Wilkins 2011). R-R interval of a normal sinus rhythm downloaded from MIT-BIH database is shown in Fig.3.

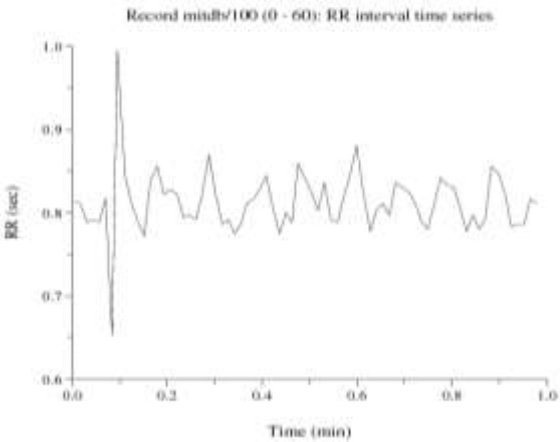


Fig. 3. R-R interval of a normal ECG wave from MIT-BIH

Two different arrhythmias which are not critical in terms of emergent care but important to detect for future cardiac problems are considered in this study: right bundle branch block (Rbbb) and paced beats. When one bundle branch is blocked: Electrical impulse will travel through intact branch and stimulate ventricle supplied by that branch. Ventricle affected by blocked or defective bundle branch is activated indirectly. There is a delay caused by this alternate route and QRS complex will represent widening beyond usual time interval of 0.12 sec. Classified as either complete (QRS measures 0.12 sec or greater) or incomplete blocks (QRS measures between 0.10 and 0.11 second). Sample of an Rbbb beat is illustrated in Fig.4.

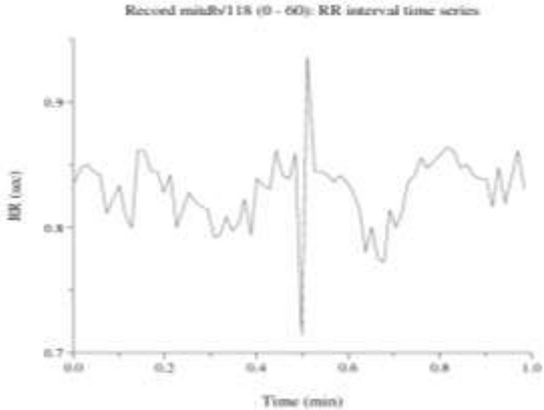


Fig. 4. R-R interval of a RBBB ECG wave from MIT-BIH

The paced beat is the artificial beat form from the device called pacemaker. A pacemaker is a treatment for dangerously slow heart beats. Slow heart beats can be the result of metabolic abnormalities or occur as a result of blocked arteries to the heart's conduction system. These conditions can often be treated and a normal heart beat will resume. Slow heart beats can also be a side effect of certain medications in which case discontinuation of the medicine or a reduction in dose may correct the problem. It can be characterized in ECG by a large peak after QRS complex (Martis et al., 2013). R-R interval of one of the paced beats from MIT-BIH database is shown in Fig. 5.

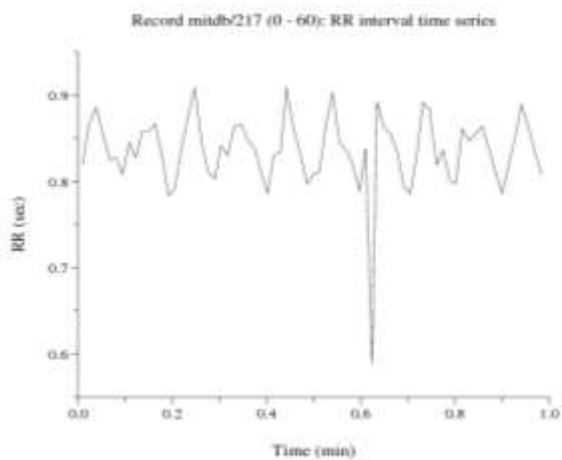


Fig. 5. R-R interval of a paced ECG wave from MIT-BIH

4.0 Wavelet Analysis

The continuous wavelet transform (CWT) has been developed as a method to obtain simultaneous, high resolution time and frequency information about a signal. The CWT unlike Short Time Fourier Transform (STFT) uses a variable sized window region. Since the wavelet may be dilated or compressed; different features of the signal are extracted. While a narrow wavelet extracts high frequency components, a stretched wavelet picks up the lower frequency components of the signal (Addison, 2002).

The CWT is computed by correlating the signal s (t) with families of time-frequency atoms (t), it produce a set of coefficients C(,b) given by :

$$C(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\Psi^{*}\left(\frac{t-b}{a}\right) dt \quad (1)$$

where is the time location (translation parameter), a is called scale factor and it is inversely proportional to the frequency (a>0), *denotes a complex conjugate and is the analyzing wavelet (mother wavelet). Each coefficient represents the similarity between the signal and the scaled and translated wavelet.

The Discrete Wavelet Transform (DWT) is a time-scale representation of the digital signal and is obtained using digital filtering techniques. It is found to yield a fast computation of wavelet transform, easy to implement and adopts dyadic scales and translations in order to reduce the amount of computation time, which results in better efficiency of calculation. DWT can be obtained by

$$C_{mn} = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\Psi_{mn}(t)\, dt \quad (2)$$

where the dyadic scaled and translated wavelet is defined as

$$\Psi_{mn}(t) = 2^{-m/2}\Psi(2^{-m}t - n) \quad (3)$$

most common wavelets providing the orthogonality properties are Daubechies, Symlets, Coiflets and Discrete Meyer in order to provide reconstruction using the fast algorithms (Addison, 2002). The successive low-pass and high-pass filters calculating three levels of DWT is shown in Fig.6.

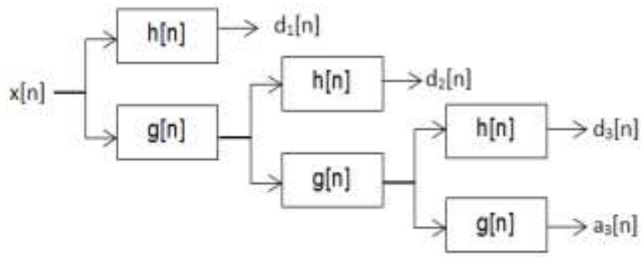


Fig. 6. Three level Wavelet decomposition tree

Each stage consists of two digital filters and two downsamplers by 2 to produce the digitized signal. The low pass filter is denoted by g[n] while the high pass filter is denoted by h[n]. At each level, the high pass filter produces detail information; , while the low pass filter associated with scaling function produces coarse approximations, The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. Only the last level of approximation is save among all levels of details, which provides sufficient data. The filter coefficients can be obtained from mother wavelet and scaling functions (Addison, 2002).

5.0 Data Acquisition and Feature Extraction

The flowchart of the overall working principle of the automatic beat classification system is given in Fig. 7. After the acquisition of the data, the preprocessing steps are applied to remove noise and artifacts, then R waves are detected to localize QRS complexes using Pan-Tompkins algorithm.

For each R-R interval 200 samples are obtained and the features are extracted by the statistics of DWT coefficients. Finally, each ECG beats are classified by artificial neural network due to its simplicity and the performance is analyzed. In this section the details of the procedure will be explained.

5.1 ECG Data Acquisition

In this study, the source of the ECG data used for training and testing is MIT-BIH Arrhythmia database from Physionet website (Physionet, 2014). The database contains 48 recordings of both routinely clinical waveforms and some complex arrhythmias sampled at 360Hz of 30 min durations selected from 24 hr recording with two channels obtained from 47 patients (Goldberger, 2000). Only one channel of 1 min long for each record is used in this work.

5.2 Preprocessing

Preprocessing step involves removal of noise from sources such as electrode contact noise, baseline drift, muscle contraction, power line interference and motion artifacts. Also QRS detection (Ozbey and Karlik, 1985) was carried out in this stage. A well known and acceptable Pan Tompkins algorithm is employed as a real time QRS detection algorithm based on the analysis of slope, amplitude and width of QRS complexes (Pan and Tompkins, 1985). The steps of preprocessing are given as

- Removing DC component
- Removing high frequency noise (low pass filter)
- Removing low frequency noise (high pass filter)
- Removing power line interference (comb filter)
- Derivative operation
- Squaring operation
- Integrator
- Thresholding
- Search procedure for R-peaks

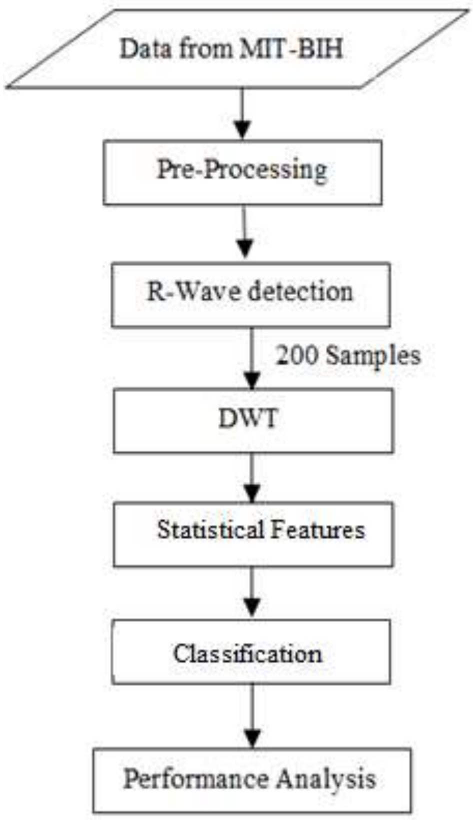
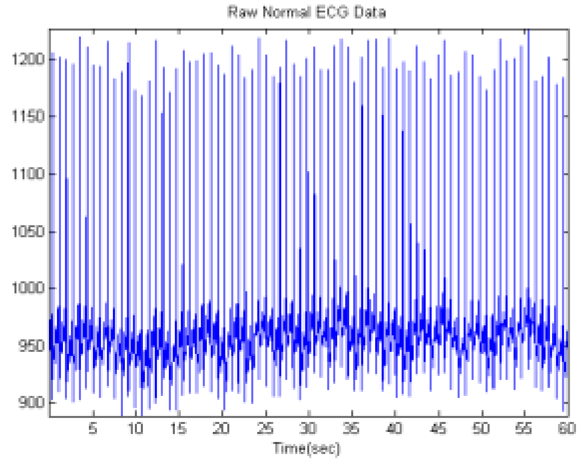
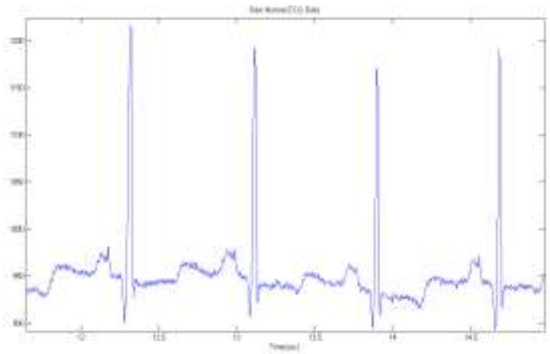


Fig. 7. Automatic ECG Beat Classification System Development Flow Chart

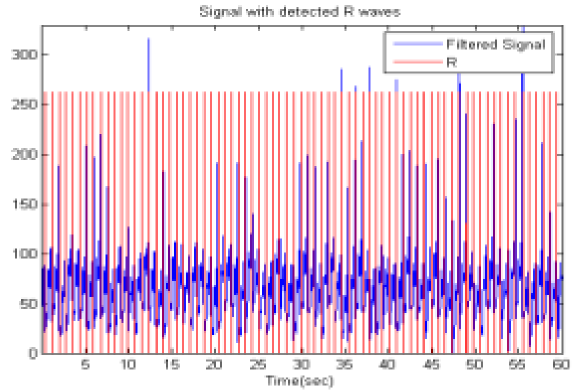
One sample of the original normal ECG recording and preprocessed ECG wave with detected R waves are shown in Fig. 8. The red lines in Fig.8.c point the detected R waves. In the feature calculation R-R intervals are taken into account.



(a)



(b)



(c)

Fig. 8.(a) Original Normal ECG for 1 minute signal, (b)zoomed in for a few beats, (c) preprocessed ECG signal

5.3 Feature extraction

ECG signal consists of many parameters and data points which characterize its behavior, extracting significant and smaller number of parameters without sacrificing accuracy of classifier is particularly important in ECG beat detection and classification using mobile devices. To achieve this, feature extraction in this work are in three stages.

5.3.1 ***Equivalent R-T interval features***: Only 200 samples from detected R-peaks have been extracted from R-R interval which corresponds to R-T interval. The feature vector is constructed depending on the number of R-peaks in each ECG record which is between 60 and 90 per record.

5.3.2 ***Statistics of DWT coefficients***: In this stage, discrete wavelet decomposition is applied to feature vector extracted from R-T interval above. Different wavelet families are considered to find the best and suitable wavelet. Another important point is to select the wavelet decomposition level. The level is chosen to cover the frequency range of the normal and abnormal ECG signals. Then, seven standard statistical parameters are used over the set of wavelet coefficients in order to reduce the feature vector dimension and to increase robustness. The mean, median, maximum, minimum, standard deviation, energy and entropy are the features that represent the time-frequency distribution of the ECG signals.

5.4 Classification

In order to classify ECG beats as normal, right bundle branch block and paced, three common classifiers as artificial neural networks, support vector machines and probabilistic neural networks are used in this study. In this section these three classifiers will be introduced briefly.

5.4.1 Artificial neural networks

The artificial neural networks (ANN) inspired by human nervous system is widely used for function approximation and system modelling. The simplest and most common ANN structure is multi layer feedforward neural network with backpropagation learning which is illustrated in Fig. 9.

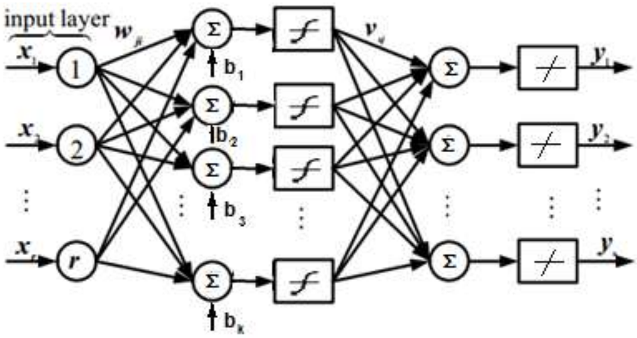


Fig. 9. Multi layer feedforward neural network

After the selection of system structure, number of layers, number of neurons in each layer, ANN is fed with training samples and weights are determined according to the learning algorithm. The basic backpropagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing most rapidly. In this study, ANN with one hidden layer containing 15 neurons of Matlab Neural Networks toolbox is used for its simplicity. The number of hidden neurons is selected heuristically. The learning algorithm is the Levenberg-Marquardt algorithm, which is the fastest method for training moderate sized feed-forward neural network (Demuth and Beale, 2001).

5.4.2 Probabilistic neural networks

Probabilistic neural networks (PNN), is another class of neural networks, implements Bayesian classification scheme. The degree of similarity of each input to training is calculated in the pattern layer which is a radial basis network. Then, the probabilities for each class are calculated and the maximum is selected as the output as shown in Fig.10 where denotes input-output training samples, □j,i and vk represents the weights of pattern layer and category layer, respectively.

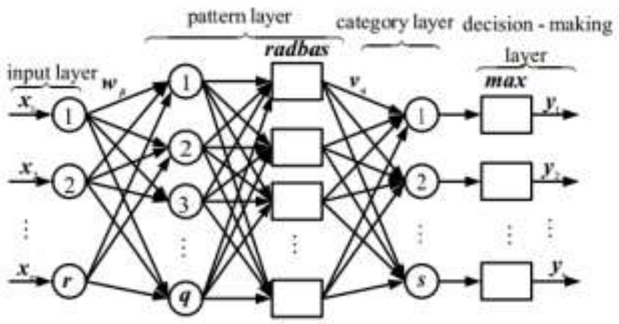


Fig. 10. Block diagram of probabilistic neural network

PNN is faster than ANN in training phase and because of Bayes optimal classification scheme it is more accurate in some classification problems, however it requires more memory space to store the model (Wasserman, 1993). The classification performance is mostly defined by the spread parameter of the radial basis function. In this study, the spread parameter of the network is selected by grid search algorithm to obtain best classification accuracy.

5.4.3 Support vector machines

Support vector machine (SVM) classifiers are binary classifiers which use risk minimization technique. In order to classify the samples which cannot be separated by linear hyperplanes, the feature space is mapped into a higher dimensional feature space by applying transformation function . In this new feature space, an optimal separating hyperplane which maximizes the distance between plane and the nearest data point is searched. Fig.11 illustrates an example of 2-dimensional separable classification problem by denoting the optimal hyperplane and maximum margin. The data points on the margin line are called as support vectors.

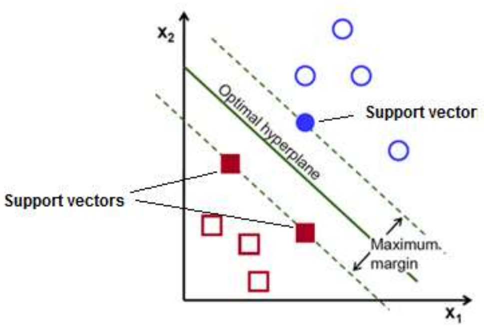


Fig. 11. An example of a separable problem in a 2 dimensional space

For the training set of N input output samples of $(x_j, y_j), j = 1, \dots, N$ and $y \in \{-1,1\}^N$ the classifier calculates the output as

$$g(x) = sign\left[\sum_{j=1}^{N} \alpha_j y_j \emptyset(x_j)^T \emptyset(x) + b\right] \quad (4)$$

where b is the bias of the hyperplane, and the α_j coefficients are the solution of the convex quadratic optimization problem assuming data is classified correctly defined as

$$\max_{\alpha} \sum_{j=1}^{L} \alpha_j - \frac{1}{2}\sum_{j=1}^{L}\sum_{i=1}^{L} y_j y_i \emptyset(x_i)^T \emptyset(x_j)\alpha_i \alpha_j$$
$$st. \sum_{j=1}^{L} \alpha_j y_j = 0 \qquad 0 \le \alpha_j \le C \quad (5)$$

where C is a regularization parameter for controlling the trade off between the margin and misclassification error. The inner product $\emptyset(x_i)^T\emptyset(x_j)$ is not calculated in explicit form but obtained by a kernel function $K(x_i^T, x_j)$ which is known as kernel trick (Cortes and Vapnik,1995). There are several different kernel functions such as radial basis function (RBF), quadratic and polynomial. In this study, all of these kernels are used with the best performing parameter sets found by grid search algorithm. Although, SVM is designed to classify data into two classes, in this study, it is used for a multi-class problem by using one-versus-all approach.

6.0 Results and Disscussion

In this paper, ECG signal from MIT-BIH database were used for training and testing. 40 ECG records were downloaded as .mat files and distributed randomly for classification of normal, paced and rbbb beats. 1602 ECG beats are fed to artificial neural network and approximately 70% is used for training and the remaining is used for validation and testing. The classification performance is considered in terms of sensitivity, specificity, positive predictive value, negative predictive value, accuracy and recognition rate. The used measures are defined as

$$Sensitivity = \frac{TP}{TP + FN} * 100\% \quad (6)$$

$$Specificity = \frac{TN}{TN + FP} * 100\% \quad (7)$$

$$Positive\ Predictive\ Value = \frac{TP}{TP + FP} * 100\% \quad (8)$$

$$Negative\ Predictive\ Value = \frac{TN}{TN + FN} * 100\% \quad (9)$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} * 100\% \quad (10)$$

$$Recognition\ Rate = \frac{TP}{TP + FP + FN + TN} * 100\% \quad (11)$$

where TP is True Positive (correctly identified), FP is False Positive (incorrectly identified), FN is False Negative (incorrectly rejected), TN is True Negative (correctly rejected) (Han et al. 2011).

6.1 Performance Analysis of Equivalent R-T Interval Features

In order to use as a benchmark, 200 samples taken from the R-T interval is fed to ANN without applying any feature extraction step. Several numbers of hidden layers are experimented in terms of recognition rate and the best result has been obtained with 15 hidden neurons.

Table 1 below shows the performance of equivalent R-T interval features extracted after QRS detection using Pan Tompkins algorithm. Although, accuracy is acceptable, the number of inputs makes the network size large.

TABLE I
PERFORMANCE MEASURES FOR R-T INTERVAL SAMPLES

ECG Class Beat	Sens. (%)	Spec. (%)	Pos. Pred. (%)	Neg. Pred. (%)	Accuracy (%)
Normal	100	98.91	97.85	100	99.27
Rbbb	97.01	97.49	94.89	98.55	97.34
Paced	95.07	99.63	99.26	97.47	98.06
Average	**97.36**	**98.68**	**97.33**	**98.67**	**98.22**

6.2 Performance Analysis of Hybrid Features

After decomposing R-T equivalent features using DWT, statistical parameters of the DWT coefficients have been calculated to further reduce the feature dimension to suit our target. While the raw feature vector contains 200 samples for each beat, after processing the size is reduce to only 77 representing features of hybrid technique. There is an improvement in the proposed hybrid system of approximately 1,6% accuracy as shown in Table 2 below. Also, the performance measures sensitivity, specificity, positive predictive value and negative predictive value show the success of the classification.

TABLE II

THE PERFORMANCE OF PROPOSED FEATURE

ECG Class Beat	Sens. (%)	Spec. (%)	Pos. Pred. (%)	Neg. Pred. (%)	Accuracy (%)
Normal	100	100	100	100	100
Rbbb	99.25	100	100	99.64	99.76
Paced	100	99.63	99.30	100	99.76
Average	**99.75**	**99.88**	**99.77**	**99.88**	**99.84**

6.3 Comparison on Wavelet Families

As another experiment, different wavelet families are classified with ANN and compared in terms of recognition accuracy. Fig. 12 gives the results of this comparison. According to the chart, Daubhechies 4 and 10 and Coiflets 5 perform better than the other wavelets.

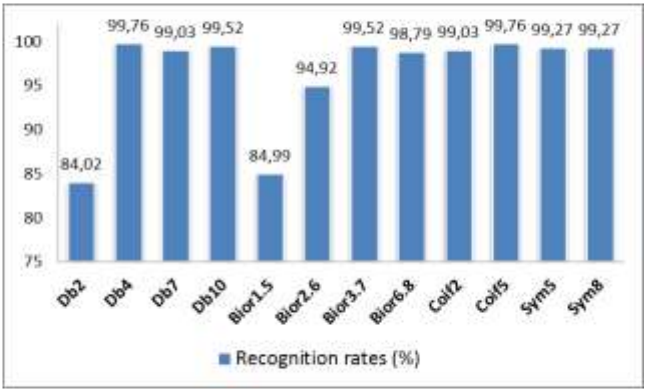


Fig. 12. Comparison of wavelet families

When the shape of the mother wavelet is similar to the analyzed waveform, this wavelet family represents the signal better. The plot of normalized average of the analyzed normal, right bundle branch block and paced beats are given in Fig.13 to compare with Db4 and Coif5 the mother wavelets. The resemblance is quite obvious.

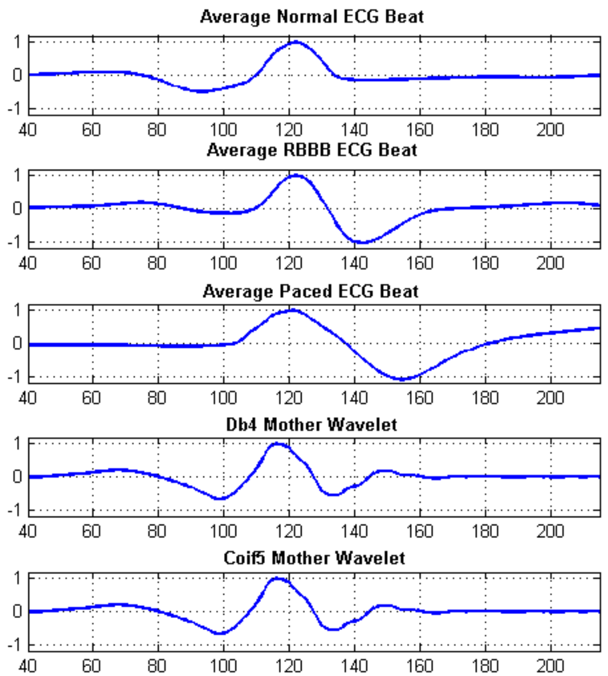


Fig. 13. Normalized average ECG beats and best performing mother wavelets

6.4 Performance Comparison of Classifiers

The discrete wavelet features with Db4 wavelet are also classified with different common classifiers. As an addition to multilayer feed forward artificial neural network with 15 hidden neurons, support vector machine with polynomial kernel of order 3, radial basis kernel, quadratic kernel and probabilistic neural network is used. The best performing parameters for each classifier is obtained by a grid search algorithm. The average sensitivity, specificity and accuracy results are summarized in Fig. 14.

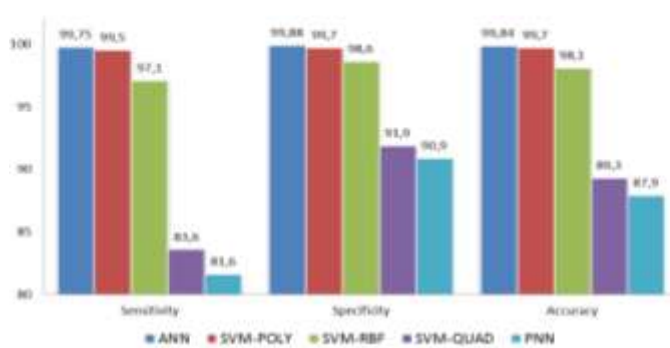


Fig. 14. Comparison of classifiers

For all of the parameters, ANN produces the best results where SVM with polynomial kernel has a performance approaching ANN. This result along with lower performance of quadratic kernel shows that at least third order of nonlinearity in kernel is required to transform the problem into a linearly separable classification task. Although, PNN is a fast algorithm which does not need training, its accuracy is lower than the other classifiers and its sensitivity is unacceptable.

7.0 Conclusion

In this paper, a novel feature extraction technique based on discrete wavelet transform is proposed for the classification of cardiac arrhythmias suitable for ECG portable devices. ECG signals are downloaded from MIT-BIH database and different filters were designed to reduce unwanted signal like baseline wander and power line interference. R peaks are detected using well known and acceptable Pan Tompkins algorithm. R-R intervals features without applying any operation or transform are used as benchmark. DWT was used to decompose R-R intervals and provide a time-frequency representation of the signal. The statistical parameters of DWT coefficients are calculated and used as hybrid feature for training and testing using neural network classifier. Based on the result obtained, RT equivalent feature and DWT with statistical feature gives 98.22% and 99.84% respectively. When different wavelet families are compared in terms of classification performance, Daubhechies 4 and Coiflets 5 performs better than the other wavelets. The more the mother wavelet resembles the ECG waveforms, the beats are represented better.

When the classifiers are compared for the same feature set, it is observed that the artificial neural network classifier and support vector machine with polynomial kernel of order 3 produces best results. Since, the final aim is to propose a classification system suitable for mobile applications; the ANN classifier is preferable due to implementation simplicity.

The design and implementation of a portable ECG recording and arrhythmia detection system which uses the proposed feature extraction algorithms is the concern of the future studies.

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