Classification of ECG Signal by Using Wavelet Transform and SVM

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ABSTRACT

Advances in computing have resulted in many engineering processes being automated. Electrocardiogram (ECG) classification is one such process. The analysis and classification of ECGs can benefit from the wide availability and power of modern computers.

This study presents a method on the usage of computer technology in the field of computerized ECG classification. Computerized electrocardiogram classification can help to reduce healthcare costs by enabling suitably equipped general practitioners to refer to hospital only those people with serious heart problems. Computerized ECG classification can also be very useful in shortening hospital waiting lists and saving life by discovering heart diseases early.

This thesis investigates the automatic classification of ECGs into different disease categories using Discrete Wavelet Transform (DWT) and Support Vector Machine (SVM) techniques. The ECG data is taken from standard MIT-BIH database. The model is developed over 20 records of MIT arrhythmia database signals of which is 30 minutes of recording time. A comparison of the use of different feature sets and SVM classifiers is presented. The feature sets include wavelet features, as well as temporal features which taken directly from time domain samples of an ECG.

Keywords: ECG, Discrete Wavelet Transform, Support Vector Machine, Arrhythmia.

ÖZ

Bilgisayar ve hesaplama alanlarındaki gelişmeler birçok mühendislik sürecinin otomasyonu sonucunu doğurmuştur. Elektrokardiyogram sınıflandınlması bu süreçlerden birisidir. Elektrokardiyogram analizi ve sınıflandırılması için modern bilgisayar ve hesaplama teknolojilerinin geniş anlamda kullanımı önemli yararlar sağlamaktadır.

Bu çalışma Elektrokardiyogram sınıflandırılması için bilgisayar teknolojisi ve tanımlama yöntemlerinin kullanımına yönelik bir içerik sunmaktadır . Bilgisayarlı elektrokardiyogram sınıflandırılması, tanıma süreçlerinin kısalması ve sadece ciddi sağlik problemleri olan hastaların hastahanelere başvurması yoluyla, sağlık harcamalarında ciddi azalmalar sağlayabilir. Ayrıca, hastahanelerde bekleme süreleninin azaltılması ve erken tanı ile hayat kurtarılması da elde edilebilecek diğer önemli kazanımlar olarak sıralanabilir.

Bu tezde otomatik elektrokardiyogram sınıflandırılması için ayrık dalgacık dönüşümü ve destek vektör makinaları yöntemleri üzerinde çalışılmıştır. Elektrokardiyogram sinyalleri MIT/BIH veri tabanından alınmıştır. Model geliştirmek amacıyla her biri 30 dakikalık 20 kayıt kullanılmıştır . Özellik kümeleri dalgacık ve zaman ekseninde çıkarılan özellikleri içerir. Tanıma başarımı için destek vektör makinaları üç farklı özellik kümesi kıllanılarak sınanmıştır.

Anahtar kelimeleri: Elektrokardiyogram, destek vektör makinaları, ritm bozukluğu.

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Finally, I would like express appreciation to my husband, Shahram. He was always there cheering me up and stood by me through the good times and bad.

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INRODUCTION

1.1 Problem description

Recently biomedical signal processing has been a hot topic among researchers. Their most effort is focused on improving the data analysis of automatic systems. Cardiologists by using various values which occurred during the ECG recording can decide whether the heart beat is normal or not. Since observation of these values are not always clear, existence of automatic ECG detection system is required.

It is reported that annually each person has 0.3 ECG recording in European countries. Electrocardiogram provides health information for patients. Cardiologists can detect various heart abnormalities by checking the ECG waveform. Electrocardiogram was created by W. Einthoven in 20th century. Since nowadays heart diseases are a common death reason of people in developed countries, many researchers are working on ECG analysis.

By using some electrode on body surface, they can record the electrical signal which is caused by cumulative heart cells action. The cells do not work simultaneously since they have different potential in a particular moment and electrical currents go through the body organs and distribute around the heart. Since human body consists of many electrical ions it is conductive of electricity so potential difference generates among two locations of the body and electrocardiography device records its changes in time.

Electrical and mechanical heart actions are joining together. So electrocardiography is essential device to estimate the heart’s work and it gives us good information of normal and abnormalities of heart actions. ECG record consists of repeatedly heart beats. Each single heart beat includes many waves and interweaves. The length and appearance will show different heart diseases. The time and potential axis are estimated by milliseconds and millivolts respectively.

As illustrated in Figure 1.1 generated waves distribute among the body and we record ECG motion and its wave component such as P-wave, Q-wave, R-peak and S-wave. P-wave shows depolarization of atria so blood current change its direction from atria to ventricles. P-Q interval shows time of distributing of generated wave from atria to ventricles. QRS complex indicate the depolarization of ventricles so blood is exited from right ventricle to arteriapulmonalis and also from left ventricle to aorta. Repolarization of atria can’t be seen during the recording since the QRS section covers it. Repolarization of ventricles is known as T-wave.

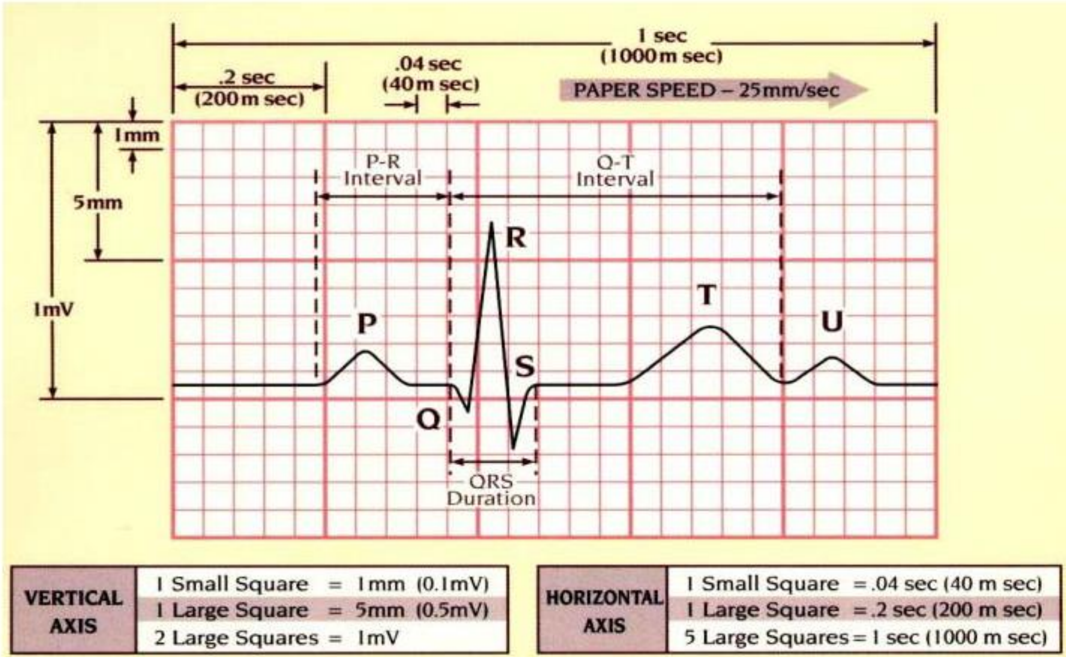


Figure 1.1: An ECG waveform with the standard ECG intervals [28].

The muscles of heart can be affected by Cardiac arrhythmias which is the reason of disorder rhythm. This problem can be an obstacle to pumping the blood. When the blood pumping is not sufficient, it will increase the risk of death.

Common clinical arrhythmia detection is based on an expert human experiment. Since it is critical to assess and monitor a patient heart's situation, various methods for automatic recognition are available recently, but majority of them have heavy computation cost to extract proper features and they can classify just a limited disease types.

Present systems are very sensitive to existence of noise and insufficient robustness is one the weakness of them. So it is obvious that the systems need to improve their classifier ability in order to classify overlapped classes and incomplete or noisy input samples.

1.2 The state of the art

There are various type of digital signal processing (DIP) procedures, varies from simple to complex, which are used for analyzing heart activity and electrocardiography. These methods can be categorized into 3 classes: time-domain approach, frequency-domain approach, and time-frequency domain approach.

Time domain and frequency domain approaches are common methods and have good performance in QRS detection and recognition its onset-offset positions. Recent methods are motivated to use combination of time and frequency domain in time-frequency approach and use the prior methods benefits. These methods use frequency analysis and combine its result with time domain features extracted.

Time-domain method doesn’t have efficient results due to its low sensitiveness. The main reason is amplitude of signal has small change in time domain. In the other hand, frequency domain approaches has more sensitivity to changes of signal amplitude, but they can’t determine the exact location of changes.

Recently, wavelet transform (WT) is commonly approach due to its easy implementation and since it is very similar to one of the famous frequency method, Fourier transform, interpretation of its results can be done in the same way. There are various model of wavelet transform so we can use it in different application. Choosing a specific kinds of wavelet transform is depends on the problem which can be varied from noise removal, detecting time and frequency elements, recognizing the essential peaks and so on.

For ECG classification different methods are introduced by the researchers but still no method is completely successful. The most important part of classification is choosing proper discriminative features from raw ECG signal. Different features types have been used in order to recognize the abnormalities of ECG automatically such as Bayesian [6] and heuristic approaches, template matching, expert systems [7], hidden Markov models [8], artificial neural networks (ANNs) [9], [10], and others [11],[12].

Most common methods are based on pattern recognition approaches. They use different morphological features of ECG [13] like interval length and amplitude of QRS complex, R-R interval, QRS component area, etc [14]. Main disadvantage of these approaches is that they have limited ability when the morphology of ECG signal changed [15].

Despite of these methods have good accuracy, they have some drawbacks too. They are focused on finding some fiducial or landmark points on ECG signal which are sensible to changes of signal morphology that may occur among inter-class variation of different patient samples or even within intra-class variation of the same patient in different time. Therefore a few types of waveforms can completely capture these features.

Some peoples use only the QRS complex features, while others add also morphological features which are extracted from the P-wave and T-wave [13], [16]. The main limitation of this method is its sensitivity to accuracy detects the location of P and T-wave and also QRS complex component. These kind of features are not suitable for analyzing special types of arrhythmias like ventricular fibrillation [15].

Other approaches use Hermite functions [9], cumulate features [17], wavelets [18], [19], correction waveform analysis [20], complexity measures [2], a total least squares-based Prony modeling algorithm [4], autoregressive modeling, non-linear measures and cluster analysis, etc.

There are different approaches which use ANN and their combination with other approaches in order to classify ECG signal such as Fourier transform NNs [21], re-current NNs [22] and back propagation (BP) NNs [23] and etc.

1.3 Classification systems for ECG signal analysis

We can categorize the automatic classification systems of ECG signals into four classes. The first class systems use some kind of decision trees for classify different types of rhythm and morphology. Second class systems use decision trees and statistic multivariate analysis for classification and analysis for assessment of morphology respectively. The third class systems combine benefits of systems of first and second classes and then utilize some expert systems in order to assess pathology and signal defects. The fourth class systems exploit first and third classes with a mathematical model of electrical excitation distribution among heart parts. The first and second classes systems are suitable for commercial use.

1.4 Pattern recognition

Pattern Recognition is the task of classifying objects into predefined categories or classes. Pattern recognition systems can perform pattern identification and classify the objects. They perform it either by using some form of prior information about the object distributions or some statistical knowledge which are embedded in the data. The objects could be assumed as sets of features or a series of experiment results which define the points in features space [24].

Pattern recognition systems consist of several subsystems: First, data acquisition section which is responsible to measure or record the raw intended data. Second, feature extraction section which is responsible to extract distinctive information from the raw data. Third, feature selection section which selects the optimal subset of extracted features. Fourth, classification section which is the main part of the system and by using the features information classifies the input data into predefined classes.

The pattern recognition systems can be divided into supervised and unsupervised group. In the supervised group, the classification performs by using some data which have already classified by an expert. On the other hand, unsupervised learning tries to find the hidden structure in unlabeled data [25].

Various implementation methods such as statistical pattern recognition, syntactic pattern recognition and AI approaches are exist for the supervised and unsupervised model and selecting the appropriate method is depend on the characteristics of the problem's pattern[26].

In statistical pattern recognition approach which is based on statistical modeling of data, we assume that patterns are produced by a stochastic system with some distribution probability. There are different type of methods such as Bayes linear classifier, the k-nearest neighbor and the polynomial classifier. Other important issues in this method are the procedure for selecting discriminative features, number of necessary features, and adjusting the model parameters. All of this setting is done by the classifier designer [26].

Syntactic or structural pattern recognition is an approach in which each pattern can be represented by a set of symbolic features. In this method, instead of dealing with numeric features, more complex multiple relationships between particular features are present. It is possible to use a sort of formal language in order to describe these features and uses some grammar syntax codes for discriminate [26], [27].

Artificial neural network (ANN) is one of the famous examples of artificial intelligence (AI) methods. ANN has been used in analyzing non-linear signal, classification and clustering, and optimization problem. Selecting the type of topology, size of the network and number of neurons are completely problem dependent.

In this thesis we use wavelet transform in order to achieve some discriminate features and combine them with other well known features like temporal and morphological features. We use SVM which is very popular in pattern classification, in order to classify an unknown heart beat signal and recognize its type of arrhythmia.

The rest of this thesis is organized as follow: Chapter 2 introduces a brief summary on the physiology of the heart and electrocardiogram methods. Chapter 3 summarizes mathematical fundamentals of wavelet transform; Chapter 4 describes support vector machines and their mechanism for classifying samples. In Chapter 5, the MIT-BIH database that is used in this thesis introduced. Chapter 6 explains the signal processing approach used to analyze and classify ECG signals and shows the implementation results on several ECG signals. Chapter 7 presents conclusions and future work plans.

Chapter 2

ELECTROCARDIOGRAM AND SIGNAL PROCESSING

Although the main focus of the thesis is on classification of ECG signals, we also need to describe briefly heart and its function. This chapter is written for this purpose- it summarizes basic facts about heart anatomy, its function and the basics of ECG measurement and showing the most common lead system used in electrocardiography. All pictures used in this section are from [28], which provides every picture freely available for any use.

2.1 Anatomy and function of human heart

The heart (Figure. 2.1) is an organ, which pumps oxygenated blood throughout the body to important organs and deoxygenated blood to lungs. It can be understood as two separate pumps - one pump (left) pumps the blood to peripheral organs, and second pump (right) pumps the blood to lungs.

Left and right sides of the heart consist of two chambers - an atrium and a ventricle. For controlling of the blood flow there exist four valves - tricuspid, pulmonary, mitral and aortic. The mitral valve separates left atrium and ventricle and the tricuspid valve separates right atrium and ventricle. Pulmonary valve control the blood flow from heart to lungs and the aortic valve directs blood to the body circulation system.

Walls of the heart are formed by cardiac muscle (myocardium). This muscle is responsible for the mechanical work done by the heart (= pumping the blood). For controlling the pumping process specialized muscle cells that conduct electrical impulses evolved. These impulses are called action potential and they are responsible for forming the ECG waveform on the body surface.

In order to distribute oxygen to whole body human heart never stops. It works in periodic cycles. A cycle works as follows: Deoxygenated blood flows through superior vena cava to the right atrium. When the atrium is contracted, blood is pumped to the right ventricle. From the right ventricle the blood flows through pulmonary artery to the lungs. Lungs remove carbon dioxide from blood cells and replace it with oxygen.

Oxygenated blood returns to the left atrium and after another contraction it is pumped to the left ventricle. Finally the blood is forced out of the heart through aorta to the systemic circulation. The contraction period is called systole, during which the heart fills with blood. The relaxation period is called diastole. From electrical point of view the cycle has two stages - depolarization (activation) and repolarization (recovery).

2.2 The conduction system of the heart

To maintain the cardiac cycle the heart developed a special cell system for generating electrical impulses and by these impulses mechanical contraction of the heart muscle is ensured. This system is called conduction system (Figure. 2.2).

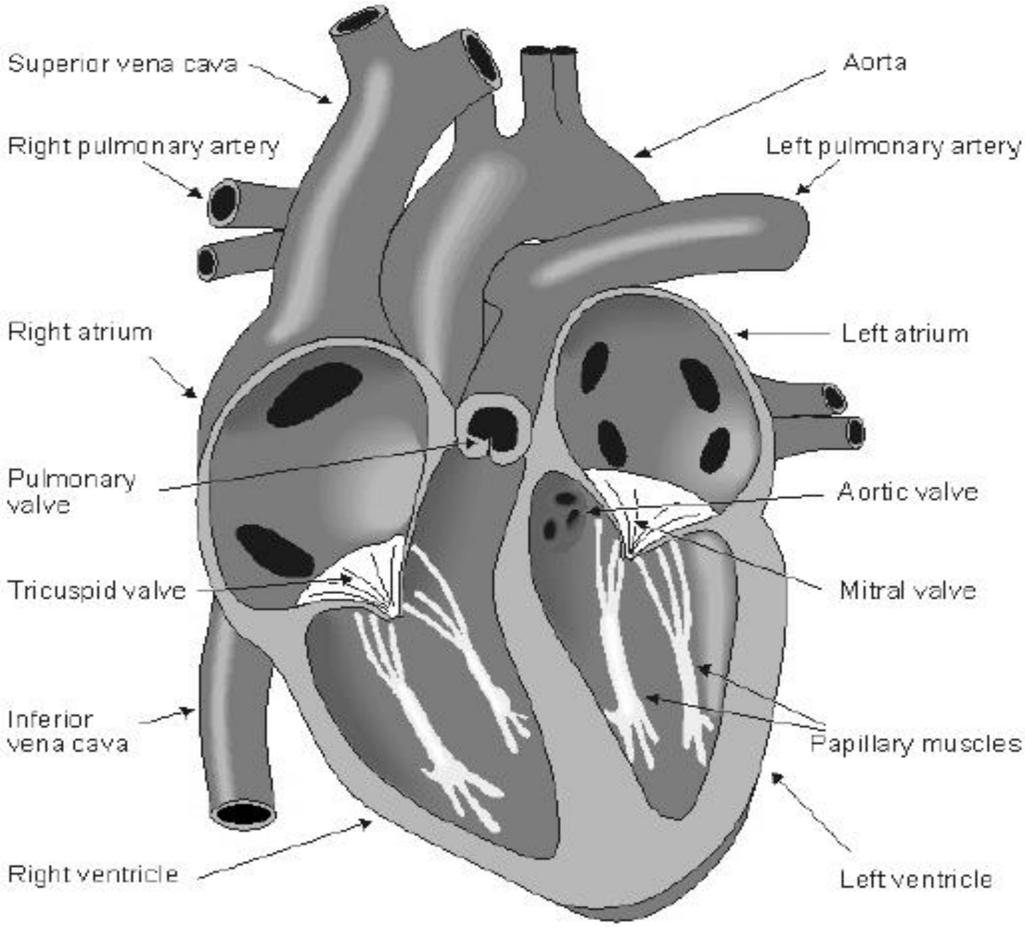


Figure 2.1: Basic heart anatomy schema - there are four chambers, two on the left (right heart) side responsible for pumping the blood to lungs and two on the right (left heart) responsible for pumping the blood to body. Picture used with permission from [28].

It conveys impulses rapidly through the heart. Normal rhythmical impulse, which is responsible for contractions, is generated in the sinoatrial (SA) node. Then propagates to the right and left atrium and to the atrioventricular node (AV). The impulse is delayed in the AV node in order to allow proper contraction of the atria. Thus all blood volume in the atria is forced out to the ventricles before its contraction. Atrium and ventricles are electrically connected by bundle of His. From here, the impulse is conducted to the right and left ventricle. The pathway to the ventricles is divided to the left bundle branch and right bundle branch. Further, the bundles ramify into the Purkinje fibers that diverge to the inner sides of the ventricular walls.

The primary pacemaker of the heart is the sinoatrial node. However, other specialized cells in the heart (AV node, etc.) can also generate impulses but with lower frequency. If the connection from the atria to the atrioventricular node is broken, the AV node is considered as the main pacemaker. If the conduction system fails at the bundle of His, the ventricles will beat at the rate determined by their own region. All cardiac cell types have also different waveform of their action potentials (Figure 2.3).

2.3 Generation and recording of ECG

Human body is a good electrical conductor; hence electrical activity of the heart can be measured using surface electrodes. Electrodes record the projection of resultant vectors, which describe the main direction of electrical impulses in the heart. The overall projection is named as electrocardiogram. Different placement of electrodes provides spatiotemporal variations of the cardiac electrical field. The difference between a pair of electrodes is referred to as a lead. A large amount of possible lead systems has been invented; depending on a diagnostic purpose, a lead system is chosen and electrodes placed on accurate positions. The most commonly used system is standard 12-lead ECG system defined by Einthoven [29]: Three bipolar limb leads (I, II, III) - electrodes are placed to the triangle (left arm, right arm and left leg) with heart in the center (Fig. 2.4). This placement is called the Einthoven’s triangle.

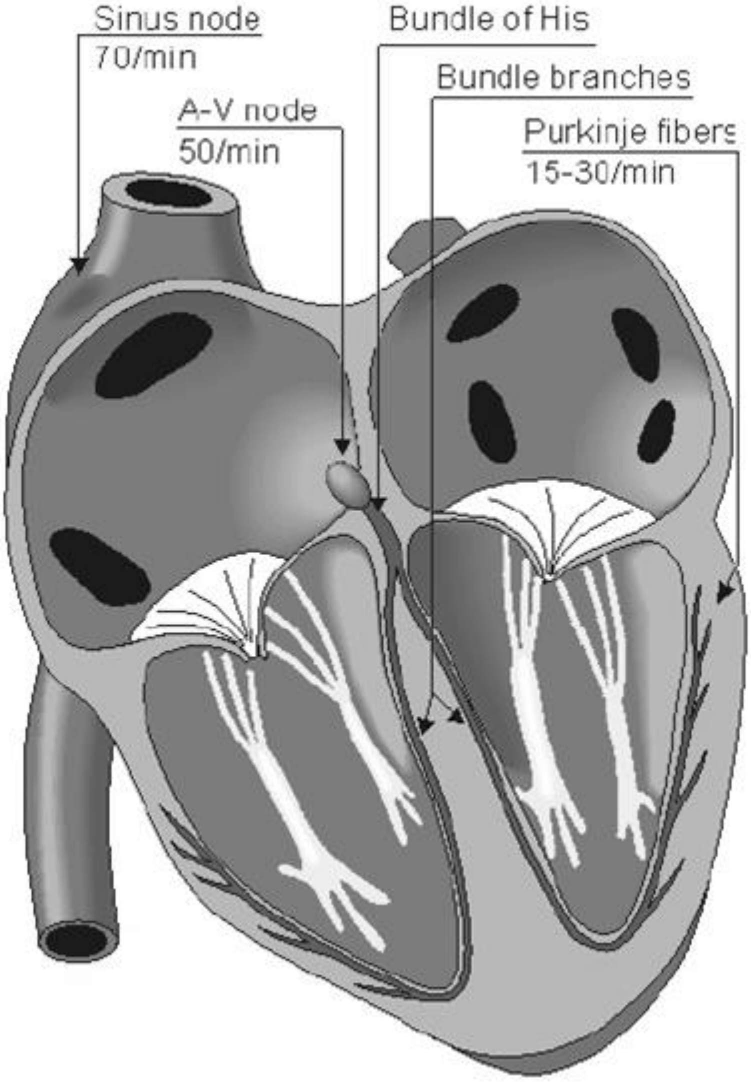


Figure 2.2: Conduction system of the heart consists of Sinus node, Atrioventricular node, Bundle of His, bundle branches and Purkinje fibers[28].

The augmented unipolar limb leads (aVF, aVL, aVF) - electrodes are placed on same positions as in case of leads I, II and III. The difference is in the definition of leads. Leads are calculated as the difference between potential of one edge of the triangle and the average of remaining two electrodes (Fig. 2.5).

Unipolar precordial leads (V1-6) - leads are defined as the difference between potential of electrode on chest and central Wilson terminal (constant during cardiac cycle and is computed as average of limb leads). For details see Fig. 2.6.

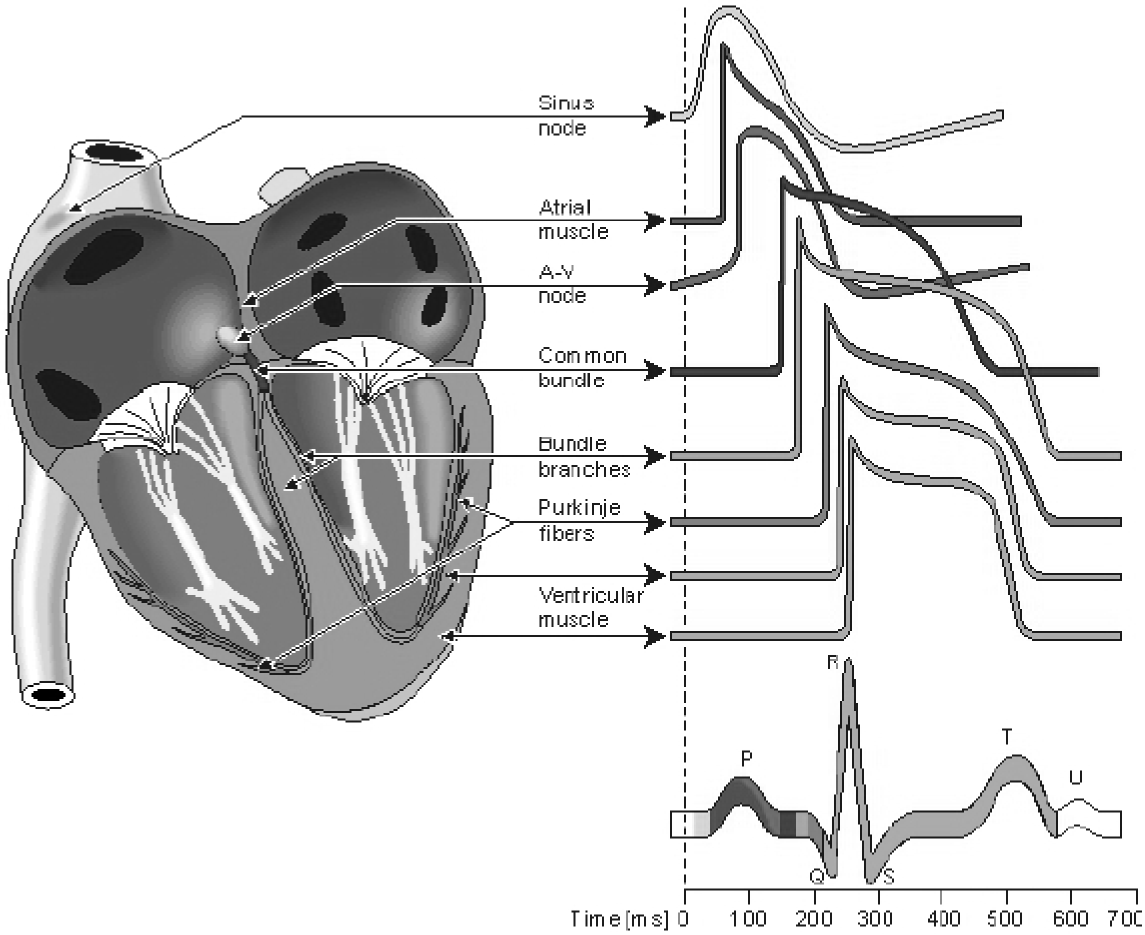


Figure 2.3: Schematic representation of ECG waveform generation by summing of different action potentials. Picture used with permission from [28].

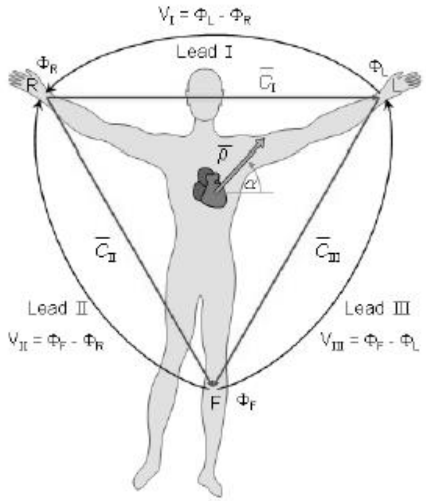


Figure 2.4: Schematic representation of Einthoven triangle electrode placement. Picture used with permission from [28].

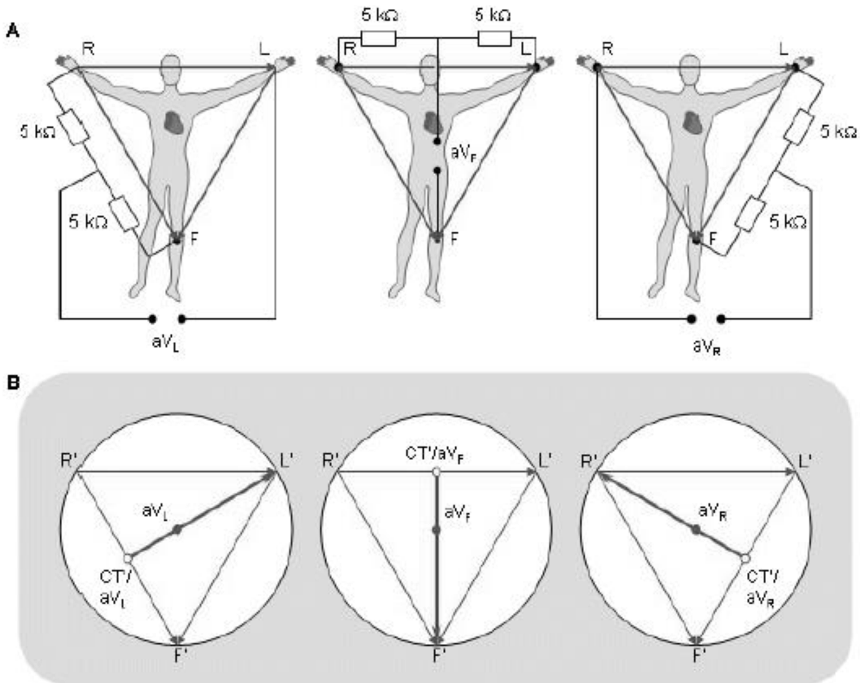


Figure 2.5: Schematic representation of augmented limb leads calculation. Picture used with permission from [28].

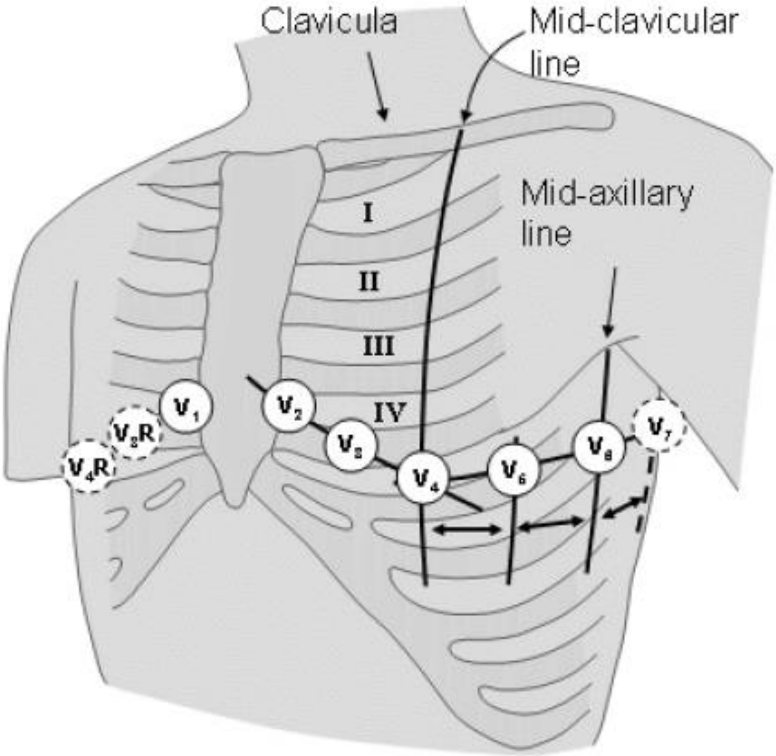


Figure 2.6: Precordial leads electrodes positions [28].

2.3.1 ECG wave form description

As we mentioned earlier ECG, wave is formed as a projection of summarized potential vectors of the heart. ECG wave has several peaks and "formations", which is useful for its diagnosis (Figure 2.7). These are:

- P-wave - indicates the depolarized wave that distributes from the SA node to the atria, and its duration is between 80 to 100 milliseconds.
- P-R interval - indicates the amount of time that the electrical impulse passing from the sinus node to the AV node and entering the ventricles and is between 120 to 200 milliseconds.
- P-R segment - Corresponds to the time between the ends of atrial depolarization to the onset of ventricular depolarization. Last about 100ms.

- QRS complex - Represents ventricular depolarization. The duration of the QRS complex is normally 0.06 to 0.1 seconds.
- Q-wave - Represents the normal left-to-right depolarization of the inter ventricular septum.
- R-wave - Represents early depolarization of the ventricles.
- S-wave - Represents late depolarization of the ventricles.
- S-T segment – it appears after QRS and indicates that the entire ventricle is depolarized.
- Q-T interval - indicates the total time that need for both repolarization and ventricular depolarization to happen, so it is an estimation for the average ventricular action duration. This time can vary from 0.2 to 0.4 seconds corresponding to heart rate.
- T-wave - indicates ventricular repolarization and its time is larger than depolarization.

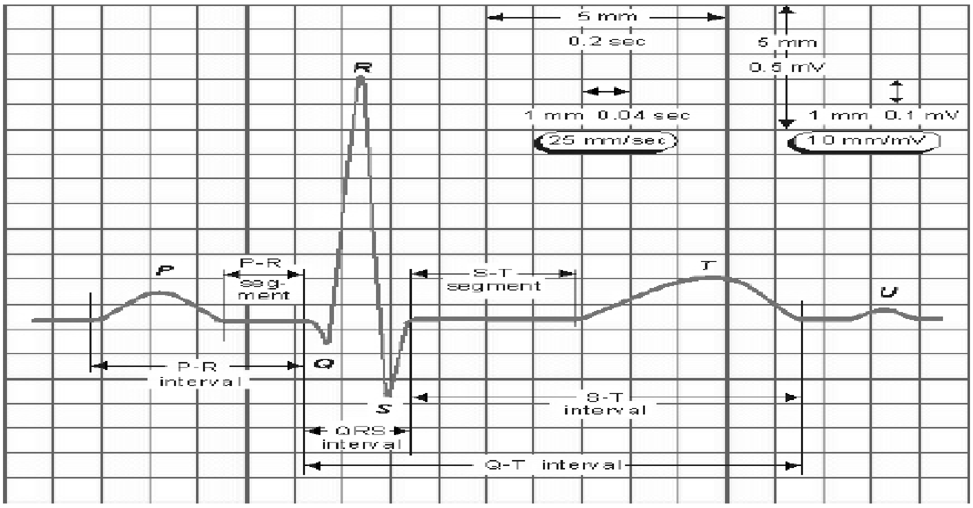


Figure 2.7: Normal ECG waveform. Picture used with permission from [28].

Chapter 3

MATHEMATICAL METHODS

3.1 Introduction

Fundamental of Wavelet transform (WT) is on the using of a series of computational analyzing elements called "wavelets". By applying the WT to a specific signal, its features store in the wavelet coefficients. Each resulting wavelet coefficient corresponds to measurement in the signal in a given time instant and a given frequency band.

3.2 Wavelets

The wavelet transform is a remarkable mathematical method with the ability to examine the signal concurrently in time and frequency, in a different way from previous mathematical methods. Wavelet analysis has been used in a wide range of applications: from climate analysis, to signal compression and medical signal analysis. The different application of WT emerged and increased in the early years of the 1990s, directly reflecting the interest of the scientific community [30].

Some of the most frequently used wavelets are depicted in Figure 3.1. We can notice that they have the shape of a small wave, localized on the time axis. Depending both on the signal we need to analyze and what characteristic we are analyzing, one wavelet can be better suited than others.

The wavelet function $\psi(t)$ has to satisfy some constrain, such as

1. Limited finite energy:

$$E = \int_{-\infty}^{\infty} |\psi(t)|^{2} \, dt < \infty \tag{3.1}$$

2. It must have no zero frequency components ($\hat{\psi}(t)(0) = 0$), or in other words, if $\hat{\psi}$is the Fourier transform of $\psi(t)$:

$$\hat{\psi}(\mathrm{f}) = \int_{-\infty}^{\infty} \psi(t) \, e^{-i(2\pi f t)} dt = \infty \tag{3.2}$$

3. It must hold the following constraint:

$$C_g = \int_{0}^{\infty} \frac{|\hat{\psi}\,(f)|^2}{f} df < \infty \tag{3.3}$$

3.2.1 Wavelet transform

Wavelet transform analysis uses 'local' wavelike functions to transform the signal under investigation into a representation which is more useful for the analysis of the desired feature (the features may range from corner detection to frequency analysis, depending on the wavelet and the transform itself). This transform is a convolution of the wavelet function with the signal.

The wavelet can be manipulated in two ways: it can change its location or its scale (Figure 3.2). If, at a point, the wavelet matches the shape of the signal, then the convolution has a high value. Similarly, if the wavelet and the signal do not correlate well, the transform results in a low value. The wavelet transform is computed at various locations of the signal and for various scales of the wavelet: this is done in a continuous way for the continuous wavelet transform (CWT) or in discrete steps for the discrete wavelet transforms (DWT).

The operations over the wavelet are defined by the parameters a (for dilation) and b (for translation). The shifted and dilated versions of the wavelet are denoted $\psi[[t - b]/a]$. For sake of simplicity, let us take the Mexican hat wavelet:

$$\psi(t) = (1 - t^2)e^{-t^2/2} \quad (3.4)$$

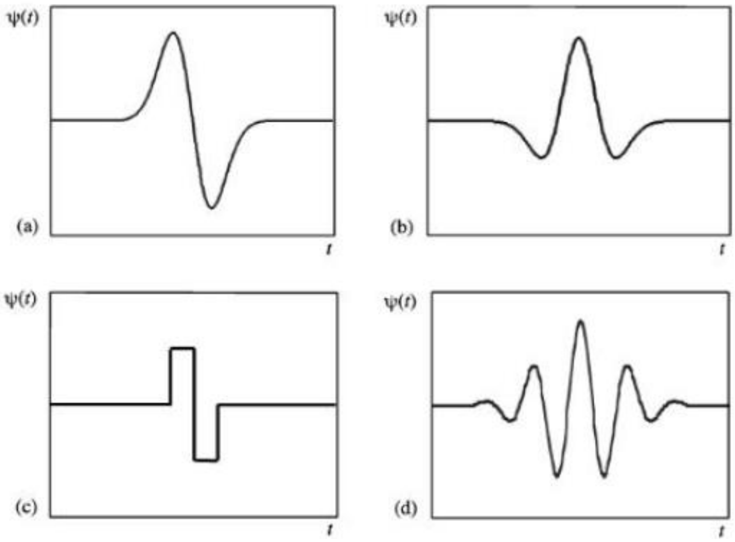


Figure 3.1: Example of wavelets: a)Gaussian wave (first derivative of a Gaussian). b) Mexican hat (second derivative of a Gaussian). c) Real part of Morlet [30].

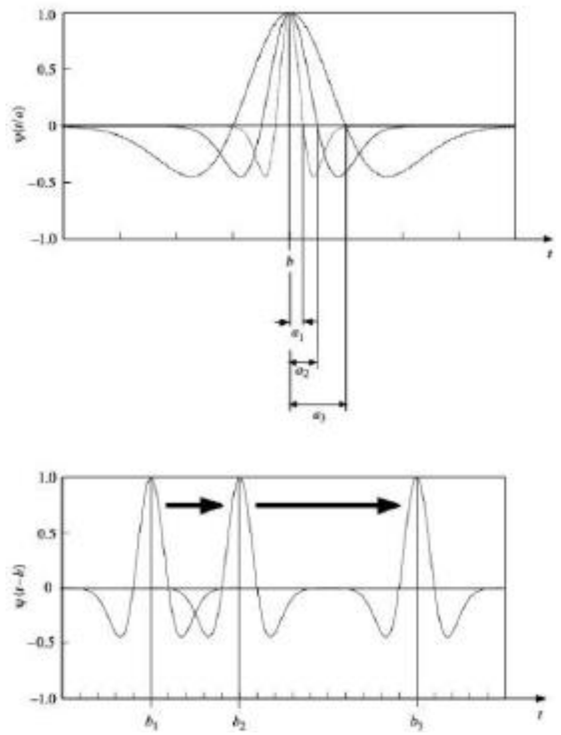


Figure 3.2: Two possible manipulations with wavelets: a) Translation (or location) and b) Scale (adapted from [30]).

The shifted and dilated equation for this version of the wavelet would be:

$$\psi\left(\frac{t-b}{a}\right) = [1-\left(\frac{t-b}{a}\right)^2]e^{-\frac{1}{2}[(t-b)/a^2]} \qquad (3.5)$$

The wavelet transform of a continuous signal with respect with the wavelet is a convolution given by:

$$T(a,b) = \omega(\mathrm{a})\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)\, dt \qquad (3.6)$$

Where ω(a) is a weighting function. Typically, for energy conservation purposes, ω(a) is set to $1/\sqrt{a}$ because it ensures that the wavelet would have the same energy on all scales.

3.3 The discrete wavelet transform

To be of any practical use in a digital computer, we need to use the discrete version of the wavelet transform, namely, the discrete wavelet transform. First we need to consider the discrete values of a and b over the wavelet, as the new discredited wavelet has the form:

$$\psi_{m,n} = \frac{1}{\sqrt{a_0^m}}\psi(\frac{t-nb_0a_0^m}{a_0^m}) \quad (3.7)$$

where m and n are integers and the wavelet translation b_0 (must be greater than zero) and the dilatation step a_0 (must be fixed, greater than 1). Therefore, the discrete wavelet transform of a continuous signal using the discrete wavelet transform would be:

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\frac{1}{a_0^{m/2}}\psi(a_0^{-m}t - nb_0)dt \quad (3.8)$$

Here, the $T_{m,n}$is the discrete wavelet transform given on a m dilation and n scale. These values are wavelet or detail coefficients. The discrete sampling of the time and scale parameters of a continuous wavelet transform (as above), is known as wavelet frame. The Energy of the wavelet functions that composes a frame lies in the bounded range:

$$AE \leq \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty}\left|T_{m,n}\right|^2 \leq BE \quad (3.9)$$

Where A and B are the frame intervals (where the wavelet is defined and nonzero), E is the original signal energy . The values of A and B depends on the values of a0 and b0 used on the selected wavelet. When A = B the wavelet family defined by the frame forms an orthonormal basis. The signal can be reconstructed by the following formula:

$$x'(t) = \frac{2}{A+B}\sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} T_{m,n}\,\psi_{m,n}(t) \quad (3.10)$$

When the wavelet family chosen is both an orthonormal basis and a dyadic grid arrangement (i.e.: the wavelet parameters a_0 = 2 and b_0= 1), they are both orthogonal to each other and have unit energy, i.e., the product of each wavelet with all the others is zero. This means that this wavelet transform has no redundancy and allows the reconstruct the original signal.

3.3.1 The multiresolution representation

Let the piecewise smooth function $\varphi_{0,0}(t)$, also known as scaling function (or father wavelet), be an orthonormal base on our dyadic system, so that our wavelet can be defined [31] by:

$$\psi(t) \coloneqq \frac{d^M}{dt^M}(t) \tag{3.11}$$

As our mother wavelet ω is a differentiated version of the ∅ function, It also has higher frequency elements, if compared with the soothed ∅wavelet, as we can see in the Figure 3.3.

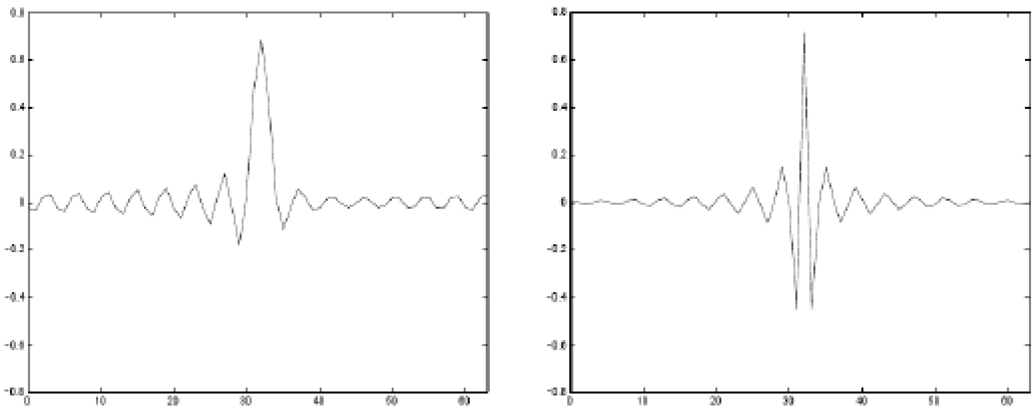


Figure 3.3: Shannon father wavelet (left) and Shannon mother wavelet (right). Notice that the father wavelet has components with lower frequency than the mother wavelet. (adapted from [31]).

The set of scaling functions is defined in the same way as we did for the wavelet:

$$\phi_{m,n} = 2^{-m/2}\phi(2^{-m}t - n) \tag{3.12}$$

With the following property:

$$\int_{-\infty}^{\infty} \phi_{0,0}(t)dt = 1 \tag{3.13}$$

If the father wavelet is convolved with the signal (equation 3.14) then the approximation $S_{m.n}$ are produced.

$$S_{m,n} = \int_{-\infty}^{\infty} x(t)\phi_{m.n}(t)dt \tag{3.14}$$

An approximation of the original signal at a given scale m can be achieved by summing a sequence of fundamental wavelets at that scale, scaled by the approximation coefficients:

$$x_m(t) = \sum_{n=-\infty}^{\infty} S_{m,n}\phi_{m,n}(t) \tag{3.15}$$

Figure 3.4 shows a sine wave and several approximations using the decomposition (3.14) and approximation (3.15) equations. The scale used was set to a various value of widths 2^0 to2^7. The widths are showed by the horizontal lines in each figure. Note that these approximations are applied on the original signal (the sine wave) with different levels (m values)[31].

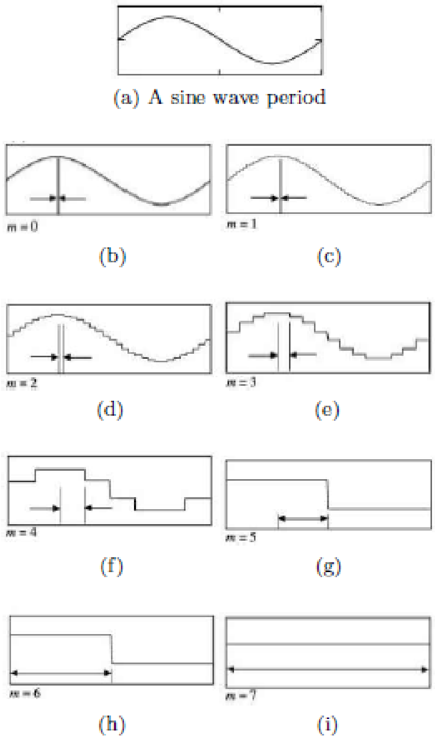


Figure 3.4: a) original signal (sine wave), b) Sine wave on scale 0 (the horizontal arrow is the width of the approximation level, 2m), from c) to i) approximation levels from 1 to 7 respectively.(adapted from [30]).

One should notice that, since the frequency of father wavelet is lower than the frequencies of the mother wavelet, the convolution of the father wavelet and a signal results as a low pass filter, and the convolution of the mother wavelet and a signal results as a high pass filter. Their frequency ranges are showed in Figure 3.5.

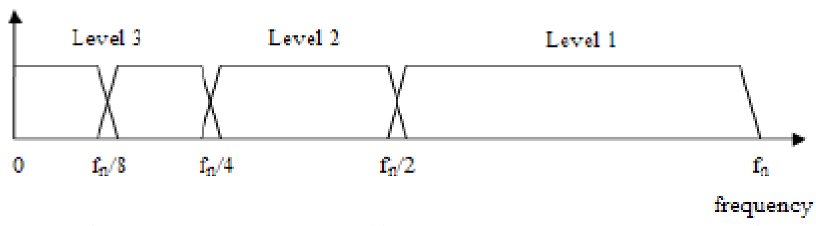


Figure 3.5: The frequency range on different levels (m values).T he frequency cut-offs overlap due to the fact the filters that form the wavelet transform are not ideal filters [30]

A signal can be completely represented as a combined series expansion using the approximation and the detail coefficients:

$$x(t) = \sum_{n=-\infty}^{\infty} S_{m0,n}\phi_{m0,n}(t) + \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} T_{m,n}\psi_{m,n}(t) \tag{3.16}$$

We can see from the above formula that the signal is decomposed into an approximation and detail of itself at an arbitrary scale (m_0). The contracted and shifted version of the father wavelet is as follows:

$$\phi(t) = \sum_k c_k\phi(2t-k) \tag{3.17}$$

Here, c_k is the scaling coefficient and k is the shift. Looking closely to this equation we can realize that one scaling function can be built up from previous scaling functions. Also, this function needs to be orthogonal (as it happens with the mother wavelet). The coefficients for the wavelet function are as follows:

$$\psi(t) = \sum_{k=0}^{N_k-1} b_k\phi(2t-k) \tag{3.18}$$

From equations 3.12 and 3.17, at a given m+1 index, the next father wavelet becomes:

$$\emptyset_{m+1,n}(t) = \frac{1}{\sqrt{2}}\sum c_k\emptyset_{m,2n+k}(t) \tag{3.19}$$

Similarly, the next mother wavelet:

$$\psi_{m+1,n}(t) = \frac{1}{\sqrt{2}}\sum b_k\emptyset_{m,2n+k}(t) \tag{3.20}$$

Substituting equation 3.19 into equation 3.14 for the new indexes of the father wavelets yields the recursive form:

$$S_{m+1,n} = \frac{1}{\sqrt{2}}\sum c_k\left[\int_{-\infty}^{\infty}\emptyset_{m,2n+k}(t)dt\right] = \frac{1}{\sqrt{2}}\sum_k c_{k-2n}S_{m,k} \tag{3.21}$$

$$T_{m+1,n} = \frac{1}{\sqrt{2}}\sum b_k\left[\int_{-\infty}^{\infty}\emptyset_{m,2n+k}(t)dt\right] = \frac{1}{\sqrt{2}}\sum_k b_{k-2n}S_{m,k} \tag{3.22}$$

Here we can see that every coefficient on the detail (3.21) and on the approximation (3.22), are recursive until m0, which is the signal itself. The above equations represent the multi resolution decomposition algorithm. By iterating those two equations, we are performing a low-pass filtering (3.22) and a high-pass filtering (3.21).

To summarize, consider the input signal $S_{0,n}$. Compute $S_{m,n}$ and $T_{m,n}$ using the decomposition equations (3.22) and (3.21). The first iteration would give us $S_{1,n}$and $T_{1,n}$. Now we apply to the same approximation $S_{1,n}$ to the equations again to get the next coefficients $S_{2,n}$ and $T_{2,n}$ and so on until only one approximation is computed (On each level, the amount of samples on the signal decreases by half. This means we have a lower maximum frequency). Now we have an array with the detail coefficients on different resolutions and one approximation, on the last level. This process is depicted in Figure 3.6.

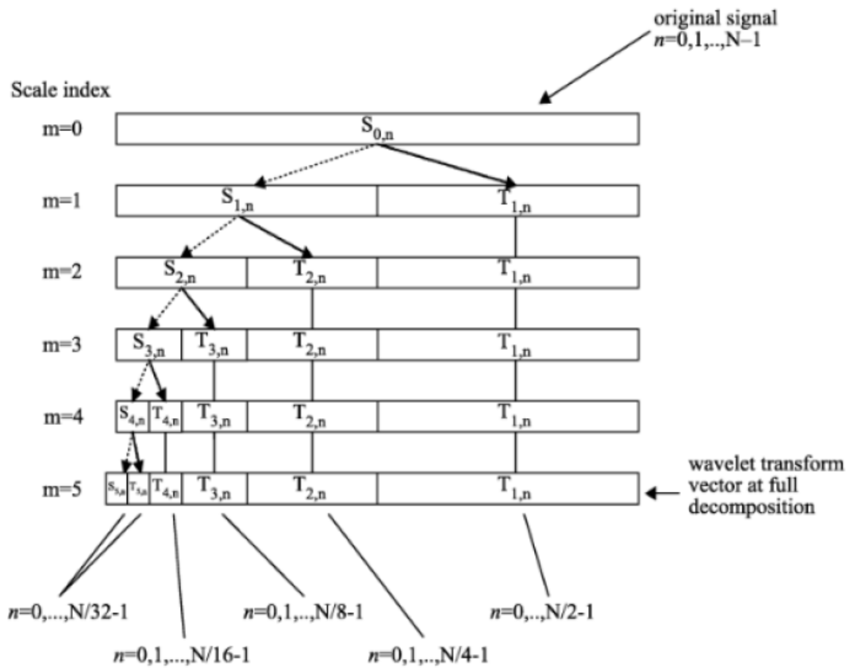


Figure 3.6: The wavelet decomposition using a filter bank: each filter receives the input from the previous levels approximation coefficients (adapted from [30]).

Chapter 4

SUPPORT VECTOR MACHINE (SVM)

4.1 Introduction

In simple terms, Machine Learning is designing an algorithm which lets the program to learn from some data or experience in order to perform special tasks like classification. Recently various methods and algorithms were introduced for this purpose [32].

Support Vector Machine (SVM) developed by Boser, Guyon, and Vapnik in 1992. SVM is a supervised learning algorithm which can be used for different applications, from pattern classification to regression analysis [32]. In other words, SVM is a tool which uses a training dataset in order to create maximum prediction accuracy classifier while it avoids over-fitting to training data. The first application which made SVM to be popular was a task for classification of handwriting. The SVM results are comparable to large NNs with complicated features [33]. Nowadays SVM is used in various areas like face recognition, text classification, signal classification and etc [34].

4.2 Learning and generalization

One of the machine learning algorithms is to learn the behaviors of the target functions. In the other words machine learning algorithms aim to generate a hypothesis that correctly classify the training data without over fitting to the data;

however in the early algorithms they didn't pay attention to this important point [35]. Generalization is defined as the ability of a classifier to correctly classify an unseen data [36].

4.2.1 Why SVM?

Neural networks (NNs) show a good performance in both unsupervised and supervised classification task. One of the famous architecture for such learning task is Multilayer Perceptron (MLP) which can be used for general function approximation. In MLP we can design multiple inputs and outputs neuron. The learning process and finding the proper weight connection can be done with input-output patterns [37].

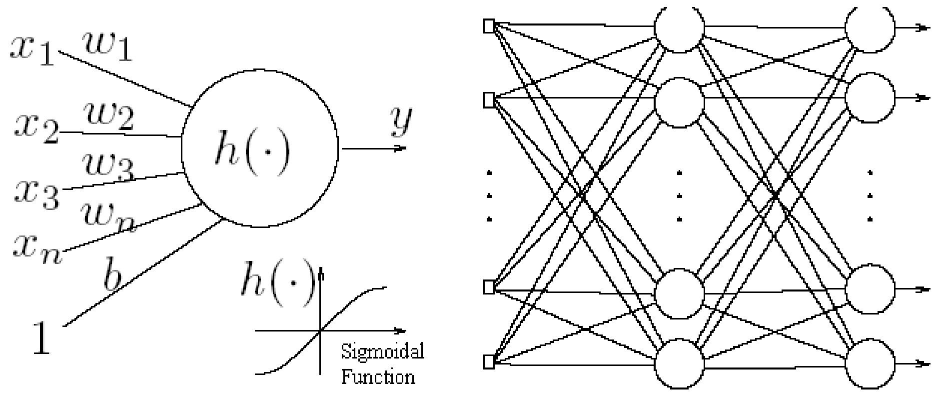


Figure 4.1: Left) Simple neural network Right)multilayer perceptron. [38].

But NNs have some drawbacks: they may convergence to local minima. Another disadvantage of NNs is that there are many tuning parameters such as number of neurons, learning rate and etc which is need to correctly selected for a specific task. In order to understand the necessity of SVM, in Figure 4.2 we plot some sample data and try to find a linear classifier for them. As we can see from the figure there are multiple lines which can correctly classify the data, but which one is the best?

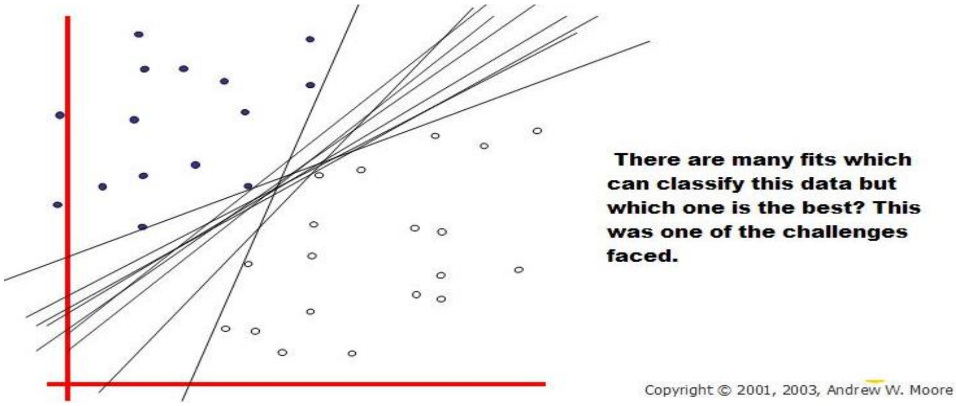


Figure 4.2: Multiple possible linear classifiers for a certain data set [33].

According to prior explanation, different linear classifier can be found to classify these data although some of them have better separation.

It is important to have maximum margin separator since if we select a hyper plane for classification, it is probable to be too much close to some of the samples in respect to the others. Then when an unseen test data entered to the system it is more likely to classify correctly. Figure 4.3 shows an example of maximum margin classifier and how it solves this problem [39].

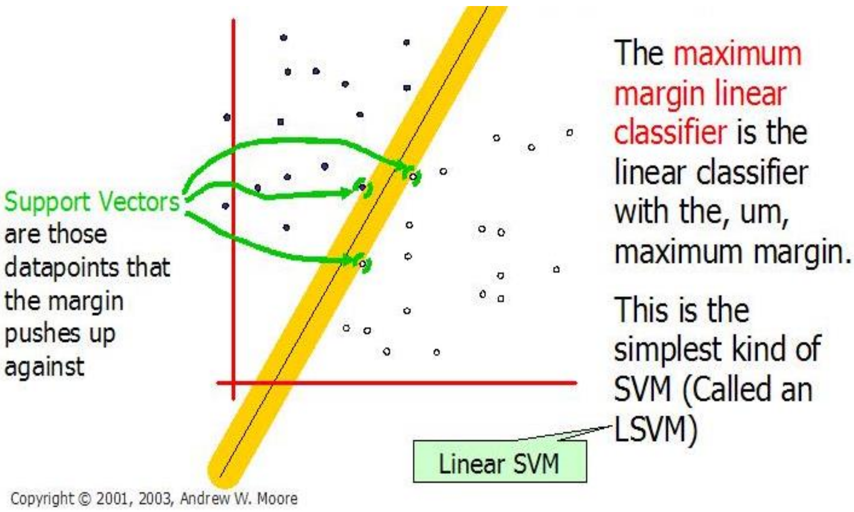


Figure 4.3: Example of Linear SVM.[33].

The equation for obtaining Maximum margins is [35][39]:

$$margin \equiv argmin_{x \in D} d(\boldsymbol{x}) = argmin_{x \in D} \frac{|\mathbf{x}.\mathbf{w}+\mathrm{b}|}{\sqrt{\sum_{i=1}^{d} w_i^2}} \tag{4.1}$$

In the previous example maximum distance is achieved by linear classifier. But why we need to maximize the margin? One of the reason is that the maximum margin classifier provide better result than the other classifiers since if a little error occurred in estimating the location and direction of classifier hyperplane, we still have chance to classify test data accurately. Another benefit of maximum margin is to avoid local minima.

The aim of SVM is finding a decision boundary so that completely separate the training data. If it is not possible to do it by a linear hyperplane then SVM map the training data into a higher dimensional feature space by using some predefined kernel functions [39]. This fundamental can be write as the following formulas:

$$\text{If } Y_i = +1 \text{ or } \mathbf{x_i} \text{ belongs to class 1 then } \mathbf{w}.\mathbf{x_i} + b \geq 1 \tag{4.2}$$

$$\text{If } Y_i = -1 \text{ or } \mathbf{x_i} \text{ belongs to class 2 then } \mathbf{w}.\mathbf{x_i} + b \leq -1 \tag{4.3}$$

We can combine these equations in the following one:

$$\forall \mathbf{x_i} : Y_{i*} (\mathbf{w}.\mathbf{x_i} + b) \geq 1 \tag{4.4}$$

In these equations $\mathbf{x_i}$ is a pattern vector and $\mathbf{w}$ is learned weight vectors. There may be multiple hyperplane in feature space that satisfy this constraint, support vector machine chooses the hyper plane where its distances to the closest sample of each classes are as far as possible.

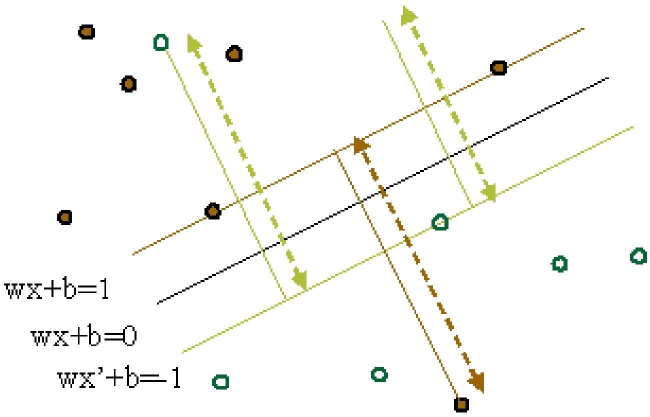


Figure 4.4: SVM hyper planes. [40]

4.5 Kernel trick

If the classes can be separated linearly, the data can be discriminate by a linear decision boundary. But in practical situation, classes cannot separate linearly and the decision boundary is a curve of higher degree than 1. For solving this problem we can uses kernels which are functions that map the input data feature vector to a higher dimensional space. The mapped data in new space can be separate linearly [32]. As an example we can define a simple mapping kernel as shown in Figure 4.5 [40]. The Kernel formula is:

$$K(x, y) = \phi(x).\phi(y) \tag{4.5}$$

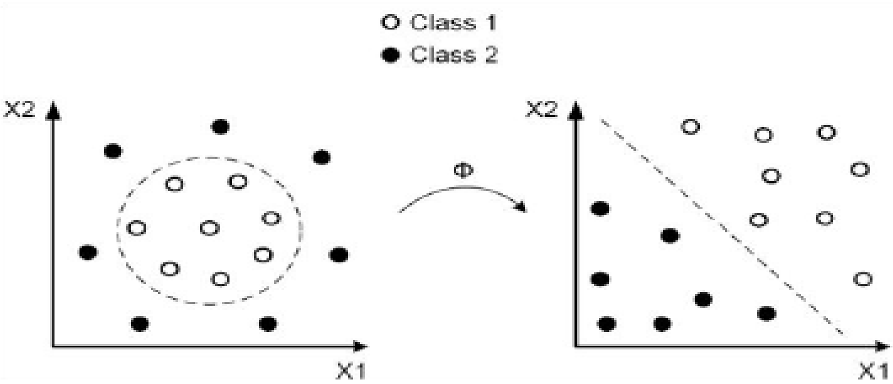


Figure 4.5: Kernels approach [40]

4.5.1 Expanding feature Space

Increasing the dimension of feature space give us a higher chance to classify the data which is not linearly separable. We show it in Figure 4.6 [32].

$$\langle x_1 . x_2 \rangle \leftarrow K(x_1, x_2) = \langle \phi(x_1) . \phi(x_2) \rangle \tag{4.6}$$

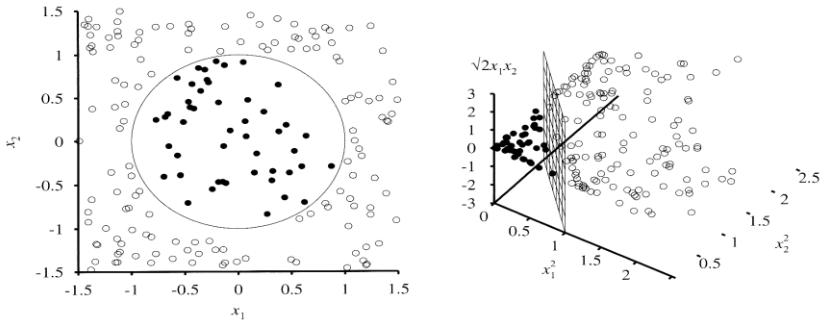


Figure 4.6: Changing the feature space dimensions from 2 into 3 [40].

4.5.2 Popular kernel functions

1) Polynomial:

$$k(x, x') = \langle x, x' \rangle^d \tag{4.7}$$

$$k(x, x') = (\langle x, x' \rangle + 1)^d \tag{4.8}$$

2) Gaussian Radial Basis Function:

$$K(x, x') = exp\left(-\frac{||x - x'||^2}{2\sigma^2}\right) \tag{4.9}$$

3) Exponential Radial Basis Function:

$$K(x, x') = exp\left(-\frac{||x-x'||}{2\sigma^2}\right) \tag{4.10}$$

Chapter 5

MIT-BIH ARRHYTHMIA DATABASE

The Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) arrhythmia database [44] is a well-established source of ECG data for researchers studying ECG classification techniques. It contains digitized ECG signals, which have been transferred from Holter tape recordings taken from various in-patients at the Arrhythmia hospital laboratory at the Beth Israel Hospital between 1975 and 1979. From 4000 Holter tape records, 48 annotated records divided into two groups were kept. Group one consists of 23 records (the lxx series) and contains examples that an arrhythmia detector might encounter in routine clinical use.

The second group consists of 25 records (the 2xx series) and contains examples of complex arrhythmias that could pose difficulties to arrhythmia detectors or of rare clinical cases. The subjects were 25 men aged 32 to 89 years, and 22 women aged 22to 89 years. About 60% of the records were obtained from in-patients. Each record is slightly over 30 minutes in length. The signals were sampled at the same frequency, 360 Hertz, but not necessarily at the same gain because during collection different equipment was used with different electrical gains for digitization of the various records. Moreover, the digital amplitude values range between [0, 2047], where 1024represents 0 volts. Therefore, the signals require normalization before use.

The variety of the patients and variation in their ages and physical conditions makes the MIT-BIH database suitable for investigations into ECG classification techniques. Lead II was the lead type used to record most of the ECG signals in the MIT-BIH database.

The MIT-BIH Arrhythmia database contains software to enable extraction of the digitized records. For the purpose of this study the following ECG types were selected from the MIT-BIH database:

1- Normal Sinus Rhythm (N): this is the term for the normal condition (Figure 5.1).

2- Left Bundle Branch Block Beat (L): this arrhythmia is caused by a problem in conduction in the His bundle in the left side ventricle. This is seen as a widening of the QRS complex. This ECG type is invariably an indication of heart disease [45]. Figure 5.2 indicates that the QRS complex is notably wider than that shown in Figure 5.1. This is due to the extra time taken for depolarization caused by poor electrical conduction (block).

3- Right Bundle Branch Block Beat (R): the cause of this arrhythmia is similar to **(L).** However, the conduction problem now occurs on the right side of the His bundle branch and the ECG indicates a problem in the heart but also can be seen in a healthy heart. This type of arrhythmia is identified by a wide bimodal QRS complex (see Figure 5.3).

4- Paced Beat (P): this problem arises in patients that have been fitted with an artificial pacemaker. Pacemakers are used when a person has bradycardia (a very slow heart rhythm), which causes poor circulation and cannot be corrected by treatment with drugs. Pacemakers stimulate the heart muscle. This type of arrhythmia is indicated by the occasional missing of the P-wave and the presence of a spike representing the stimulus from the pacemaker, followed by a wide QRS complex (see Figure 5.4).

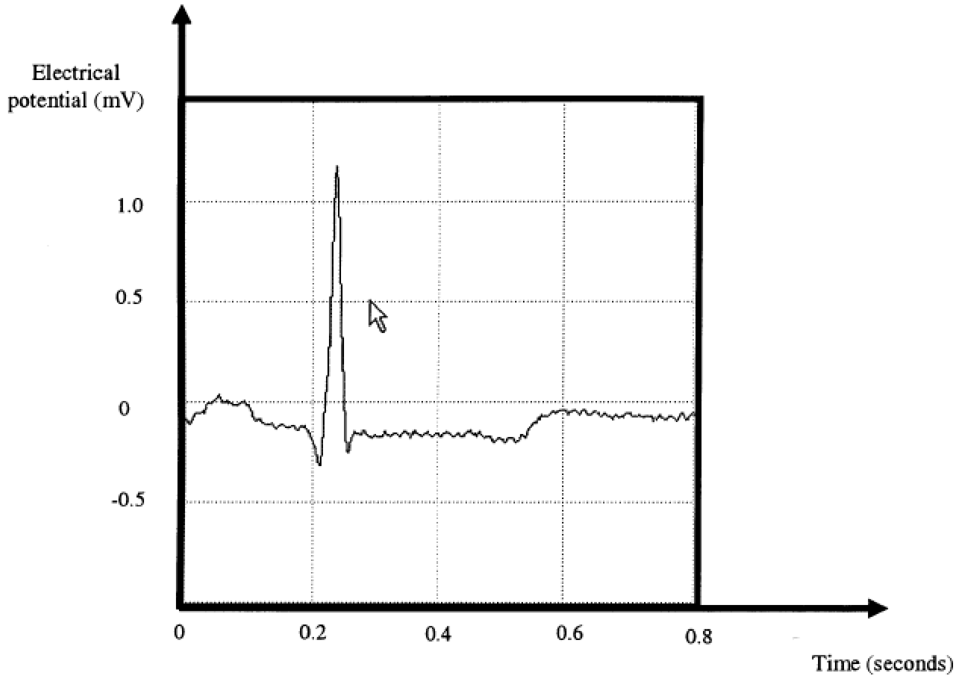


Figure 5.1: Normal sinus rhythm (N) type (MIT-BIH database, record 100)

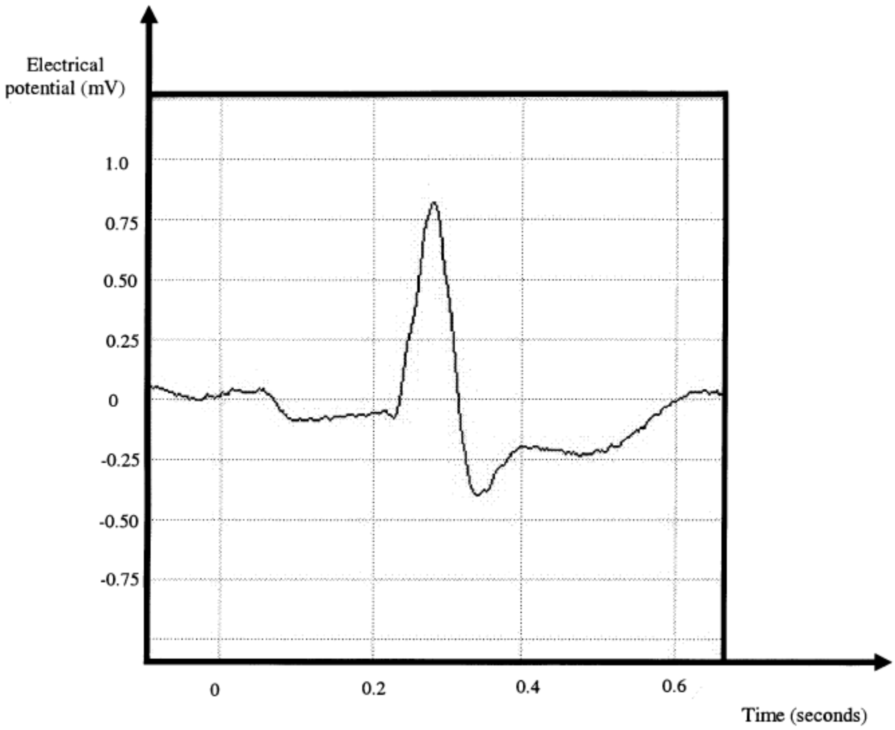


Figure 5.2: Left bundle branch block (L) type (MIT-BIH database, record 109)

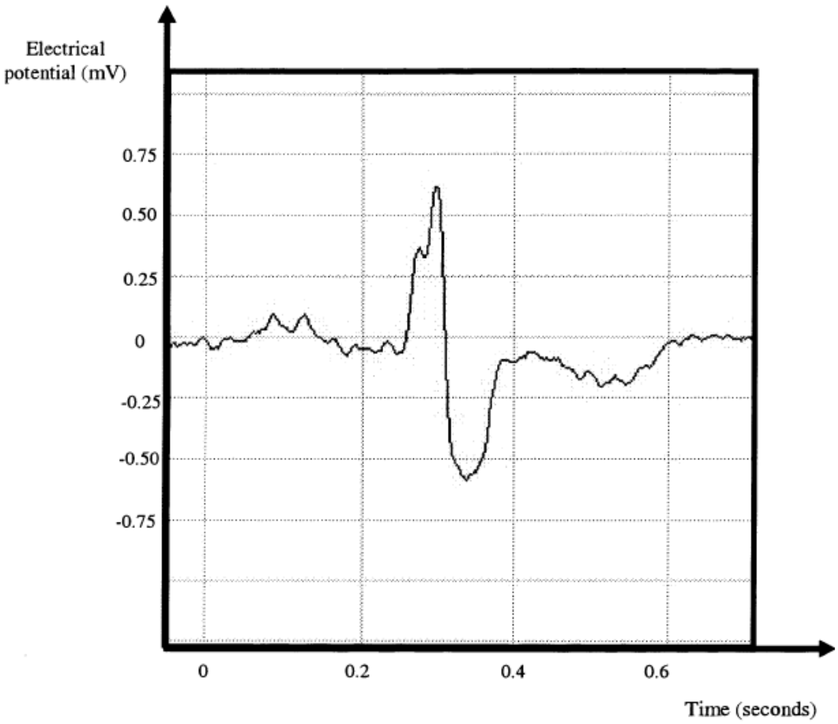


Figure 5.3: Right bundle branch block (R) type(MIT-BIH database, record 118)

5- Premature Ventricular Contraction (V): this arrhythmia occurs when the heartbeats earlier than it should. This is because of the abnormal electrical activity of the ventricles which causes premature contraction of the lower chambers of heart, the ventricles. The premature contraction is followed by a pause as the heart's electrical system "resets" itself. The contraction following the pause is usually more forceful than normal. With this type, the QRS complex is misshapen and prolonged representing ventricular contraction without earlier atrial stimulation (see Figure 5.5).

6- Atrial Premature Beat (A): this arrhythmia is associated with early depolarization of atrium this type can be identified by a premature, small and distorted P-wave (see Figure 5.6).

7- Aberrated Atrial Premature Beat (a): early depolarization of atria. These manifest itself as an abnormal P-wave (wide prolonged), narrow R-wave, and distorted QRS complex (see Figure 5.7).

8- Nodal (junctional) Escape Beat (j): the cause of this arrhythmia is that the region around the AV node takes over as the focus of the depolarization; the rhythm is called "nodal" or 'junctional' escape. Figure 5.8 shows one beat cycle of this arrhythmia which has no Q- and S-waves. Also, the P-wave has an inverse polarity compared to that of the normal sinus rhythm

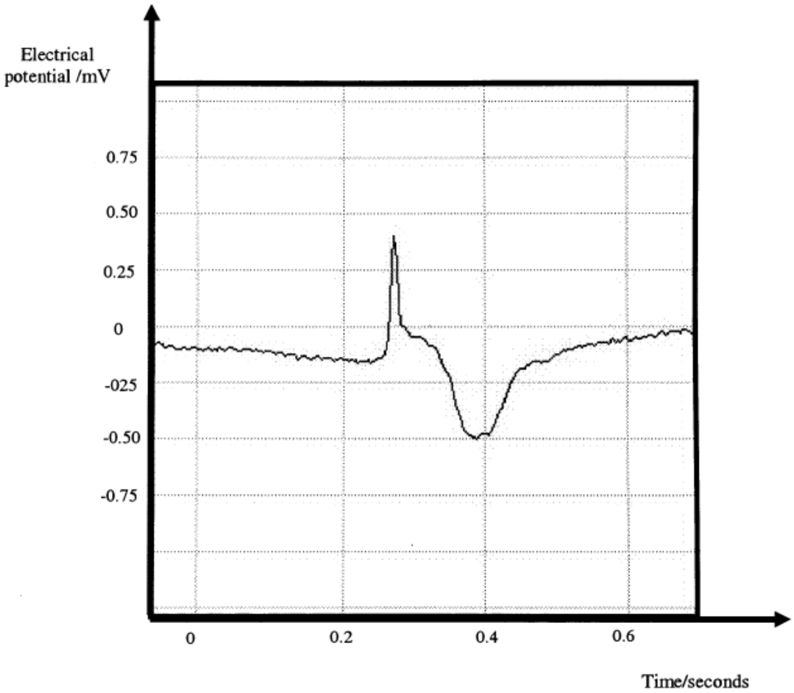


Figure 5.4: Beat stimulated by an artificial pacemaker (‘Pace’) type (MIT-BIH database, record 104)

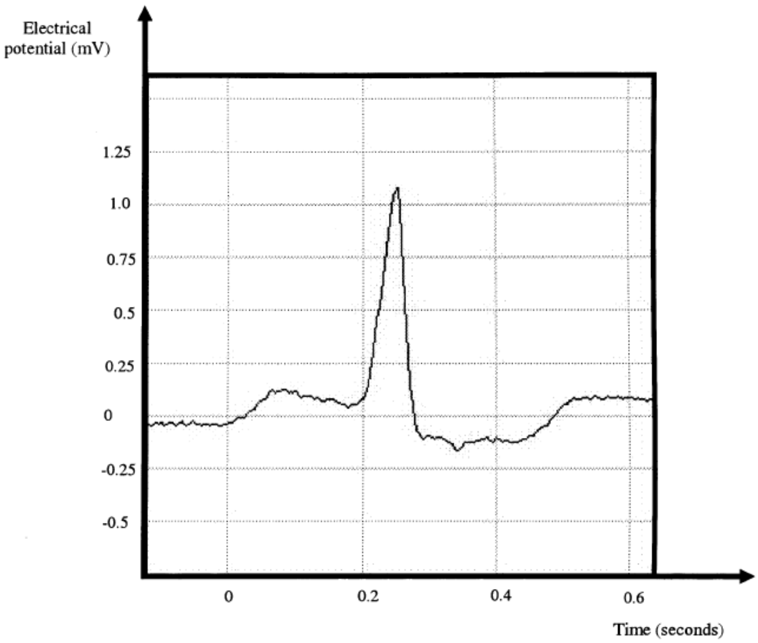


Figure 5.5: Premature ventricular contraction (V) type (MIT-BIH database, Record 105)

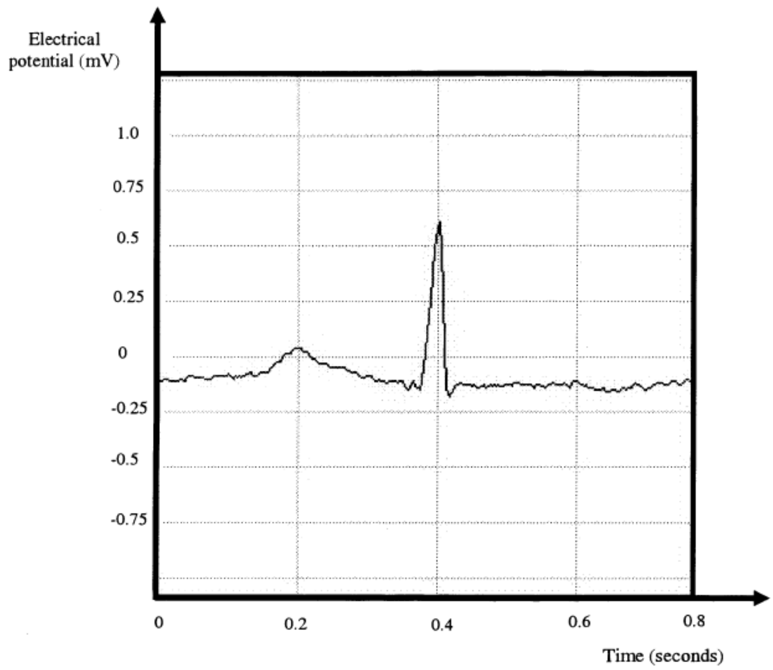


Figure 5.6: Atrial premature beat (A) type (MIT-BIH database, Record 100)

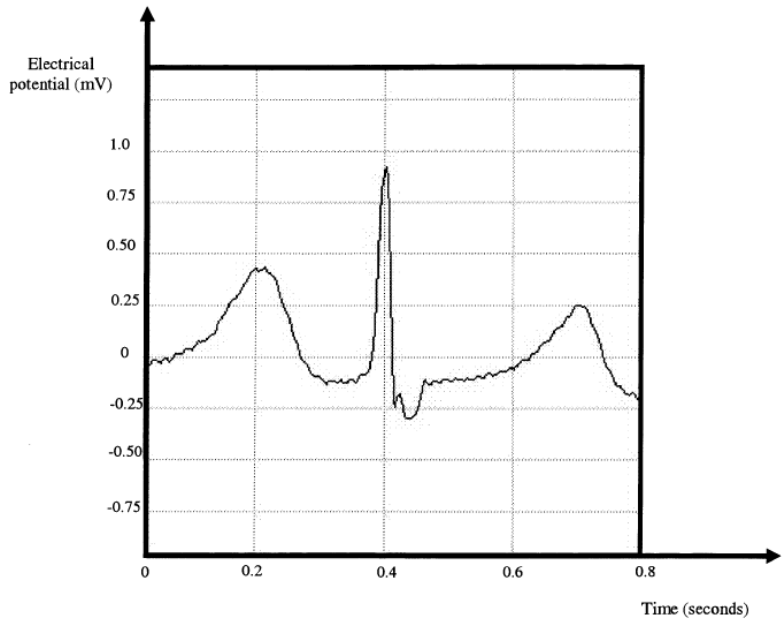


Figure 5.7: Aberrated atrial premature beat (a) type (MIT-BIH database, Record 105)

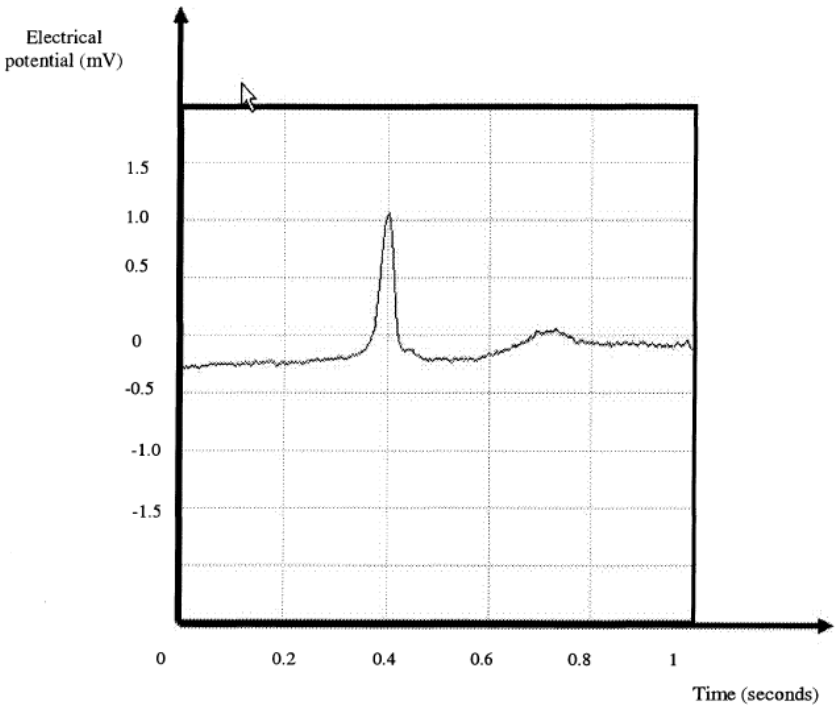


Figure 5.8: Nodal (junctional) escape beat (j) type (MIT-BIH database, Record 201)

9- Ventricular Escape Beat (E): this most commonly occurs when the ventricle contracts without nodal stimulation. This is classically associated with complete heart blockage. The QRS complexes are wide whereas the P-waves are occasionally absent as demonstrated in Figure 5.9.

Examples of the above arrhythmias and normal ECGs were extracted from records100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 111, 112, 113, 114, 115, 116, 117,118, 119, 121, 122, 123, 124, 200, 201, 202, 203, 205, 207, 208, 209, 210, 212, 213,214, 215, 217, 219, 220, 221, 222, 223, 228, 230, 231, 232, 233, 234.

There are two points to be taken into account concerning the above examples: intra patient and inter-patient variability. Intra-patient variability occurs due to changes in the patient’s emotional and physical states and inter-patient variability is due to different physical conditions between the different patients. As a result of intra- and inter-patient variability, different beat waveforms and different lengths of a beat cycle are observed.

Table 1 provides an overview of the different beat types in the MIT−BIH database. In this table, for each record from database, numbers of heart beats which are indicate a special kind of arrhythmia is shown.

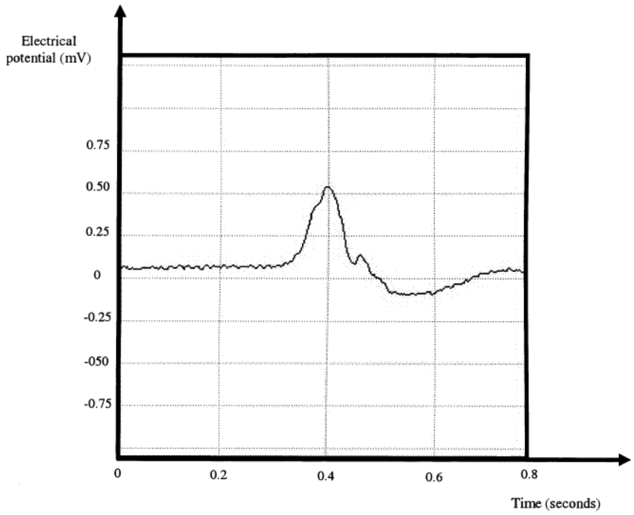


Figure 5.9: Ventricular escape beat (E) type (MIT-BIH database, Record 207)

Table 1: ECG database. A statistical overview of different beat types in the MIT−BIH Arrhythmia database [46].

Record	Normal beat	LBBB	RBBB	Atrial premature beat	Abberated atrial premature beat	Nodal premature beat	Supraventricular premature beat	Ventricular premature beat	Fusion of ventricular or normal beat	Ventricular flutter wave	Atrial escape beat	Nodal escape beat	Ventricular escape beat	Paced rhythm	Fusion of paced or normal beat	Pause	Unclassified beat
100	2239	-	-	33	-	-	-	1	-	-	-	-	-	-	-	-	-
101	1860	-	-	3	-	-	-	-	-	-	-	-	-	-	-	-	2
102	99	-	-	-	-	-	-	4	-	-	-	-	-	2028	56	-	-
103	2082	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-
104	163	-	-	-	-	-	-	2	-	-	-	-	-	1380	666	-	18
105	2526	-	-	-	-	-	-	41	-	-	-	-	-	-	-	-	5
106	1507	-	-	-	-	-	-	520	-	-	-	-	-	-	-	-	-
107	-	-	-	-	-	-	-	59	-	-	-	-	-	2078	-	-	-
108	1739	-	-	4	-	-	-	17	2	-	-	1	-	-	-	11	-
109	-	2492	-	-	-	-	-	38	2	-	-	-	-	-	-	-	-
111	-	2123	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-
112	2537	-	-	2	-	-	-	-	-	-	-	-	-	-	-	-	-
113	1789	-	-	-	6	-	-	-	-	-	-	-	-	-	-	-	-
114	1820	-	-	10	-	2	-	43	4	-	-	-	-	-	-	-	-
115	1953	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
116	2302	-	-	1	-	-	-	109	-	-	-	-	-	-	-	-	-
117	1534	-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-
118	-	-	2166	96	-	-	-	16	-	-	-	-	-	-	-	10	-
119	1543	-	-	-	-	-	-	444	-	-	-	-	-	-	-	-	-
121	1861	-	-	1	-	-	-	1	-	-	-	-	-	-	-	-	-
122	2476	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
123	1515	-	-	-	-	-	-	3	-	-	-	-	-	-	-	-	-
124	-	-	1531	2	-	29	-	47	5	-	-	5	-	-	-	-	-
200	1743	-	-	30	-	-	-	826	2	-	-	-	-	-	-	-	-
201	1625	-	-	30	97	1	-	198	2	-	-	10	-	-	-	37	-
202	2061	-	-	36	19	-	-	19	1	-	-	-	-	-	-	-	-
203	2529	-	-	-	2	-	-	444	1	-	-	-	-	-	-	-	4
205	2571	-	-	3	-	-	-	71	11	-	-	-	-	-	-	-	-
207	-	1457	86	107	-	-	-	105	-	472	-	-	105	-	-	-	-
208	1586	-	-	-	-	-	2	992	373	-	-	-	-	-	-	-	2
209	2621	-	-	383	-	-	-	1	-	-	-	-	-	-	-	-	-
210	2423	-	-	-	22	-	-	194	10	-	-	-	1	-	-	-	-
212	923	-	1825	-	-	-	-	-	-	-	-	-	-	-	-	-	-
213	2641	-	-	25	3	-	-	220	362	-	-	-	-	-	-	-	-
214	-	2003	-	-	-	-	-	256	1	-	-	-	-	-	-	-	2
215	3195	-	-	3	-	-	-	164	1	-	-	-	-	-	-	-	-
217	244	-	-	-	-	-	-	162	-	-	-	-	-	1542	260	-	-
219	2082	-	-	7	-	-	-	64	1	-	-	-	-	-	-	133	-
220	1954	-	-	94	-	-	-	-	-	-	-	-	-	-	-	-	-
221	2031	-	-	-	-	-	-	396	-	-	-	-	-	-	-	-	-
222	2062	-	-	208	-	1	-	-	-	-	-	212	-	-	-	-	-
223	2029	-	-	72	1	-	-	473	14	-	16	-	-	-	-	-	-
228	1688	-	-	3	-	-	-	362	-	-	-	-	-	-	-	-	-
230	2255	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-
231	314	-	1254	1	-	-	-	2	-	-	-	-	-	-	-	2	-
232	-	-	397	1382	-	-	-	-	-	-	-	1	-	-	-	-	-
233	2230	-	-	7	-	-	-	831	11	-	-	-	-	-	-	-	-
234	2700	-	-	-	-	50	-	3	-	-	-	-	-	-	-	-	-

5.2 Previous work on ECG/arrhythmia classification

Several authors have looked at ECG arrhythmia classification using different means such as statistical methods, expert systems, and supervised neural networks. Automated interpretation of ECGs began more than 52 years ago ([47],[48]). Since that time there has been continuous development of expert systems for automated interpretation of ECGs. Automated interpretation of ECGs consists of three main methods. First method is a kind of expert system such that the information from a cardiologist stored in a knowledge base. The system tries to simulate the decision processes of an expert person. The second approach utilizes statistical pattern recognition methods to classify the patterns [49]. The third approaches employing neural networks [50] and machine learning [51] have also been developed.

Recently many physicians use automated interpretation of ECGs for supporting their decisions. The performance and accuracy of some ECG analyzing approximately as well as expert physician.

Neural networks have been utilized with positive results in various medical diagnoses ([52], [53], [54]). In computerized ECG, the developed applications have concentrated mainly on beat and diagnostic classification ([55],[56]). According to Lippmann [57], recent interest in neural networks is directed towards practical research. This includes areas of study encompassing pattern recognition and artificial intelligence applications where real-time response is required. Both areas are relevant to ECG classification.

Pedrycz et al. [58] used a combination of two pattern recognition techniques, cluster analysis and feed-forward back propagation neural networks, for the diagnostic classification of a 12-lead ECG. The principle of cluster analysis based on the Euclidean distance in parameter space was also applied to the original learning set. The classification accuracy results varied between 51.9% and 84.0% for classifying 7 classes of ECG abnormality.

Silipo and Bortolan[59] compared statistical methods and neural network architectures with supervised and unsupervised learning approaches in performing the automatic analysis of the diagnostic ECG, where seven beat types and39 features were used. The classification results varied between 91.0% and 94.0%correct classification for all seven types, showing that a classifier based on neural networks can produce a performance at least comparable with those of traditional classifiers. As for the neural network architectures trained with unsupervised techniques, they produced a reasonable classification performance. Interestingly, two additional features used were the age and sex of the subjects. This information is not given in the MIT-BIH database.

A neural network based system, the GNet 2000 ambulatory ECG monitor, was developed by Gamlyn et al. [60]. This is a portable, battery-powered unit capable of analyzing an ECG in real time. A panel of Kohonen networks is embedded in a 32-bit micro-controller. The system is able to detect variations in the heart rate and P-R interval, changes to the ST segment, 'ectopic' beats and certain arrhythmias. Features include 24-hour monitoring and printout of detailed reports.

The product is now commercially available. Hu et al.[61] used a patient-adaptable approach to classify ECG beats in the MIT-BIH arrhythmia database. They concentrated on four categories of ECG beats, namely, normal, ventricular premature beat, fusion of normal and ventricular beat and unclassifiable beat. They used a mixture of the Self Organising Feature Map(SOFM) and Learning Vector Quantisation (LVQ) algorithms to develop two expert programs, the global expert program capable of classifying ECG beats from the whole database and the local expert program, which is a patient-specific expert system The classification accuracy varied between 62.2%-95.9% for different records. The main drawback of the method is the need to create a local expert program for each individual patient.

Edenbrandt et al. [62] used single output MLPs to classify seven different classes of ST-T segments found in the ECG. They used the ST slope and the positive and negative amplitudes of the T-wave as inputs to the MLP. They trained and tested ten MLPs with different configurations of hidden layers and neurons in the hidden layers. The average classification accuracy was between 90.0% and 94.4%.

Izeboudjen and Farah [63] proposed an arrhythmia classifier using two neural network classifiers based on the MLP model. The morphological classifier groups the P-waves and QRS complexes into normal or abnormal beats. The timing classifier takes as the input the output of the morphological classifier and the duration of the PP, PR and RR intervals. An accuracy of 93.0% was reported in classifying 13 arrhythmia classes from 48 examples scanned from different ECG signals using a PC.

Dorffher et al. [64] compared the performance of neural networks with the performance of skilled cardiologists in classifying coronary artery disease during stress and exercise testing. He performed three experiments, two of which used recurrent networks, while the third one employed an MLP. This neural network approach produced results comparable to the diagnosis of experts. Only in some cases did the neural networks outperform the experts.

Nugent et al. [65] used single-output bi-group MLPs to detect the presence or absence of a specific ECG class. Three different feature selection techniques were adopted, namely, rule based, manual and statistical. The results of the bi-group neural networks were combined using orthogonal summation. The methodology was applied to recognize three classes, namely, normal, left ventricular hypertrophy and inferior myocardial infarction. On average, the classification accuracy was only 78.0%.

Biel et al. [66] suggested that the distinction between ECG signals of different people is sufficiently great to identify individuals using just one lead of an ECG.

Bortolan et al. [67] used a feed forward network with back-propagation to classify seven beat types using 39 features. Results of over 90.0%correct classification for all seven types were achieved. Interestingly, two features used were the age and sex of the subjects. Such information is not given in the MIT-BIH database. The same seven beat classes were investigated by Silipo et al. [68] using a neural classifier with Radial Basis Function (RBF) pre-processing.

Here again, correct beat type designation was consistently made for over 90.0 % for all classes.

The influences of various network parameters on multilayer neural network performance were researched by Edenbrandt et al. [62]. ECG STT segments were the basis of the study which found that increasing the number of input features did not necessarily improve classification. Similarly, increasing the number of neurons in the hidden layer beyond five gave no benefit. It was also reported that networks with two hidden layers showed only a very slight improvement over those with one hidden layer. Problems were encountered with training networks to recognize uncommon patterns, the best results being obtained, as expected, for those beats with the most examples in the training set.

Magleveras et al. [63] advised against using digital filtering of signals at the pre-processing stage to avoid corrupting the components of the ECG.

Modular neural networks were applied to ECG classification [Kidwai, 2001]. These employed a more logical step-by-step approach by breaking the problem of classification down into stages rather than using a one-hit approach.

Suzuki [70] and Hamilton and Tompkins [71] researched methods of QRS complex detection. Their aim was reliably to break down a continuous ECG signal into individual beats. This is in contrast to supplying information from a database where signals have already been pre-divided into beats, such as the MIT-BIH database. Recognition of the QRS complex was proposed by Suzuki as the first step in the development of a real-time ECG analysis system His self-organising neural network was capable of detecting R-waves in real time, in order to divide the ECG into cardiac cycles. An Adaptive Resonance Theory (ART) network then performed classification according to QRS complex features. Hamilton and Tompkins [Hamilton and Tompkins, 1986] claimed that their system carried out QRS detection at 100 times the rate of the cardiac cycle, and gave a 99.8 % success rate for QRS identification.

Dokur et al. [72] used a Kohonen neural network to detect four ECG waveforms: Normal beat (N), Premature ventricular contraction (V), Paced beat (P)and Left bundle branch block (L). The network was trained with data from the MIT-BIH arrhythmia database and gave 90.0% classification accuracy.

Chapter 6

METHODOLOGY

6.1 Step by step design method

In order to classify ECG signals, our proposed system consist of the following subsystems: Preprocessing, Feature extraction, Training the classifier and Evaluation. We illustrate the detail of these steps in Figure 6.1.

In the first step we perform baseline elimination and noise removal on the raw ECG signal as preprocessing. In the second step, we apply forth-level wavelet decomposition on the output signal of previous step and calculate the approximation and detail coefficients of them. These coefficients are used as a part of morphological features. In the next step we apply an algorithm in order to find fiducial points such as P-QRS-T peaks, inter-waves locations and etc in ECG signal. These points are used in the temporal and morphological feature extraction process.

After extracting all temporal and morphological features we construct a feature vector for each heart beat by concatenating these features and also the heart beat type which is obtained from annotations file.

In the classification step, we train 7 separate SVM classifier, one SVM for NORMAL class and the six remaining SVMs for LBBB, RBBB, PVC, FOV, APC and PACED Arrhythmia.

For final decision we use maximum voting technique, so an unknown heart beat is given to all SVM and the SVM which is modeling the type of this heart beat generate 1 and all other SVMs produce 0. So we can assign the class label of this SVM to that particular heart beat.

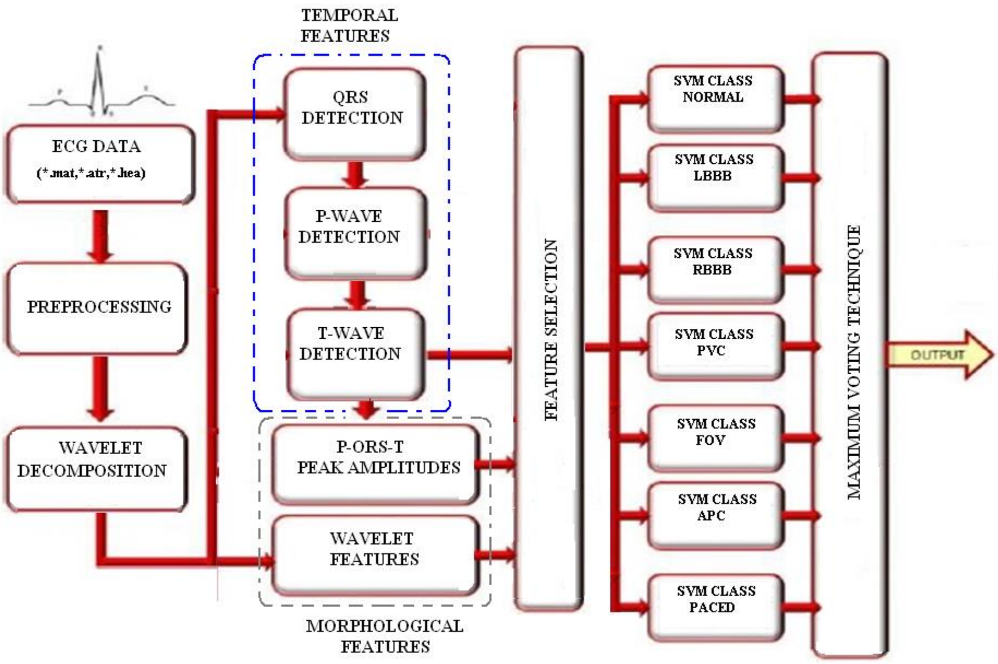


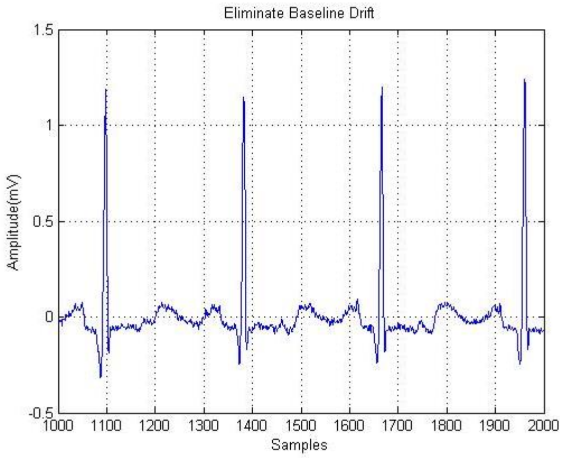
Figure 6.1: Structure of purposed ECG signal processing approach.

6.2 Preprocessing of ECG signals

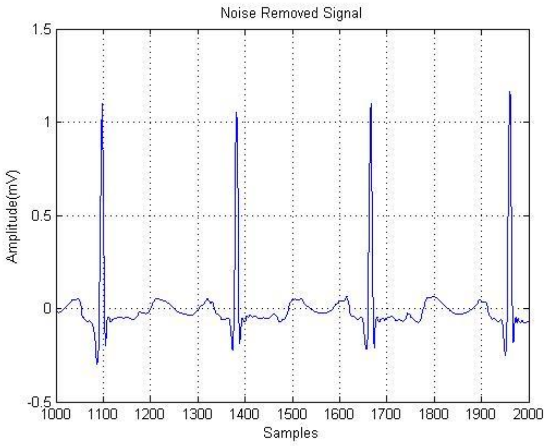
ECG signal inherently contains of various type of unwanted noise and artifact effects like baseline drift, noise of electrode contact, polarization noise, the internal amplifier noise, noise due to muscle movement, and motor artifacts. The movements of electrodes induced artifacts noise. Therefore in order to make the ECG signal ready for feature extraction step, we must remove baseline wander and eliminate above noise.

We propose to use wavelet filtering to filter the ECG signal since this technique is suitable for computing the R-peak locations without change of the shape or position of the original signal. According to the previous experimental knowledge, in order to optimize the signal filtering, we must consider these two criteria: the signal sampling frequency and the knowledge that most of the noises are located outside of the frequency interval between 1.5 Hz to 50 Hz [73]. For this purpose, we use a band pass filter which is constructed by a high pass filter with cutoff frequency 1.5 Hz. This filter eliminates baseline variations. The output of this filter is cascade with a low pass filter with cutoff frequency 50 Hz. This filter removes high frequency noise.

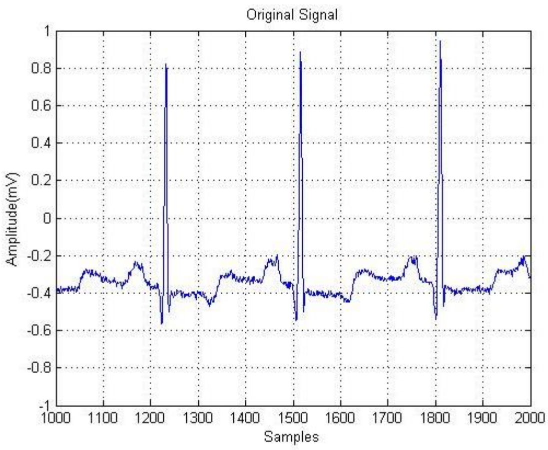
The scale and type of the mother function parameters are specific to each filter. Thus, the automatic compute of optimal scale for high pass filtering when the sampling frequency is 256 is equal to order 6. The optimal scale order for the low pass filtering is equal to order 2. The results of above steps are shown in the Figure 6.2.



(a)



(b)



(c)

Figure 6.2: Implementation results of preprocessing on record [100] from MIT-BI database (a) original signal, (b)eliminated baseline, (c) noise removal

6.3 QRS detection

Each ECG cycle is consists of a P-wave which is corresponding to the atrial depolarization, a QRS complex which is corresponding to the ventricular depolarization and a T wave which is point to the rapid repolarization of the ventricles. A normal ECG signal and its time intervals are shown in Figure 6.3.

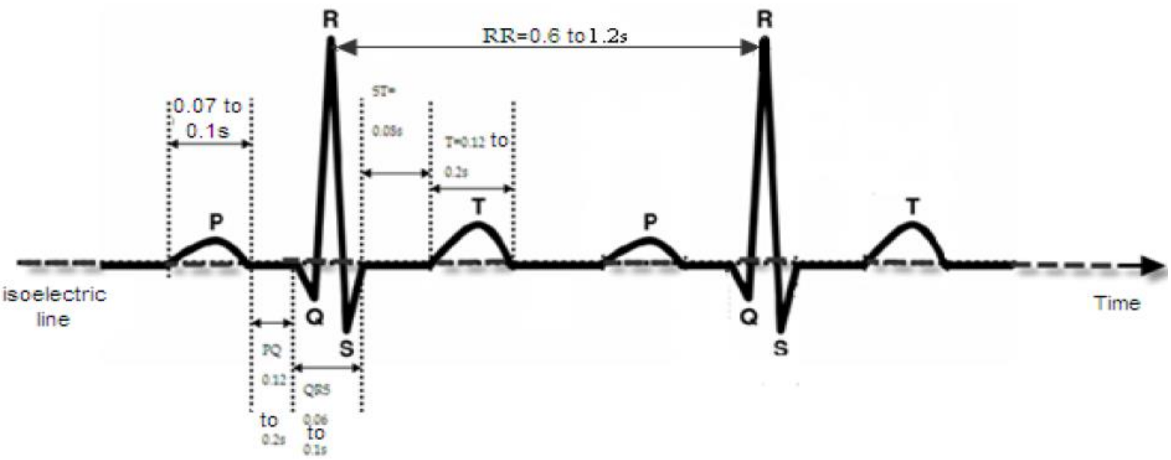


Figure 6.3: Standard waves of a normal electrocardiogram [73].

Most of the clinically features which are useful for diagnostic the disease can be found in the time interval between components of ECG and the value of the signal amplitude. For example, the Q-T feature is used to recognition one dangerous disease, the Long Q-T Syndrome (LQTS), which is responsible of thousand deaths each year [1]. The shape of T wave is a critical factor and it is essential to identify it correctly since inverted T waves can be caused as an effect of a serious disease named coronary ischemia [74].

Designing an algorithm in order to extract the ECG features automatically is very hard since ECG signal has a time-variant behavior. As a result of these signal properties, we face with multiple physiological constraints and the existence of noise.

In recent years several algorithms have been proposed for detection those features. In [74] they introduced a method to extract wavelet features and used SVM for classification. In Their purposed method, the classification is done without completely identify ECG components. Castro et al. introduced a method that used wavelet based features and classify various form of abnormal heartbeats [75]. Tadejko and Rakowski proposed an algorithm which is based on computational morphology [76]. Their main goal is the assessment of various automatic classifiers for detection of disorder in the ECG. In [77] they proposed a method to extract feature from ECG based on a multi resolution wavelet transform. First, they remove noise from ECG signal by discarding the coefficient which caused noise. In next step, they detect QRS complexes and by using them the start and end of each wave part is determined. They assess proposed method on some records from MIT-BIH Arrhythmia Database.

In this thesis, we proposed a method for recognition of time interval and amplitude of various wave parts of ECG. In the First stage of our approach, the R-peak is detect accurately. For this purpose we used wavelet. In the second stage, the other ECG components are identified by using a local search around the detected R-peak. We can summarize this approach:

The location of the R-wave has been identified by using wavelet transform.

Each R-R interval from ECG signal is segmented as follow:

Within an interval, finding the maximum and minimum of the wave which are corresponding to the Q and S waves

Since P-wave and T-wave are dependant to other factors; we must provide some deterministic point in order to find their location. These points are including the end point of S-wave or Soff, the start point of T-wave or Ton, and the start point of Q-wave or Qon.

6.4 R-peaks detection

The detection of R-peak is the first step of feature extraction. For this purpose, we used DWT due to its ability to recognize different locations of the waves accurately. Similarly to the preprocessing, we apply the same steps in order to compute the scale and choose the mother function. We have the QRS complex signal as an input which has the frequencies between 5Hz and 15Hz, so we select scale of order 4 and choose the Db4 mother wavelet. The Db4 wavelet is very popular for the detection and location of R peaks due to the strong similarity of its shape to the ECG signal. Our method is organized in the following steps. By performing wavelet decomposition, we down sampling the input. Therefore the amount of unnecessary information is reduced but the component of QRS is not changed.

In order to find the location of R-peak, first we choose the locations which their amplitude are greater than 60% of the max value of the whole input signal. Since we remove the noise from the signal in the previous step, it is useful for R-peak detection.

Since we decompose the signal into 4^{th} level, the R-peak location in the modified signal is at least 0.25 of the R-peak location in the original signal. So in order to find the actual location of R-peal we must convert the founded positions by multiplying them with 4.

Another important point is that R-peak location in modified signal is not exactly on the original signal at a scale of 4. Position of the signal will change during the down sampling, so we must to do local search around the R-peaks which calculated in previous part. The interval of this search can be limited to a window of ± 20 samples.

6.5 P, Q and S detection algorithms

The accuracy of detecting R-peak completely affected on P, Q and S detection parts since their location is determined relatively to R-peak. In the other hand, detect the location of R-peaks are corresponding to recognize the heart beat interval.

One of the most popular features in ECG signal processing is the R-R interval which can be computed by the following formula:

$$R\_R(i) = R(i+1) - R(i) \qquad (6\text{-}1)$$

Where R(i) and R(i + 1) are the indexes of the current and next R wave peak respectively.

6.5.1 S wave detection

The S-wave is located on the end of the QRS complex so in order to find its location we must start from R-peak location plus 6 units because range of the shortest length of it is between 0.016 and 0.036 seconds. This range is corresponding to 6 and 13 samples. The stop point of search interval is related to the value of R-R interval.

However the maximum length of the RS intervals is recorded is around 0.27 seconds where its R-R interval was 1.41 seconds [78].

6.5.2 Q-wave detection

The Q-wave indicates the start point of the QRS complex section. It is reported that Q-wave peak location can be found in the range between 0.02 to 0.06 seconds from R-peak. In the other hand, this interval is equal to 8 and 22 samples. But this interval must be relevant to the value heart beat length. Therefore Q-R interval varies from one patient to another, for example a patient with a R-R equal to 235 can have a Q-R interval equal to 19 and another one can have Q-R equal to 8 while has a R-R equal to 292. As a result, the range for search will be larger for longer R-R interval. The process of Q-wave detection is illustrated in Figure 6.4.

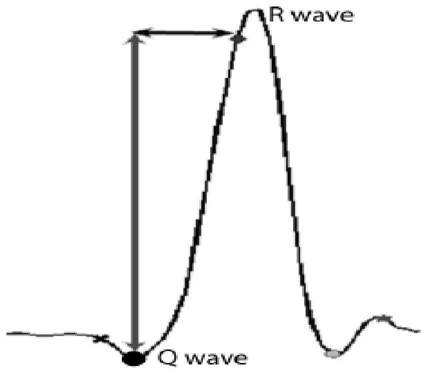


Figure 6.4: Q wave identification (150 samples in this case)

6.5.2.1 Q-wave onset detection

The start point of Q, Qon can be indicated as the point with the maximum value of amplitude near the negative peak location of the Q-wave. Therefore the search interval for finding the Qon started from Q-12 and continues till Q-5. Since some points before Qon may have larger amplitude, its index may need some corrections. For this purpose, it is necessary to:

- Compute the amplitude difference between Qon and Q by the following equation

$$level = y_{Qon}(i) - y_Q(i) \tag{6-2}$$

- if amplitude(P)-level>0.25 then threshold=0.90 else set it to 0.87
- Start searching from Qon in order to find the first value which

$$\text{Point\_ amplitude} < \text{level(i)} * \text{threshold} \tag{6-3}$$

6.5.3 P- wave detection

Since P-wave can be located far or near from Q-wave, it is necessary for its interval to be relative to the R-R interval value.

It is reported that duration of the P-R interval is between 0.09 and 0.19 seconds and this interval also depends on the R-R interval. This interval is equal to 19 and 38 samples. From the point of view of proportional, the limits are 14% to 22% of the respective RR range. One of the benefits of this approach is that we can detect P-waves with low amplitude, so according to the search area interval, we have two cases:

- Case 1:search_interval set to $0.81 * \text{R\_R(i)} - 7$ to $\text{Q(i)} - 18$. This interval is works for most of the patient but have some problem with records 111,215 and 218.
- Case 2:search_interval=$0.71 * \text{R\_R(i)} - 7$ to $\text{Q(i)} - 18$. This search interval solve the above problem but now when we can't find P-wave and the S-T

segment is depressed, we must start searching the P-wave from the start point in its equation.

6.6 T-wave detection

Finding T-wave in ECG signal is the most complicated task. Designing a procedure for detecting T-wave is difficult since it has a time variant behaviors. By checking the ECG waveform someone can see that the T- wave is located as the interval which has largest amplitude between S and the middle of the R-R interval. Therefore, the search interval for T started from S-wave and finished at the middle point of the R-R interval.

6.6.1 T-wave Onset detection

Another important point in analyzing the ECG signal is the start point of T-wave or Ton because it is used as a support point for determining the polarity of T which can be positive, negative or flat. Existence of negative or flat T waves in ECG shows a serious disease, the cardiac ischemia. The searching area is start from the S-wave plus small offset till T-wave and Ton is a point with minimum value in this interval.

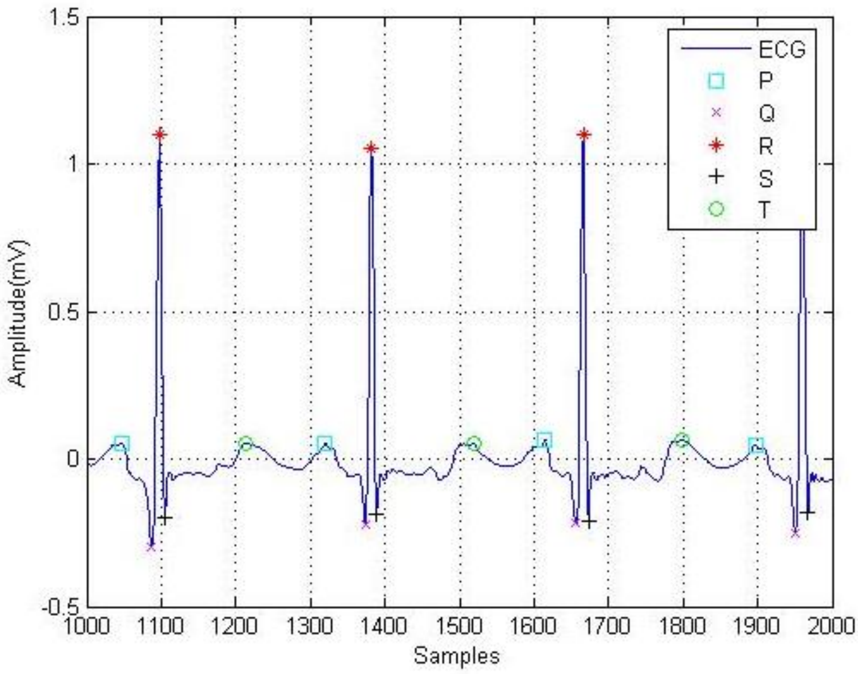
6.6.2 T-wave end detection

Detection of end point of T-wave, Toff, is another difficult task in this domain since there is still discussion between specialists about it. The best properties for detect Toff is finding the point which has the lowest amplitude after T within a limited range. For this purpose, it is necessary to make the signal smooth. We can do it by adding previous values of the signal to it. If a point amplitude be larger than the amplitude's of all the previous 3 samples, it can be consider as a Toff point.

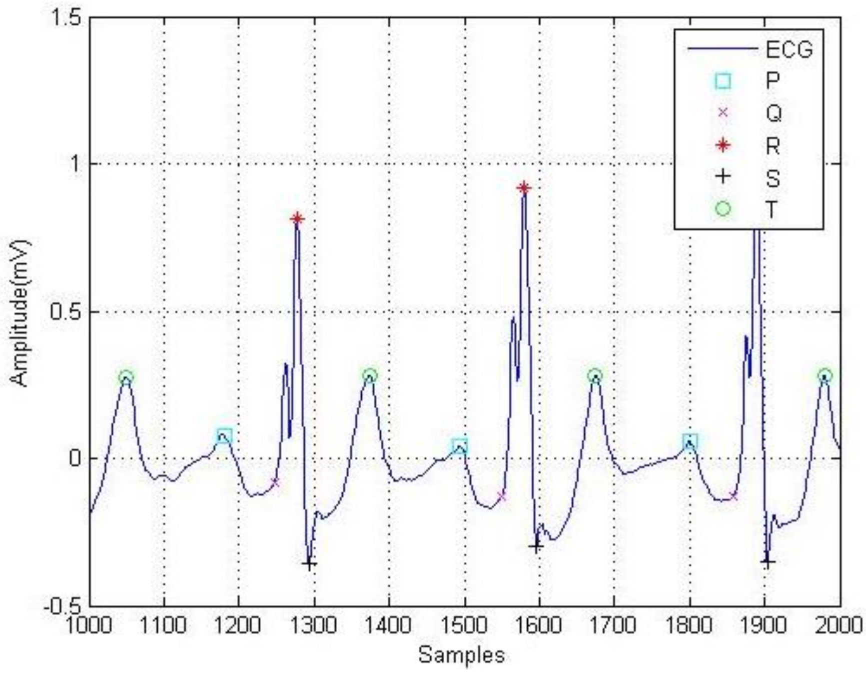
Table 2 summarizes the search intervals used to find ECG components. It shows the indexes of the start and the end ranges of the search[78]. The results of implementation of PQRS detection algorithm for some ECG records from MIT-BIH database are shown in Figure 6.5.

Table 2: Search intervals [78]

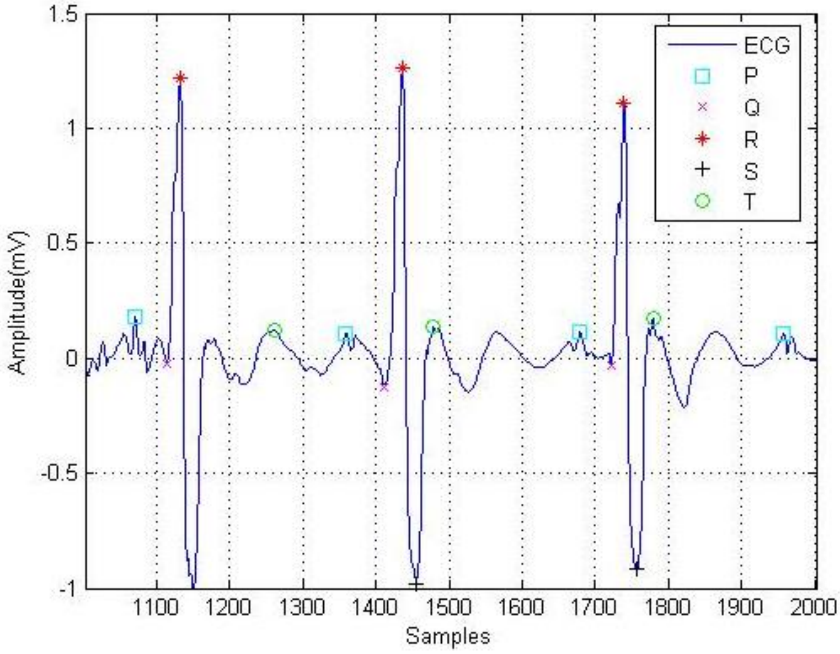
Wave	Beginning	End	Type
P	$0.71 * \mathrm{R\_R(i)} - 7$	$\mathrm{Qon(i)} - 12$	max
Q	$\mathrm{R\_R(i)} - 25$	$\mathrm{R\_R(i)} - 7$	min
Qon	$\mathrm{Q(i)} - 12$	$\mathrm{Q(i)} - 5$	max
S	$\mathrm{R(i)} + 6$	$\mathrm{R\_R(i)}/5 - 10$	min
Ton	$0.7 * ((\mathrm{T(i)} - \mathrm{S(i)})$	$\mathrm{T(i)} - 10$	min
T	$S(\mathrm{i}) + 15$	$\mathrm{R\_R(i)}/2$	max



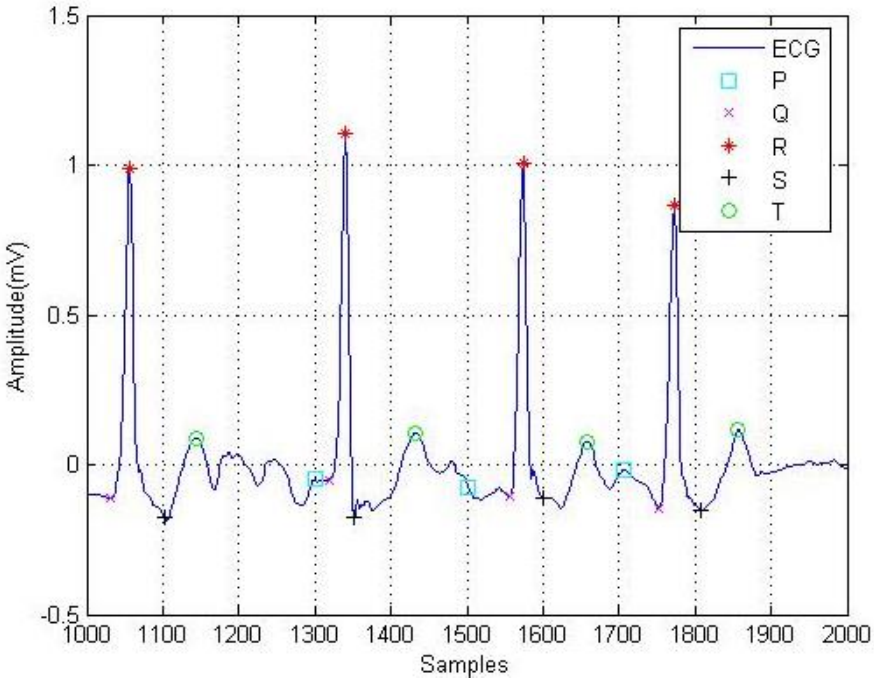
(a) PQRST detected in record [100].



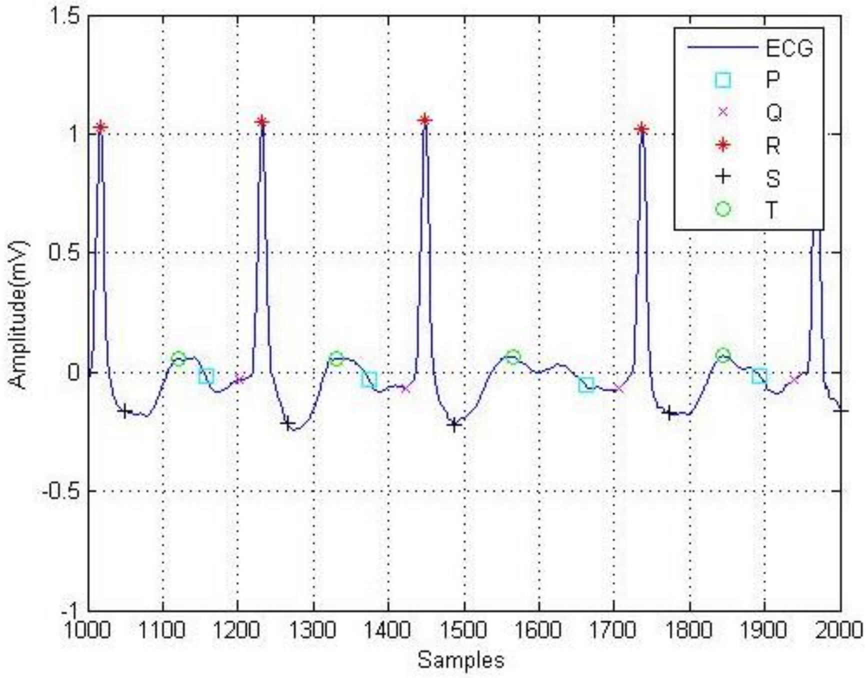
(b) PQRST detected in record [111].



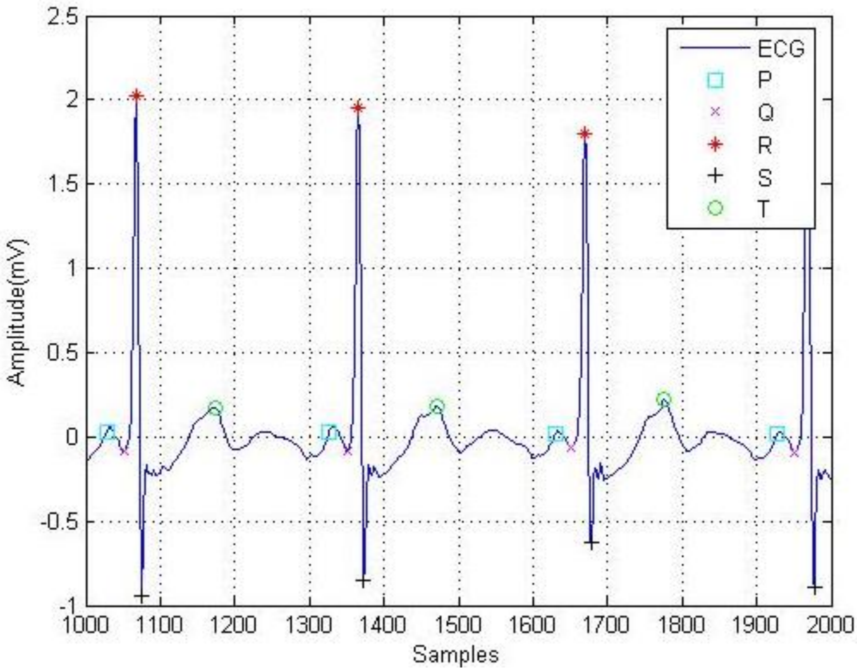
(c) PQRST detected in record [118].



(d) PQRST detected in record [201].



(e) PQRST detected in record [210].



(f) PQRST detected in record [220].

Figure 6.5: Implementation result of PQRST detection method in (a) record [100], (b) record [111], (c) record [118], (d) record [201], (e) record [210], (f) record [220] from ECG MIT-BIH arrhythmia database.

We test the algorithm on MATLAB 2012 using 26 records of MIT-BIH arrhythmia database. Sensitivity and specificity parameters are calculated to evaluate the detection performance and the results are given by Table 3 and Table 4 respectively. Sensitivity measures the accuracy in detection while specificity gives an indication of rejection of false detections. The formulas used for calculation of sensitivity and specificity are given as follow:

$$S_e = \frac{TP}{TP+FN} \tag{6.3}$$

$$S_p = \frac{TP}{TP+FP} \tag{6.4}$$

Sensitivity is conditional probability that the case correctly classified and specificity is conditional probability that non-cases are correctly classified. Both S_e and S_p take a value of 1.0 for an ideal recognition algorithm.

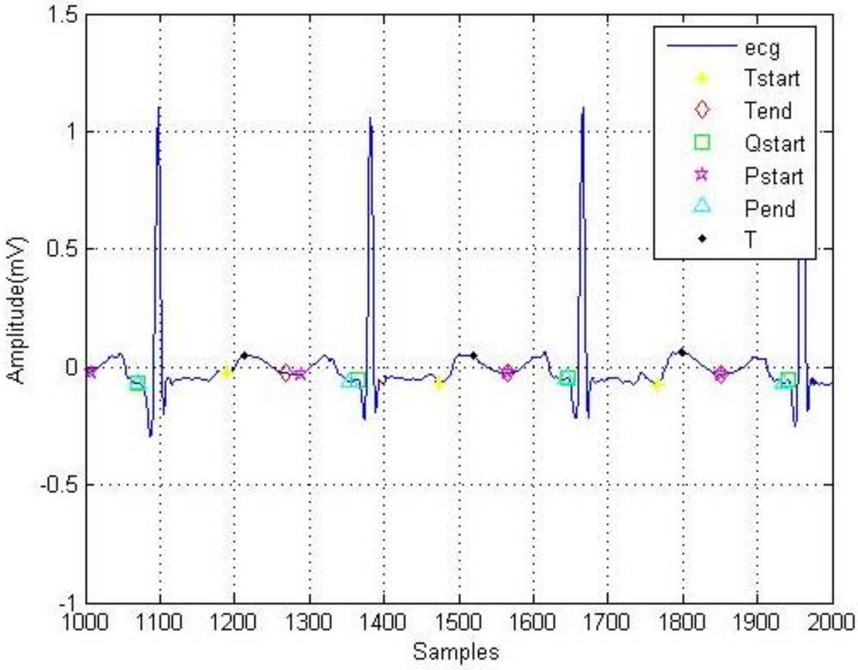
The results of implementation of $Onset\ and\ Offset$ detection algorithm for previous ECG records are shown in the Figure 6.6

Table 3: Sensitivity calculation of PQRST detection on MIT-BIH arrhythmia database.

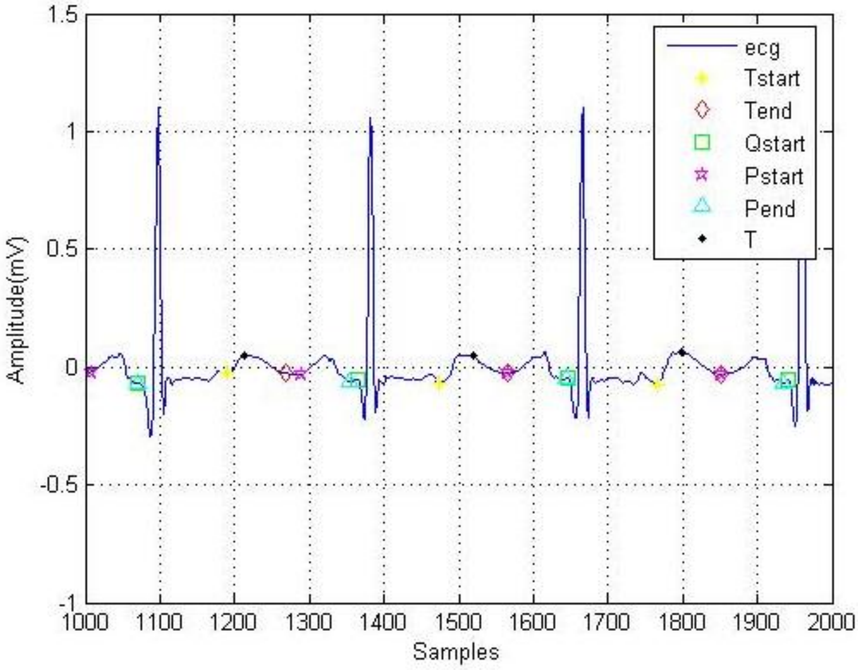
Record No.	Sensitivity Calculation in Percentage (%)				
	P	**Q**	**R**	**S**	**T**
100	92	100	100	100	90
101	100	100	100	100	100
103	100	100	100	100	100
105	100	100	100	100	100
106	77	100	80	100	100
112	100	80	82.35	82.35	100
115	92	100	100	100	100
116	100	100	100	100	100
118	100	100	92	100	100
119	89	100	100	100	90
121	100	100	100	100	100
200	100	82	82	82	82
201	100	100	100	100	100
202	100	100	100	100	100
203	91	94.5	94.5	94.5	94.5
205	100	100	100	100	100
207	100	100	100	100	100
209	100	74	75.23	76.19	94.54
210	100	93.5	93.5	93.5	100
214	97	100	100	97	100
219	100	100	100	100	100
220	100	100	100	100	100
221	86	100	100	100	100
223	100	100	100	100	100
230	84	100	100	100	84
234	100	100	100	100	100
Average	**96.72**	**97.12**	**96.04**	**97.32**	**97.56**

Table 4: Specificity calculation of PQRST detection on MIT-BIH arrhythmia database.

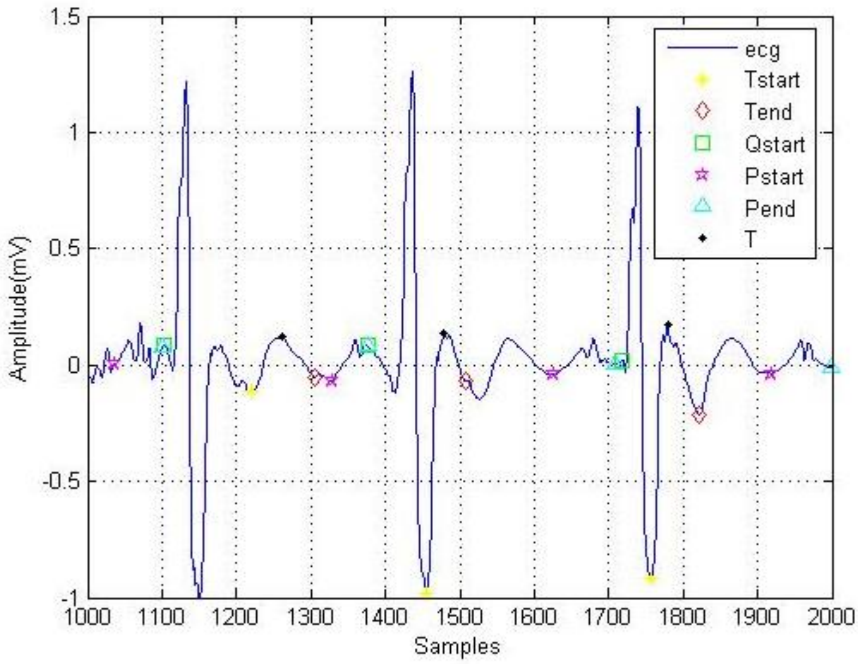
Record No.	**Specificity Calculation in Percentage (%)**				
	P	**Q**	**R**	**S**	**T**
100	100	100	100	100	50
101	91	100	100	100	70
103	100	100	100	100	70
105	83	100	100	100	50
106	100	100	100	100	70
112	82	100	100	100	74.3
115	100	100	100	100	80
116	91	100	100	100	100
118	92	100	100	100	90
119	90	90	100	91	100
200	79	100	100	100	72
201	69	100	100	100	84
202	100	100	100	100	100
203	100	100	100	100	100
205	60	100	100	100	54
207	100	100	100	100	100
209	60	100	100	100	42.85
210	13	100	100	100	82
219	90	100	100	100	100
220	100	100	100	100	94
221	70	100	100	100	94
222	50	100	100	100	100
223	83.33	100	100	100	100
230	55	100	95	100	50
231	100	100	100	100	70
234	93.33	100	100	100	62
Average	**83.47**	**99.61**	**99.80**	**99.68**	**80.41**



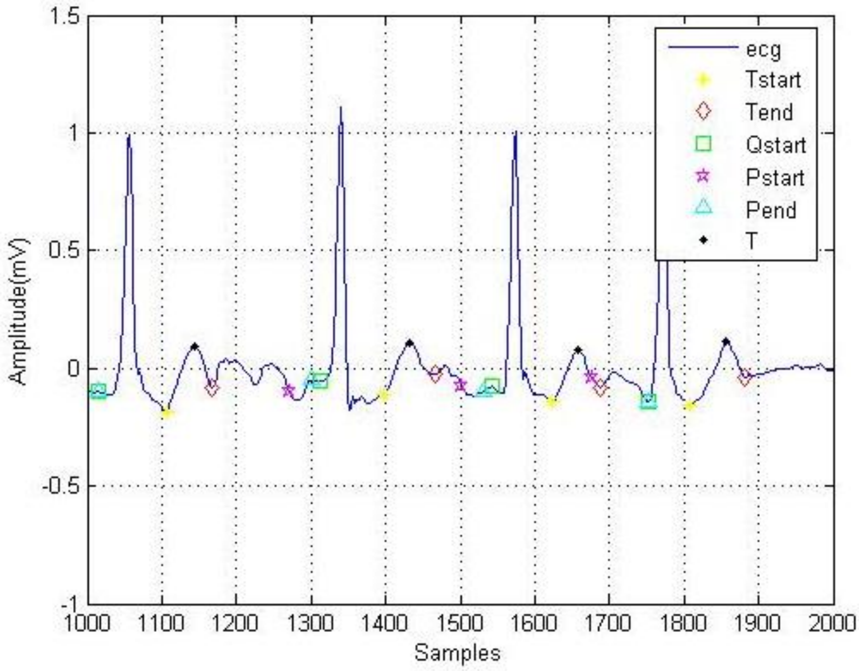
(a) Onset-Offset of inter-waves detected in record [100].



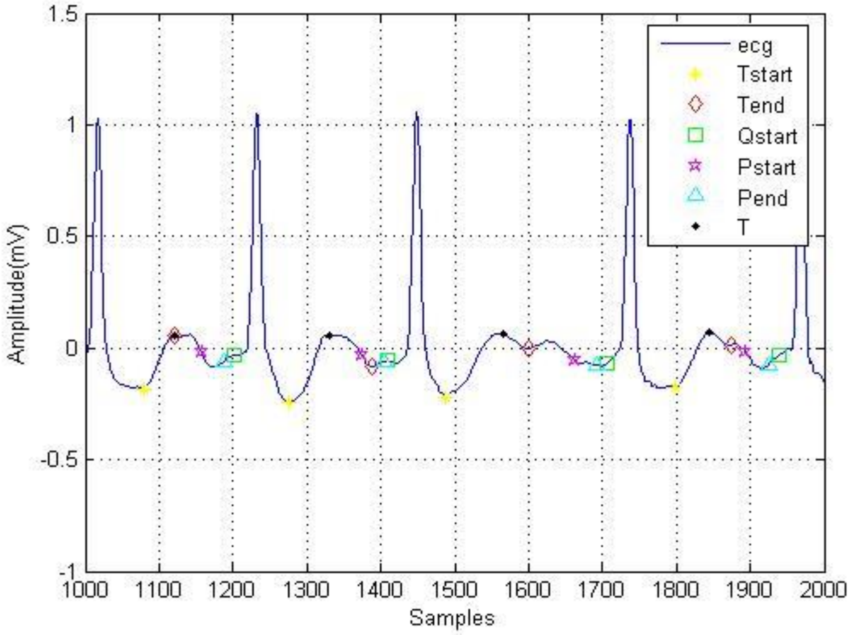
(b) Onset-Offset of inter-waves detected in record [111].



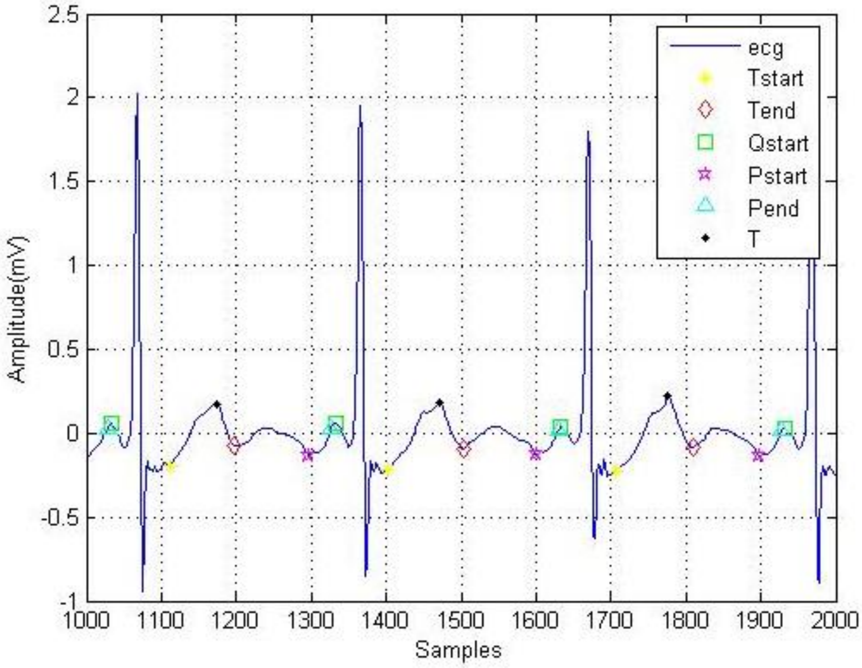
(c) Onset-Offset of inter-waves detected in record [118].



(d) Onset-Offset of inter-waves detected in record [201].



(e) Onset-Offset of inter-waves detected in record [210].



(f) Onset-Offset of inter-waves detected in record [220].

Figure 6.6: Onset-Offset of waves detected in (a) record [100], (b) record [111], (c) record [118], (d) record [201], (e) record [210], (f) record [220] from ECG MIT-BIH arrhythmia database

6.7 Feature extraction

There are various features in ECG analyzing which someone can select among them and it is a hard task to select the right feature combinations. The first approach is to use all features found in the literature, however if the number of selected features be too large, it causes heavy computational cost. Therefore we chose those features that are relevant for a specific type of disease. Those features are identified from literature and are mixed to form a single feature vector which consists of the following categories.

- Temporal features consist of heart rate and interval features which discussed before.
- Morphological features, gives the characteristic morphology details that include coefficients from wavelet decomposition, their maxima minima etc.

For morphological feature, first we decomposed the ECG signal to level 4 by using daubechies as the mother wavelet. Then the maximum and minimum values of Detail coefficient and Approximation coefficients for each level are used. We also used the peak values of P-wave, Q-wave, R- wave, S-wave and T-wave [18].

In order to compose the feature vector, we combine all of the above features so we have 30 features for each single beat. This feature vector is given as the input to the SVM classifier.

6.8 Identification

Classification process includes two phases: training phase and testing phase. We use an integrated software for support vector classification, SVMlib, with linear kernel. For training and testing the system, we used "one against all" approach, so we collect all of data in one file, each time we select one class as "Target class" and the other remaining classes as undesired , and give it to a separate SVM for each type of arrhythmia and train a model to detect a target class.

We chose 60% of data from each file as training data and the remaining data as test data. The total numbers of beats used in training are about 20600 beats and 13700 beats have been left for testing. The detail of selected record number and the number of beats that are used in the experiment are shown in Table 5.

The accuracy of each SVM for test set is shown in Table 6. The best performance achieved for PVC arrhythmia by 99.97% accuracy, and then Paced, FOV, APC and LBBB have the next rank. The lowest performance belongs to Normal beats and RBBB arrhythmia.

Table 5: ECG samples used for training and testing.

Class label	Beat Type	# of Beat per Data file	MIT-BIH Data File
1	N	2230	100
		1860	101
		2080	103
		1730	113
		1950	115
		1510	123
2	LBBB	2490	109
		2120	111
		1450	207
		2000	214
3	RBBB	2160	118
		1530	124
		1820	212
		1250	231
5	PVC	990	208
		830	233
6	FOV	370	208
		360	213
8	APC	380	209
		90	220
		70	223
		1380	232
12	Paced	2070	107
		1540	217

Table 6: Accuracy of detection different type of arrhythmia on MIT-BIH arrhythmia database.

Arrhythmia type	Model Accuracy
Normal	94.16 %
Atrial premature beat	99.04 %
Left bundle branch block beat	98.5 %
Right bundle branch block beat	92.33 %
Premature Ventricular Contraction	99.97 %
Fusion of ventricular and normal beat	99.51 %
Paced beat	99.63 %
Average	97.59%

As we discussed before, other researchers used various kind of methods for ECG classification such as Combining KNN and DWT [74], MLP and VQ [76] and SOM with SVD [77]. Their system performance is shown in Table 7.

As we can see, there are multiple factors and reasons cause the comparison between ours system results and theirs inaccurate. For example the number of selected arrhythmia by each researcher is varied to the others, also the selected records or even the number of extracted beat from a specific record for training and testing are not mentioned clearly. Nevertheless our system results are comparable with the others.

Table 7: Accuracy of the proposed method and other methods for ECG classification

Method	Number of beat type	Accuracy (%)
KNN-DWT	4	96.65
Neuro Fuzzy	4	98
MLP-VQ	2	96.8
SOM-SVD	3	92.2
Wavelet-SVM (proposed method)	7	97.59

Chapter 7

CONCLUSION AND FUTURE WORK PLANS

A multiple ECG classifier is implemented based on temporal and wavelet features that are submitted individual SVM classifiers for six different types of cardiac arrhythmia. The use of MIT-BIH ECG signals enabled the use of reliable and long duration recordings for the extraction of characteristic ECG features.

Combining temporal and wavelet features resulted in the description of ECG signals in time, frequency and morphological dimensions. Effectiveness of using this set of features can easily be seen on the achieved recognition rates. Using simple SVM classifiers for each of the six cardiac arrhythmia, the recognition rates achieved change from 92.33% to 99.97%. Compared to well-known methods such as KNN-DWT and neuro-fuzzy classifier with four beat types, the purposed SVM-DWT exhibited better performance with seven beat types. The purposed method also performs better than MLP-VQ and SOM_SVD algorithms even though they considered two or three beat types only.

Feature work is planned on extending our work using statistical features together with wavelet and temporal features. Including more beat types, heterogeneous multiple classifiers are also within the contents of our future work plans. Additionally, real-time implementation of the developed system in cooperation with

EMU-Faculty of Medicine will be considered as a near- future study to put the system into practical use.

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