1. Introduction

1.1 Overview

Electrocardiogram (ECG) is a nearly periodic signal that reflects the activity of the heart. A lot of information on the normal and pathological physiology of heart can be obtained from ECG. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyse them. Thus the need is there for computer based methods for ECG signal Analysis.

A lot of work has been done in the field of ECG signal Analysis using various approaches and methods. The basic principle of all the methods however involves transformation of ECG signal using different transformation techniques including Fourier Transform, Hilbert Transform, Wavelet transform etc. Physiological signals like ECG are considered to be quasi-periodic in nature. They are of finite duration and non-stationary. Hence, a technique like Fourier series (based on sinusoids of infinite duration) is inefficient for ECG. On the other hand, wavelet, which is a very recent addition in this field of research, provides a powerful tool for extracting information from such signals. There has been use of both Continuous Wavelet Transform (CWT) as well as Discrete Wavelet Transform (DWT).

But our Approach is quite different from them. Firstly, Segmentation of beat is done by detecting the R-peak and correspondingly finding the Q,P,S,T Peaks. Then using Levenberg Marquardt algorithm curve fitting is done on each beat to find their corresponding mean, amplitude and sigma values.Detection of Cardiac problems (Normal Sinus Rhythm, Arythmia, Supraventricular Arythmia, Atrial Fibrillation, ST-change) using Support Vector Machine having 110 features set.

1.2 Motivation

ECG reflects the state of cardiac heart and hence is like a pointer to the health conditions of a human being. ECG, if properly analysed, can provide us information regarding various diseases related to heart. However, ECG being a non-stationary signal, the irregularities may not be periodic and may show up at different intervals. Clinical observation of ECG can hence take long hours and can be very tedious. Moreover, visual analysis cannot be relied upon. This calls for computer-based techniques for ECG analysis. Various contributions have been made in literature regarding beat detection and classification of ECG. Most of these use frequency or time domain representation of ECG signals. But the major problem faced by the coders is the vast variations in the morphologies of ECG signals. Moreover, we have to consider the time constraints as well. Thus our basic objective is to come up with a simple method having less computational time without compromising with the efficiency.

2. Problem Definition And Scope

2.1 Problem Definition

With this project we aim to develop a system that takes ECG data of a person and displays the cardiac problem, he is suffering from .

2.2 Scope

1. Since ECG being a non – stationary signal, the irregularities may not be periodic and may show up at different intervals. Clinical observation of ECG can hence take long hours and can be very tedious. Our software assist doctors to detect Cardinal Problems efficiently and within the time domain.

2. It can also be used at places where specialised doctors are not available.

3. LITERATURE SURVEY

Several techniques have been introduced for ECG beat classification in general, and ST-segment analysis of ECG waves in particular.

1. **Personal computer system for ECG ST-segment recognition based on neural networks [4]:** They developed a ST-segment recognition system based on neural networks with large data sets for training and obtained an average accuracy of 95.7% within a 10ms error. However, a large amount of memory is needed for their learning phase.

2. **Grey Relational Algorithm for ECG Signal Pattern Recognition[8**] : They proposed a learning algorithm for analysing the gray relations between templates and test data set. The database of templates used in this work was large and the system only classified two classes.

3. **Transient ST-Segment Episode Detection for ECG Beat Classification[2]:** They proposed the morphological feature vector including ST-segment information for heart beat classification by supervised learning using the support vector machine approach and classifying six problems i.e. Normal, Venticular, Atrial, Fusion, Right Bundle,and Left Bundle Branch Block beats . Major portion of Problems is left untouched.

4. Description of Hardware and Software Used

Minimum Hardware Configurations

- **Microsoft Windows XP Professional SP3:**
  - **Processor:** 800MHz Intel Pentium III or equivalent
  - **Memory:** 512 MB
  - **Disk space:** 750 MB of free disk space

- **Microsoft Windows Vista SP1:**
  - **Processor:** 800MHz Intel Pentium III or equivalent
  - **Memory:** 512 MB
  - **Disk space:** 750 MB of free disk space

- **Microsoft Windows 7:**
  - **Processor:** 800MHz Intel Pentium III or equivalent
  - **Memory:** 512 MB
  - **Disk space:** 750 MB of free disk space

- **Ubuntu 9.04:**
  - **Processor:** 800MHz Intel Pentium III or equivalent
  - **Memory:** 512 MB
  - **Disk space:** 650 MB of free disk space

- **Solaris OS version 10 (SPARC):**
  - **Processor:** UltraSPARC II 450 MHz
  - **Memory:** 512 MB
  - **Disk space:** 650 MB of free disk space

- **Solaris OS version 10 (x86/x64 Platform Edition):**
  - **Processor:** AMD Opteron 1200 Series 1.8 GHz
  - **Memory:** 512 MB
  - **Disk space:** 650 MB of free disk space

- **Macintosh OS X 10.5 Intel:**
  - **Processor:** Dual-Core Intel
  - **Memory:** 512 MB
  - **Disk space:** 650 MB of free disk space

Recommended Hardware Configurations

- **Microsoft Windows XP Professional SP3:**
  - **Processor:** 2.6 GHz Intel Pentium IV or equivalent
  - **Memory:** 2 GB
  - **Disk space:** 1 GB of free disk space

- **Microsoft Windows Vista SP1:**
  - **Processor:** 2.6 GHz Intel Pentium IV or equivalent
  - **Memory:** 2 GB
  - **Disk space:** 1 GB of free disk space
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- **Microsoft Windows 7:**
  - **Processor:** 2.6 GHz Intel Pentium IV or equivalent
  - **Memory:** 2 GB
  - **Disk space:** 1 GB of free disk space
  -
- **Ubuntu 9.04:**
  - **Processor:** 2.6 GHz Intel Pentium IV or equivalent
  - **Memory:** 2 GB
  - **Disk space:** 850 MB of free disk space

- **Solaris OS version 10 (SPARC):**
  - **Processor:** UltraSPARC IIIi 1 GHz
  - **Memory:** 2 GB
  - **Disk space:** 850 MB of free disk space

- **Solaris OS version 10 (x86/x64 platform edition):**
  - **Processor:** AMD Opteron 1200 Series 2.8 GHz
  - **Memory:** 2 GB
  - **Disk space:** 850 MB of free disk space

- **Macintosh OS X 10.5 Intel:**
  - **Processor:** Dual-Core Intel
  - **Memory:** 2 GB
  - **Disk space:** 850 MB of free disk space

Used

- **Microsoft Windows 7:**
  - **Processor:** 2.3 GHz Intel core i3
  - **Memory:** 3 GB
  - **Disk space:** 150 GB of free disk space

Software

MATLAB

MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. MATLAB is used to analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java™.

MATLAB is used for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology.

Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and Model-Based Design for dynamic and embedded systems.

MATLAB users come from various backgrounds of engineering, science, and economics. MATLAB is widely used in academic and research institutions as well as industrial enterprises.

5. THEORETICAL ASPECTS

5.1 Heart

The heart, located in the mediastinum, is the central structure of the cardiovascular system. It is protected by the bony structures of the sternum anteriorly, the spinal column posteriorly, and the rib cage.

Sinoatrial (SA) node is the dominant pacemaker of the heart, located in upper portion of right atrium. It has an intrinsic rate of 60–100 bpm.

Atrioventricular(AV) node is a part of AV junctional tissue. It slows conduction, creating a slight delay before impulses reach ventricles. It has an intrinsic rate of 40–60 bpm [10].

Table 1: Electrophysiology

Action	Effects
Depolarization	Shifting of electrolytes across the cell membrane causes change in electric charge of the cell. It results in contraction.
Repolarization	Internal negative charge is restored and the cells return to their resting state.

Table 2: Conduction System Structure and Functions

Structure	**Function and Location**
Sinoatrial (SA) Node	Dominant pacemaker of the heart, located in upper portion of right atrium. Intrinsic rate 60–100 bpm.
Internodal Pathways	Direct electrical impulses between SA and AV nodes.
Atrioventricular (AV) node	Part of AV junctional tissue. Slows conduction, creating a slight delay before impulses reach ventricles. Intrinsic rate 40–60 bpm.
Bundle of His	Transmits impulses to bundle branches. Located below AV node.
Left bundle Branch	Conducts impulses that lead to left ventricle.
Right bundle Branch	Conducts impulses that lead to right ventricle.
Purkinje system	Network of fibers that spreads impulses rapidly throughout ventricular walls. Located at terminals of bundle branches.

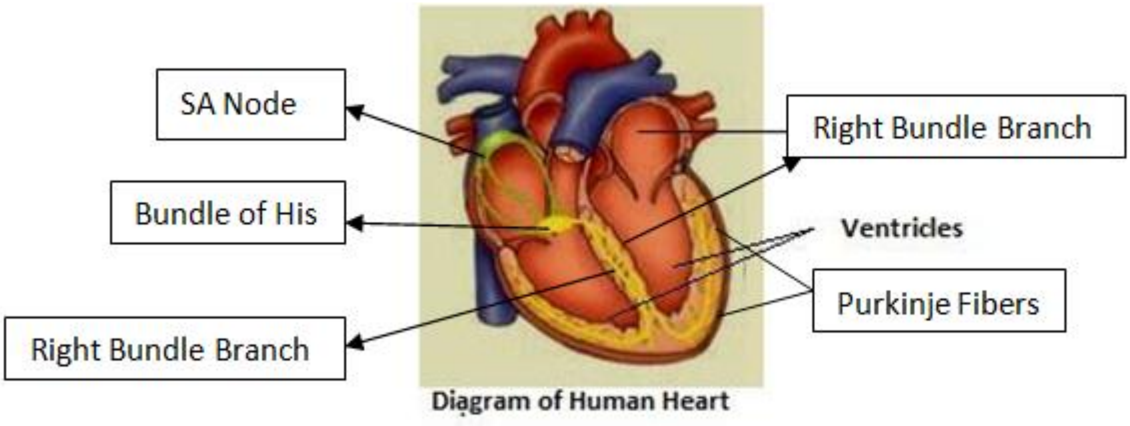


Fig.2 Conduction System structure

The Heart: Phases

There are two phases of the cardiac cycle [10].

Systole: The ventricles are full of blood and begin to contract. The mitral and tricuspid valves close (between atria and ventricles). Blood is ejected through the pulmonic and aortic valves.

Diastole: Blood flows into the atria and through the open mitral and tricuspid valves into the ventricles.

5.2 Electrocardiogram (ECG)

An ECG is a series of waves and deflections recording the heart's electrical activity from a certain "view". Many views, each called a lead, monitor voltage changes between electrodes placed in different positions on the body.

Each cardiac cell is surrounded by and filled with solutions of Sodium (Na+), Potassium (K+), and Calcium (Ca++). The interior of the cell membrane is considered to be negative with respect to outside during resting conditions. When an electric impulse is generated in the heart, the interior part becomes positive with respect to the exterior. This change of polarity is called depolarization. After depolarization the cell comes back to its original state. This phenomenon is called repolarization. The ECG records the electrical signal of the heart as the muscle cells depolarize (contract) and repolarize.

A normal ECG signal is shown in Fig.4.

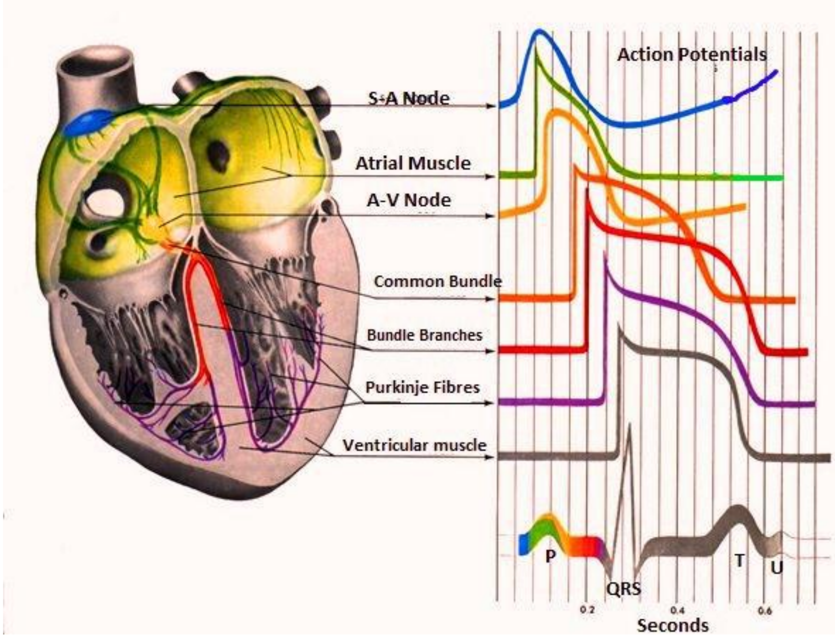


Fig.3The various views of ECG

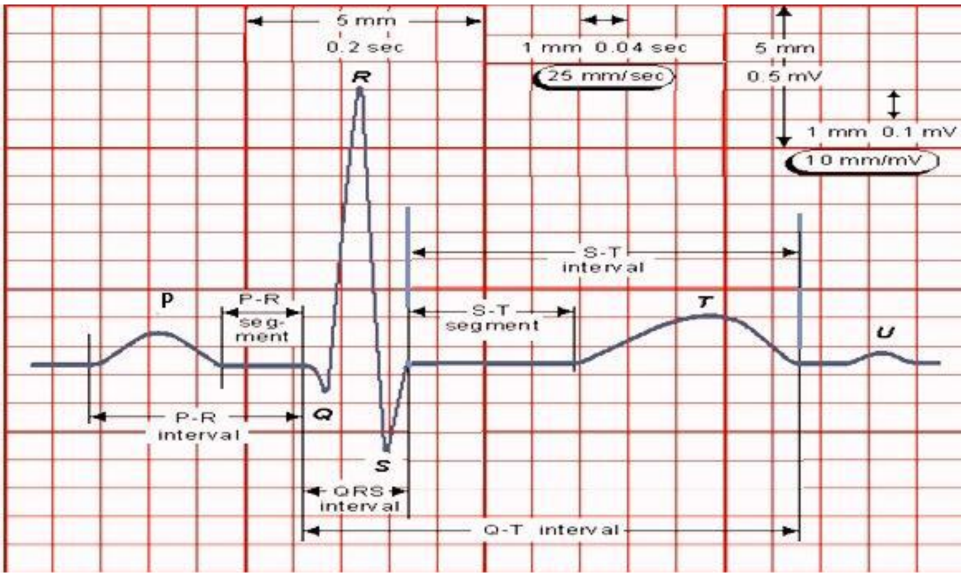


Fig.4. Normal ECG Signal and its various components

The impulses of the heart are recorded as waves called P-QRS-T deflections.

The following is the description and significance of each deflection and segment [10].

PR Interval measures time during which a depolarization wave travels from the atria to the ventricles.

QRS Interval includes three deflections following P wave which indicates ventricular depolarization (and contraction). Q wave is the first negative deflection while R wave is the first positive deflection. S wave indicates the first negative deflection after R wave.

ST Segment measures the time between ventricular depolarization and beginning of repolarization.

T wave represents ventricular repolarization.

QT Interval represents total ventricular activity.

5.3 Arrhytmia

Normally, the SA Node generates the initial electrical impulse and begins the cascade of events that result in a heart-beat. For a normal healthy person the ECG comes off as a nearly periodic signal with depolarization followed by repolarization at equal intervals. However, sometimes this rhythm becomes irregular.

Cardiac arrhythmia (also dysrhythmia) is a term for any of a large and heterogeneous group of conditions in which there is abnormal electrical activity in the heart. The heart beat may be too fast or too slow, and may be regular or irregular.

Arrthymia comes in varieties. It may be described as a flutter in chest or sometimes “racing heart”. The diagnosis of Arrthymia requires Electrocardiogram. By studying ECG, Doctors can diagnose the disease and prescribe the required medications.

5.4 Wavelet Transform

Wavelets are a powerful tool for the representation and analysis of ECG signal. They have been implemented for the analysis of physiological waveforms like ECG, Phonocardiogram etc. This is because wavelet has finite duration as compared to Fourier methods based on sinusoids of infinite duration.

Wavelet Transform involves the decomposition of signal into various components. They provide both time and frequency view. Unlike Fourier transform, they are very efficient for non-stationary signals like ECG.

The Fourier Transform is a widely used tool for many scientific purposes but it is well suited for stationary signals. Gabor introduced a local Fourier analysis. He used the concept of a sliding window. This method, however, gives results when the coherence time is independent of frequency. Morlet introduced Wavelet Transform to have a coherence time proportional to the period. In Wavelet Transform, a fully scalable modulated window is used which solves the signal-cutting problem. The window is shifted along the signal. Spectrum is calculated for every position. This process is repeated by varying the length of the window. So we have a collection of representations, hence the name multi-resolution analysis.

5.4.1 Continuous Wavelet Transform

Wavelet transforms are applied to decompose the signal into a set of coefficients that describe the signal frequency content at given times. The continuous wavelet transform of the signal, x(t), is defined as [3]:

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

Here Ψ(t) is the analyzing wavelet function
a is the dilation parameter and
b is the location parameter of the wavelet

Actually the wavelets are generated from a single basic wavelet Ψ(t), the so called mother wavelet, by scaling and translation.

$$\Psi s,\tau\,(t) = \frac{1}{\sqrt{s}}\,\Psi\left(\frac{t-\tau}{s}\right) \qquad (2)$$

Here τ is the scaling factor and √ (1/s) is for normalization across the different scales. Due to the scaling and translation, Wavelet Transform is localized in both time and frequency.

Several Mother Wavelets like Mexican-hat and Morlet have been used in ECG signal analysis. The mother wavelet has a lot of significance for the efficiency of the process. In this project we have used Haar Wavelet as the mother wavelet. We have gone for Haar wavelet because the oscillatory nature of other mother wavelets results in several ridges for each ECG component, while only one pair of ridges is generated via the Haar wavelet due to its configuration.

5.4.2 Daubechies Wavelets: *dbN*

In *dbN*, *N* is the order. Some authors use 2*N* instead of *N*. More about this family can be found in [Dau92] pages 115, 132, 194, 242. By typing waveinfo('db), at the MATLAB command prompt, you can obtain a survey of the main properties of this family.

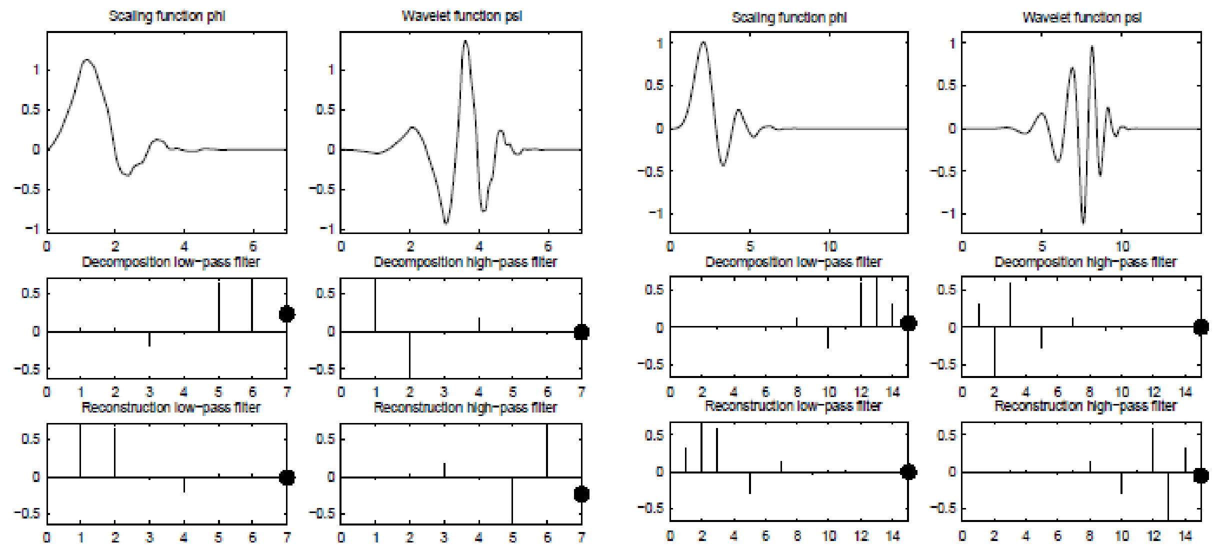


Figure 6-12: Daubechies Wavelets db4 on the Left and db8 on the Right

This family includes the Haar wavelet, written *db*1, the simplest wavelet imaginable and certainly the earliest. Using waveinfo('haar'), you can obtain a survey of the main properties of this wavelet.

Haar

$$\psi(x) = 1, \quad \text{if} \quad x \in [0, 0.5[$$

$$\psi(x) = -1, \quad \text{if} \quad x \in [0.5, 1[$$

$$\psi(x) = 0, \quad \text{if} \quad x \notin [0, 1[$$

$$\phi(x) = 1, \quad \text{if} \quad x \in [0, 1]$$

$$\phi(x) = 0, \quad \text{if} \quad x \notin [0, 1]$$

dbN

These wavelets have no explicit expression except for *db*1, which is the *Haar* wavelet. However, the square modulus of the transfer function of *h* is explicit and fairly simple.

- Let $P(y) = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k$, where C_k^{N-1+k} denotes the binomial coefficients.

Then

$$|m_0(\omega)|^2 = \left(\cos^2\left(\frac{\omega}{2}\right)\right)^N P\left(\sin^2\left(\frac{\omega}{2}\right)\right)$$

$$\text{where } m_0(\omega) = \frac{1}{\sqrt{2}}\sum_{k=0}^{2N-1} h_k e^{-ik\omega}$$

- The support length of ψ and ϕ is $2N$ - 1. The number of vanishing moments of ψ is N.
- Most *dbN* are not symmetrical. For some, the asymmetry is very pronounced.
- The regularity increases with the order. When N becomes very large, ψ and ϕ belong to $C^{\mu N}$ where μ is approximately equal to 0.2. Certainly, this asymptotic value is too pessimistic for small-order N. Note that the functions are more regular at certain points than at others.
- The analysis is orthogonal.

We have chosen CWT over DWT because unlike DWT there is no dyadic frequency jump in Continuous wavelet transform [3]. Also high resolution in time-frequency domain is achieved.

5.5 Correlation Coefficient

Correlation is the phenomena to established relation between two variables. It may be positive relationship, negative relationship or no relationship. If one variable increases as the other variable increases then a positive relationship is there. If one variable increases as the other variable decreases then it is a negative relationship**.** Correlation shows relationship between two variables. But it does not show how strong the relationship is. A single number which determine how strong the relationship between two variables or how closely one variable related to other variable we use correlation coefficient .

The following mathematical formula is used to compute the correlation coefficient between X and Y, where, X and Y are matrices or vectors of the same size.

$$r = \frac{\sum_m \sum_n (X_{mn} - \overline{X})(Y_{mn} - \overline{Y})}{\sqrt{\left(\sum_m \sum_n (X_{mn} - \overline{X})^2\right)\left(\sum_m \sum_n (Y_{mn} - \overline{Y})^2\right)}}$$

Where, $\overline{X} = mean\ of\ X$ and $\overline{Y} = mean\ of\ Y$

5.6 Levenberg-Marquardt algorithm

In mathematics and computing, the Levenberg–Marquardt algorithm (LMA), also known as the damped least-squares (DLS) method, provides a numerical solution to the problem of minimizing a function, generally nonlinear, over a space of parameters of the function. These minimization problems arise especially in least squares curve fitting and nonlinear programming.
The LMA interpolates between the Gauss–Newton algorithm (GNA) and the method of gradient descent. The LMA is more robust than the GNA, which means that in many cases it finds a solution even if it starts very far off the final minimum. For well-behaved functions and reasonable starting parameters, the LMA tends to be a bit slower than the GNA. LMA can also be viewed as Gauss–Newton using a trust region approach.
The LMA is a very popular curve-fitting algorithm used in many software applications for solving generic curve-fitting problems. However, the LMA finds only a local minimum, not a global minimum.

The problem

The primary application of the Levenberg–Marquardt algorithm is in the least squares curve fitting problem: given a set of m empirical datum pairs of independent and dependent variables, (x_i, y_i), optimize the parameters β of the model curve $f(x,\boldsymbol{\beta})$ so that the sum of the squares of the deviations
becomes minimal.

$$S(\boldsymbol{\beta}) = \sum_{i=1}^{m} [y_i - f(x_i,\ \boldsymbol{\beta})]^2$$

The solution

Like other numeric minimization algorithms, the Levenberg–Marquardt algorithm is an iterative procedure. To start a minimization, the user has to provide an initial guess for the parameter vector, $\boldsymbol{\beta}$. In cases with only one minimum, an uninformed standard guess like $\boldsymbol{\beta}^T=(1,1,...,1)$ will work fine; in cases with multiple minima, the algorithm converges only if the initial guess is already somewhat close to the final solution.

In each iteration step, the parameter vector, $\boldsymbol{\beta}$, is replaced by a new estimate, $\boldsymbol{\beta} + \boldsymbol{\delta}$. To determine $\boldsymbol{\delta}$, the functions $f(x_i, \boldsymbol{\beta} + \boldsymbol{\delta})$ are approximated by their linearizations

$$f(x_i, \boldsymbol{\beta} + \boldsymbol{\delta}) \approx f(x_i, \boldsymbol{\beta}) + J_i\boldsymbol{\delta}$$

where

$$J_i = \frac{\partial f(x_i, \boldsymbol{\beta})}{\partial \boldsymbol{\beta}}$$

is the gradient (row-vector in this case) of f with respect to $\boldsymbol{\beta}$.

At the minimum of the sum of squares, $S(\beta)$, the gradient of S with respect to $\boldsymbol{\delta}$ will be zero. The above first-order approximation of $f(x_i, \boldsymbol{\beta} + \boldsymbol{\delta})$ gives

$$S(\boldsymbol{\beta} + \boldsymbol{\delta}) \approx \sum_{i=1}^{m} (y_i - f(x_i, \boldsymbol{\beta}) - J_i\boldsymbol{\delta})^2$$

.

Or in vector notation,

$$S(\boldsymbol{\beta} + \boldsymbol{\delta}) \approx \|\mathbf{y} - \mathbf{f}(\boldsymbol{\beta}) - \mathbf{J}\boldsymbol{\delta}\|^2$$

.

Taking the derivative with respect to $\boldsymbol{\delta}$ and setting the result to zero gives:

$$(\mathbf{J^T J})\boldsymbol{\delta} = \mathbf{J^T}[\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]$$

where $\mathbf{J}$ is the Jacobian matrix whose i^{th} row equals J_i, and where $\mathbf{f}$ and $\mathbf{y}$ are vectors with i^{th} component $f(x_i, \boldsymbol{\beta})$ and y_i, respectively. This is a set of linear equations which can be solved for $\boldsymbol{\delta}$.

Levenberg's contribution is to replace this equation by a "damped version",

$$(\mathbf{J^T J} + \lambda\mathbf{I})\boldsymbol{\delta} = \mathbf{J^T}[\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})]$$

where $\mathbf{I}$ is the identity matrix, giving as the increment, $\boldsymbol{\delta}$, to the estimated parameter vector, $\boldsymbol{\beta}$.

The (non-negative) damping factor, λ, is adjusted at each iteration. If reduction of S is rapid, a smaller value can be used, bringing the algorithm closer to the Gauss–Newton algorithm, whereas if an iteration gives insufficient reduction in the residual, λ can be increased, giving a step closer to the gradient descent direction. Note that the gradient of S with respect to $\boldsymbol{\beta}$ equals $-2(\mathbf{J}^T[\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})])^T$. Therefore, for large values of λ, the step will be taken approximately in the direction of the gradient. If either the length of the calculated step, $\boldsymbol{\delta}$, or the reduction of sum of squares from the latest parameter vector, $\boldsymbol{\beta} + \boldsymbol{\delta}$, fall below predefined limits, iteration stops and the last parameter vector, $\boldsymbol{\beta}$, is considered to be the solution.

Levenberg's algorithm has the disadvantage that if the value of damping factor, λ, is large, inverting $\mathbf{J}^T\mathbf{J} + \lambda\mathbf{I}$ is not used at all. Marquardt provided the insight that we can scale each component of the gradient according to the curvature so that there is larger movement along the directions where the gradient is smaller. This avoids slow convergence in the direction of small gradient. Therefore, Marquardt replaced the identity matrix, **I**, with the diagonal matrix consisting of the diagonal elements of $\mathbf{J}^{\mathrm{T}}\mathbf{J}$, resulting in the Levenberg–Marquardt algorithm:

$$(\mathbf{J}^{\mathbf{T}}\mathbf{J} + \lambda\,\mathbf{diag}(\mathbf{J}^{\mathbf{T}}\mathbf{J}))\boldsymbol{\delta} = \mathbf{J}^{\mathbf{T}}[\mathbf{y} - \mathbf{f}(\boldsymbol{\beta})].$$

5.7 Support Vector Machine

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

In addition to performing linear classification, SVMs can efficiently perform non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

5.8 Pearson’s chi-squared test

Pearson's chi-squared test is used to assess two types of comparison: tests of goodness of fit and tests of independence.

- A test of **goodness of fit** establishes whether or not an observed frequency distribution differs from a theoretical distribution.
- A **test of independence** assesses whether paired observations on two variables, expressed in a contingency table, are independent of each other (e.g. polling responses from people of different nationalities to see if one's nationality affects the response).

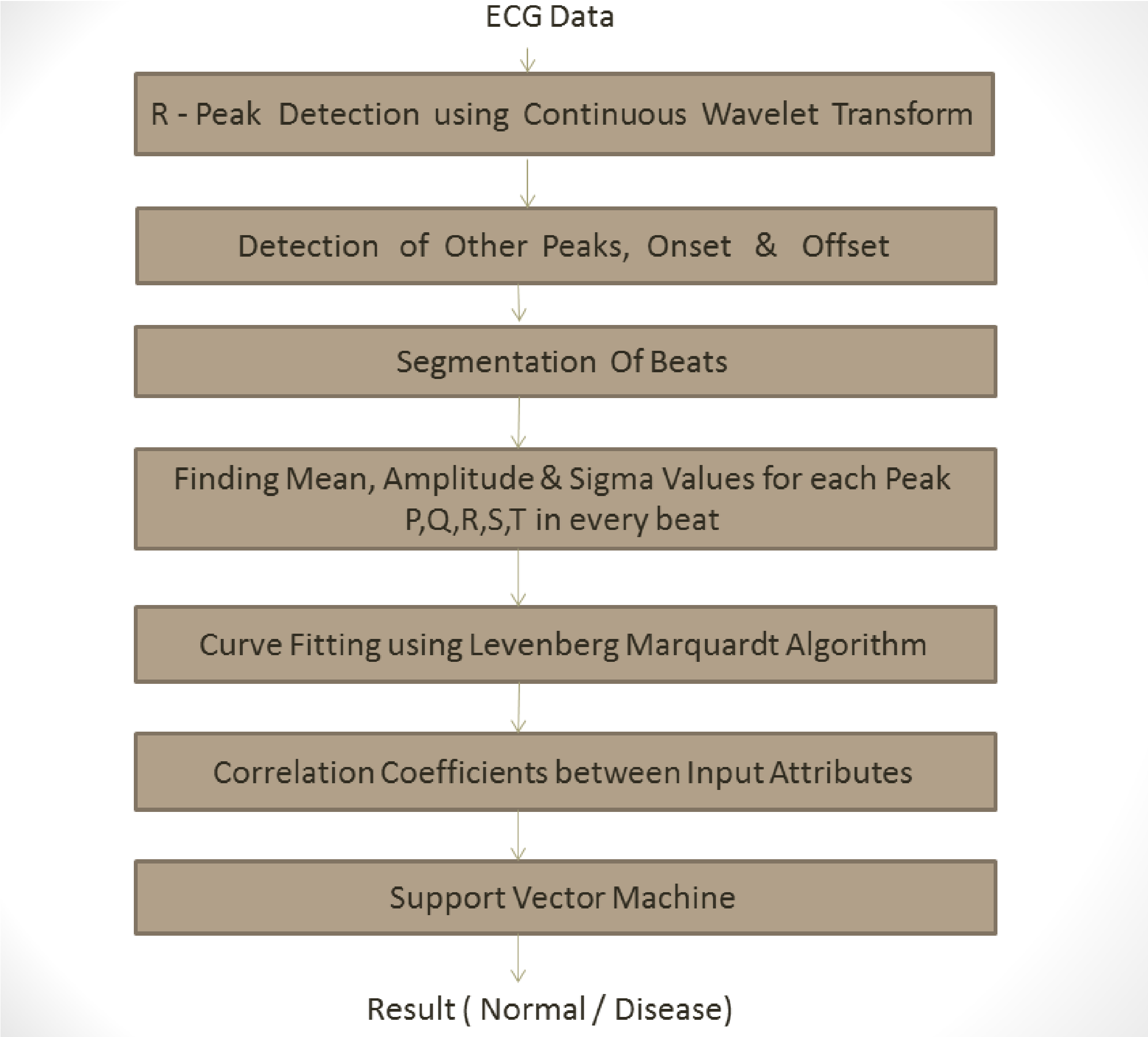
The procedure of the test includes following steps:

1. Calculate the chi-squared test statistic, X^2, which resembles a normalized sum of squared deviations between observed and theoretical frequencies (see below).
2. Determine the degrees of freedom, *d*, of that statistic, which is essentially the number of frequencies reduced by the number of parameters of the fitted distribution.

3. Compare X^2 to the critical value from the chi-squared distribution with *d* degrees of freedom, which in many cases gives a good approximation of the distribution of X^2

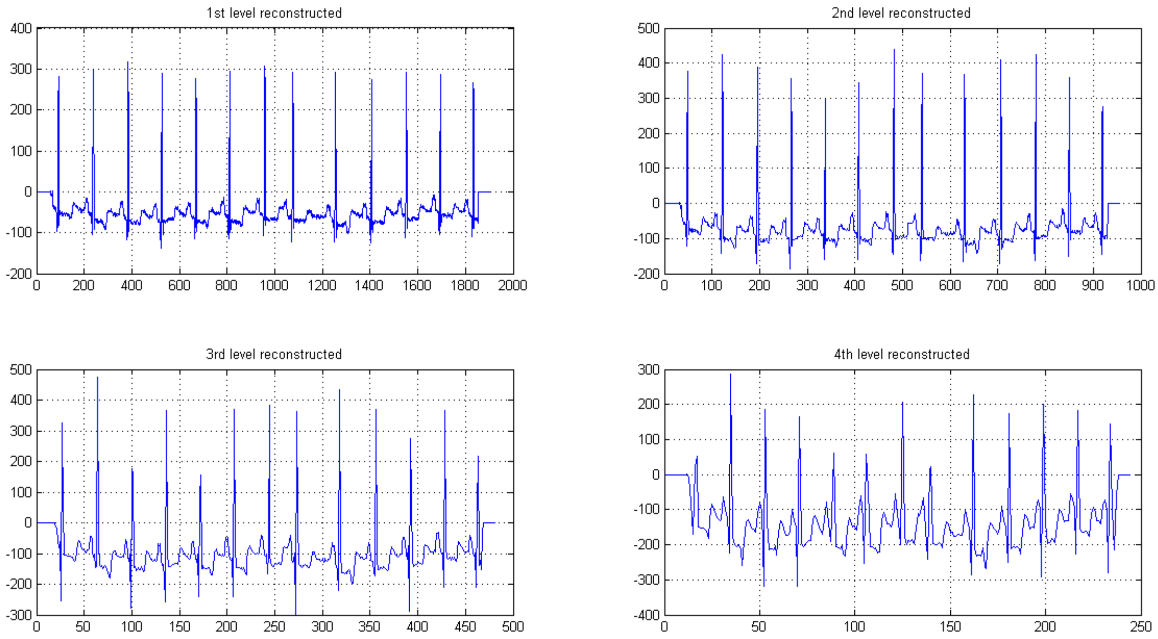
6. METHODOLOGY

The whole algorithm can be divided into seven main stages which are shown in fig.

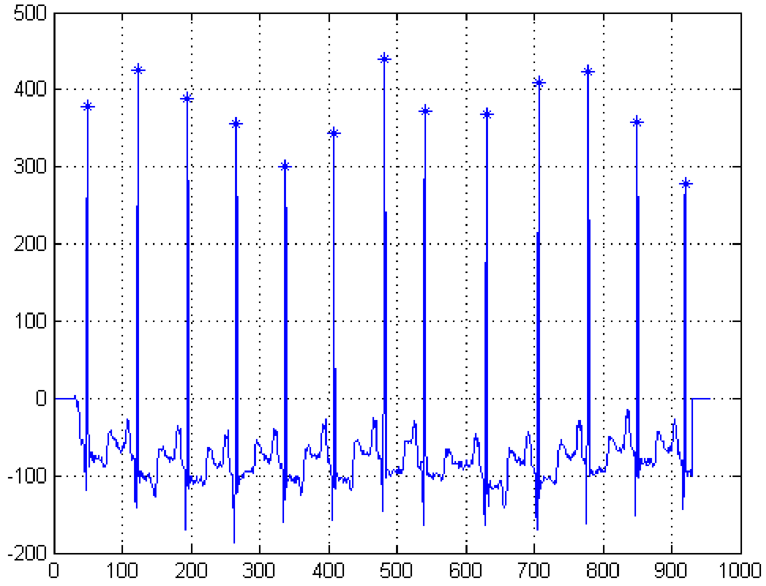


6.1 R-Peak Detection Using Continuous Wavelet Transform

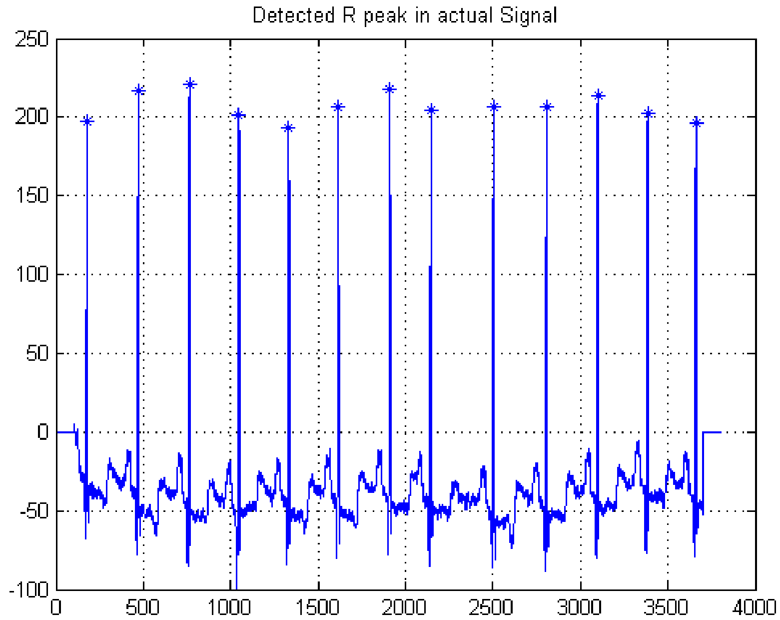
The key of the wavelet denoising is to filter out the wavelet coefficients produced by noises, particularly the detail coefficients corresponding to high-frequency components. The optimal denoising requires a more subtle approach called thresholding to involve discarding only the portion of the detail coefficients that exceeds a certain limit. It is obvious that the choice of thresholding functions and threshold values directly influences the efficiencies of the denoising algorithm. For example, too high a threshold could destroy many detail components of the original signal, while too low a threshold could not achieve the expected denoising effects. Thus, appropriate threshold values should be chosen and applied to the detail coefficients. In general, four threshold selection rules, i.e., universal, minimax, Stein's unbiased risk estimator and hybrid, and two threshold functions, i.e., hard and soft, have been frequently used for noise reduction. In this study, the Daubechies Db4 type wavelet was selected as a mother wavelet (Singh & Tiwari, 2006) and the ECG signal was decomposed at scale 2. The universal threshold was selected as a threshold selection rule and the soft threshold function was applied to the detail coefficients.



From the 2nd level reconstructed plot R-peak is detected using threshold value of 50% from the maximum value. Then these points from 2nd level reconstructed plot are mapped into the "Actual Signal" to find the R-peaks in the actual signal.



R-Peak in 2nd level Reconstructed plot

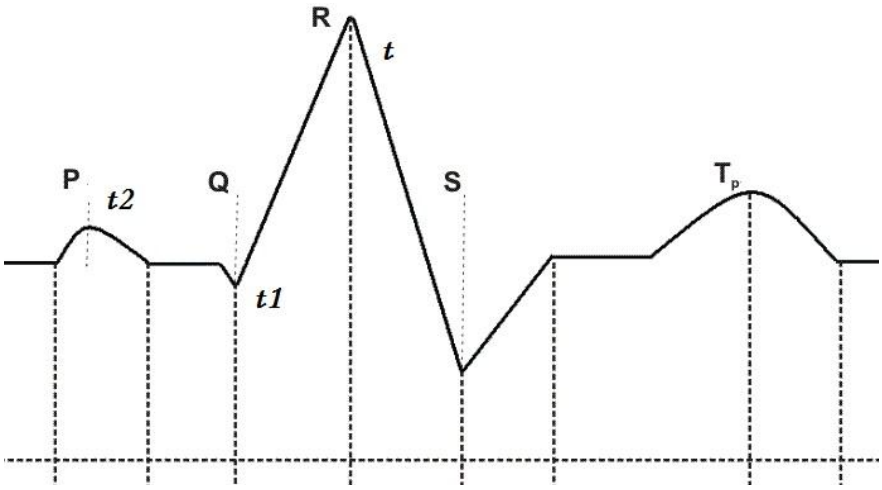


R-Peak in Actual Signal

6.2 Detection Of Other Peaks , Onset And Offset

6.2.1 Q-Peak Detection

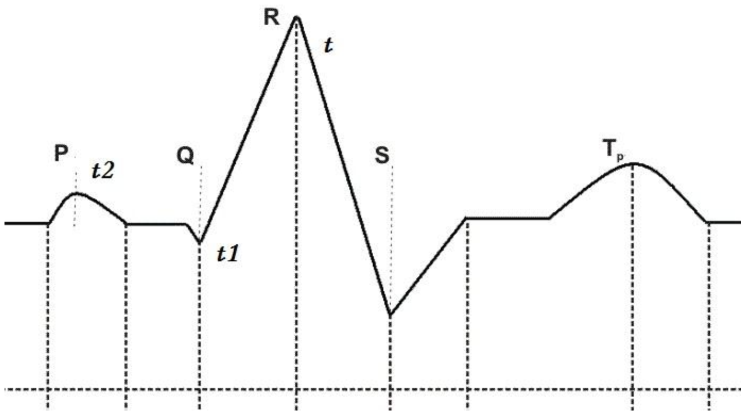
Q - Peak is found within the 1/10th of the R-R distance from R-peak . Using this distance, the minimum point within this range before R-peak is termed as Q-Peak. And From there, Onset and Offset for the Q-peak is detected.



←1/10th R-R→

6.2.2 P-Peak Detection

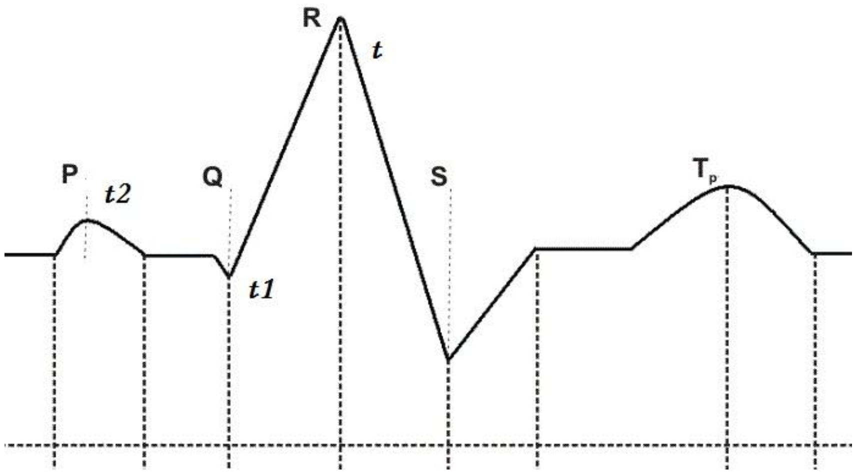
P - Peak is found within the 1/2th of the R-R distance from R-peak before the Onset of the Q-Peak. Using this distance, the maximum point within this range before R-peak is termed as P-Peak. And From there, Onset and Offset for the P-peak is detected. Onset of P-peak is used as a Cut –Point from where the beat is segmented (starting of beat) .



←1/2th of R-R Distance→

6.2.3 S-Peak Detection

S - Peak is found within the 1/10 th of the R-R distance from R-peak . Using these distance, the minimum point within this range after R-peak is termed as S-Peak. And From there, Onset and Offset for the S-peak is detected.

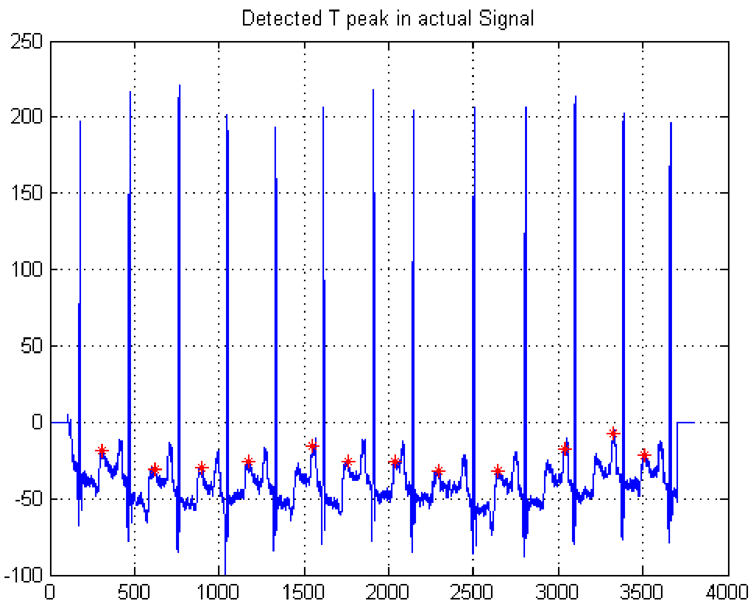


←1/10th of R-R →

6.2.4 T-Peak Detection

1. Continuous Wavelet Transform is applied on the data in the range from S-peak Offset to Cut – Point of Another Beat using DB2 as the mother wavelet at scale 2.

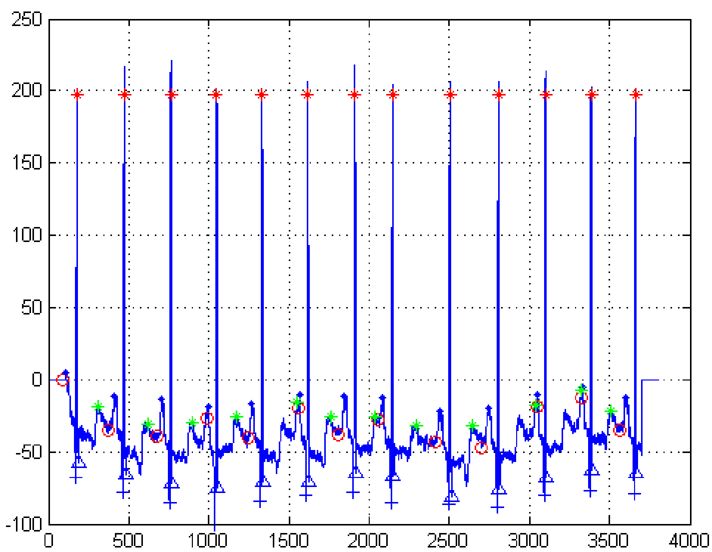
2. From the 2nd level reconstructed plot, T-peak is detected using threshold value 60% from the maximum value. Then these points from 2nd level reconstructed plot are mapped into the "Actual Signal" to find the T-peaks in the actual signal.



This is how All the peaks with their Onset and Offset values are Calculated. Detection of all peaks is done so that while applying levenberg marquardt algorithm having five Gaussian function ,Amplitude Mean and Sigma values for these five peaks can be used for initialisation of Curve fitting algorithm to increase the efficiency of the Curve Fitting Algorithm.

6.3 Segmentation of Beats

These Cut points (Onset of P-Peak) is marked as the beginning of the Beat.That is how beat is segmented.



Segmented ECG Beat
(“ o ” denotes Cut Points in fig)

6.4 Calculate Mean, Amplitude and Sigma for Each Peak in Every Beat

Mean, Amplitude and Sigma for Each Peak in Every Beat is calculated as shown in fig.

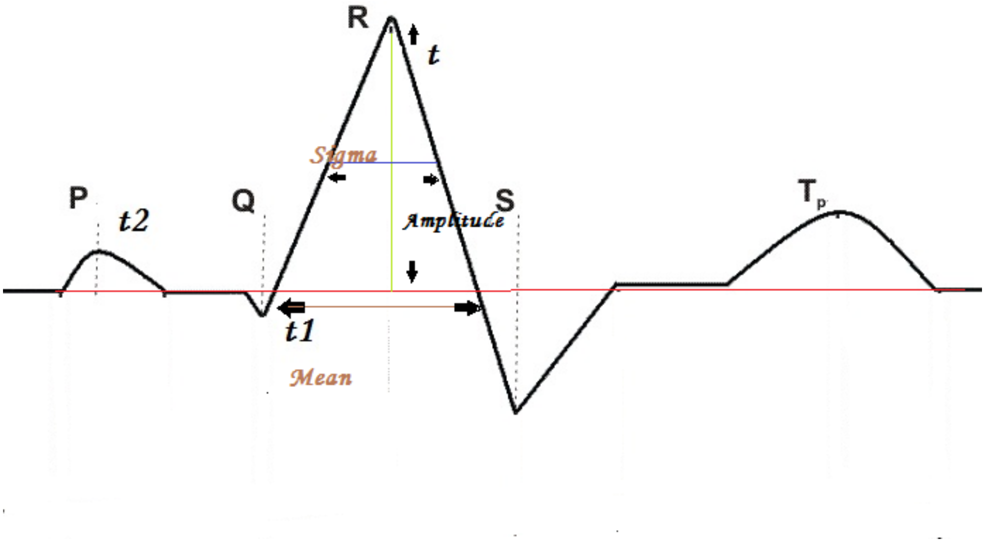


Fig 10.
Amplitude, Mean And Sigma Detection

Mean, Amplitude and Sigma from these five peaks can be used for initialisation of Curve fitting algorithm to increase the efficiency of the Curve Fitting Algorithm.

6.5 Curve Fitting Using Levenberg Marquardt Algorithm

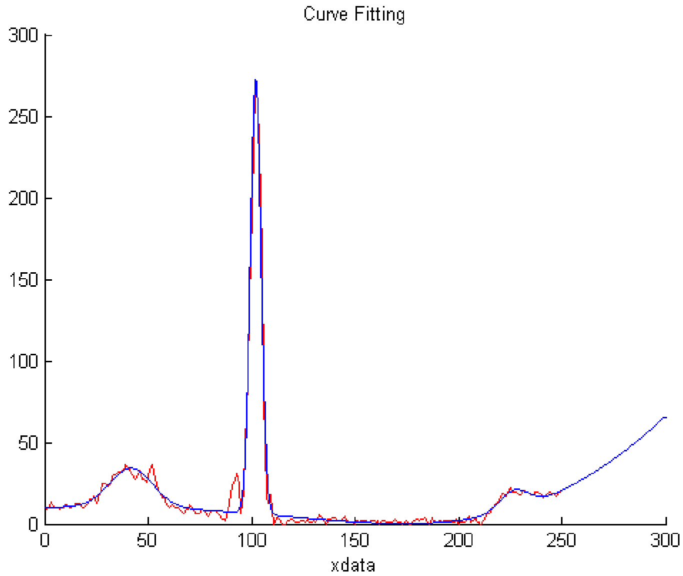
The aim of curve fitting is to find a best fit mathematical function for the data. The standard way of finding the best fit is to choose the parameters of the function that would minimize the deviations of the theoretical curve from the experimental points. This method is also called "chi-square minimization". Chi-square is defined as follows:

$$\chi^2 = \sum_{i=1}^{n} w_i \left[Y_i - f\left(x_i^{'}; \hat{\theta} \right) \right]^2$$

where $x_i^{'}$ is the row vector for the i^{th} (i = 1, 2,...,n) observation; $\hat{\boldsymbol{\theta}}$ are the parameters we need to compute; w_i is the i^{th}weight.

For nonlinear fitting Levenberg-Marquardt algorithm iteratively adjust the parameters to get the minimum chi-square value.

Heart Beats are modelled using Levenberg Marquardt Algorithm .Each heartbeat is divided into five Gaussian.



Curve Fitting using LevenBerg Marquardt Algorithm

Actual Amplitude, Mean and Sigma for each beat is calculated from the function obtained which is used for finding Correlation coefficients between these values.

6.6 Correlation Coefficient using Input Variables

Correlation is the phenomena to established relation between two variables. It may be positive relationship, negative relationship or no relationship. If one variable increases as the other variable increases then a positive relationship is there. If one variable increases as the other variable decreases then it is a negative relationship**.** Correlation shows relationship between two variables.

Finding correlation coefficient between each value as shown ig fig.

	PA	QA	RA	SA	TA	PM	QM	RM	SM	TM	PS	QS	RS	SS	TS
PA															
QA															
RA															
SA															
TA															
PM															
QM															
RM															
SM															
TM															
PS															
QS															

RS															
SS															
TS															

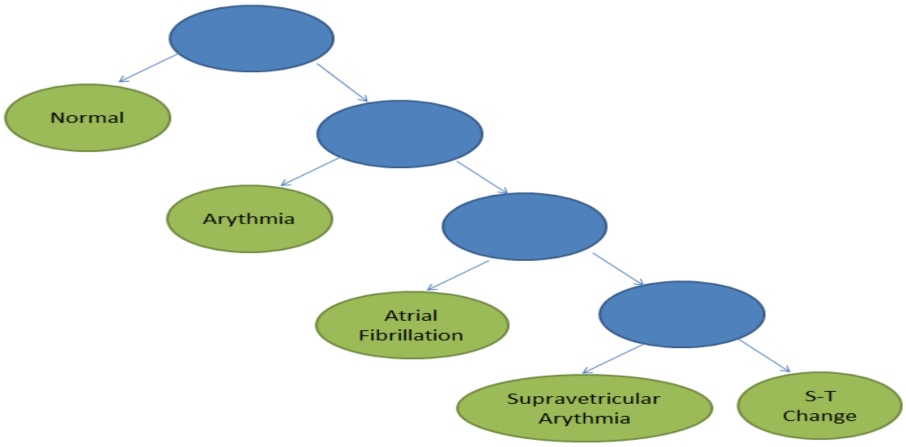
Correlation Coefficient between Each Values
A-amplitude
M-mean
S-sigma

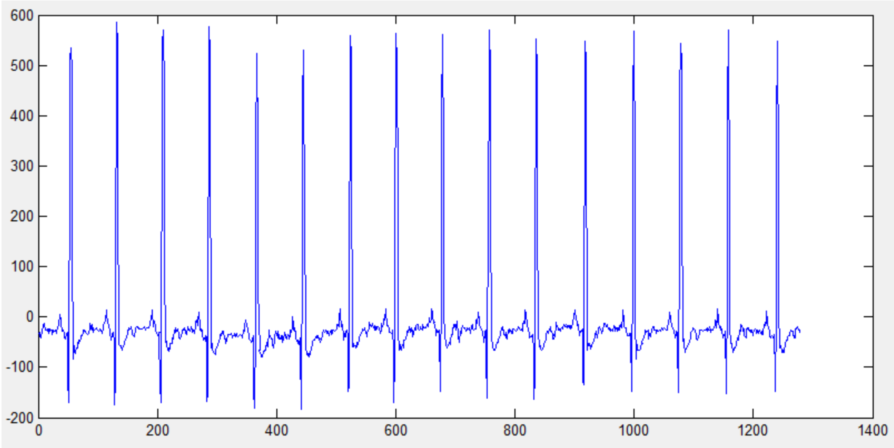
6.7 Classification using Support Vector Machine

Features used for classifying the ECG data are:
1. P-R distance
2. R-R distance
3. S- T distance
4. Amplitude of S-Peak
5. Amplitude of T-Peak
6. 105 Correlation Coefficient obtained from 6th Step.

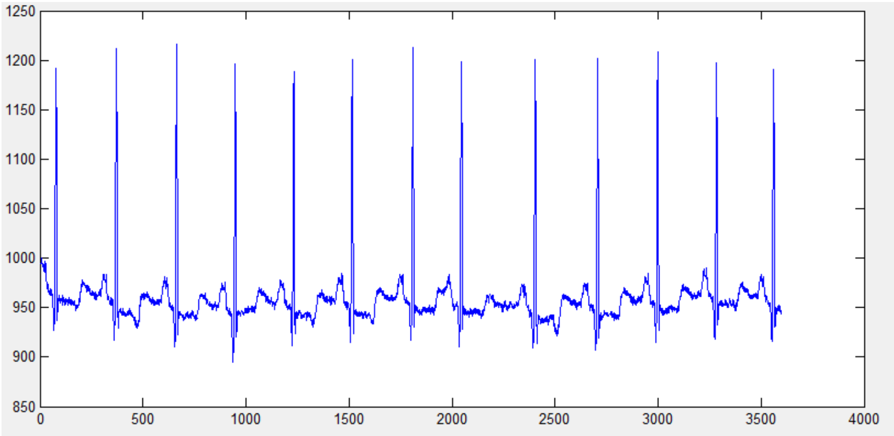
Using these 110 features we classify the ECG data whether it belongs in Normal or Disease. Classifier classify the data into 5 classes:
1. Normal Sinus Rhythm
2. Arythmia
3. Atrial Fibrillation
4. Supraventricular Arythmia
5. S-T Change

For classification, Binary SVM classifier is used and the hierarchy is shown as in fig.

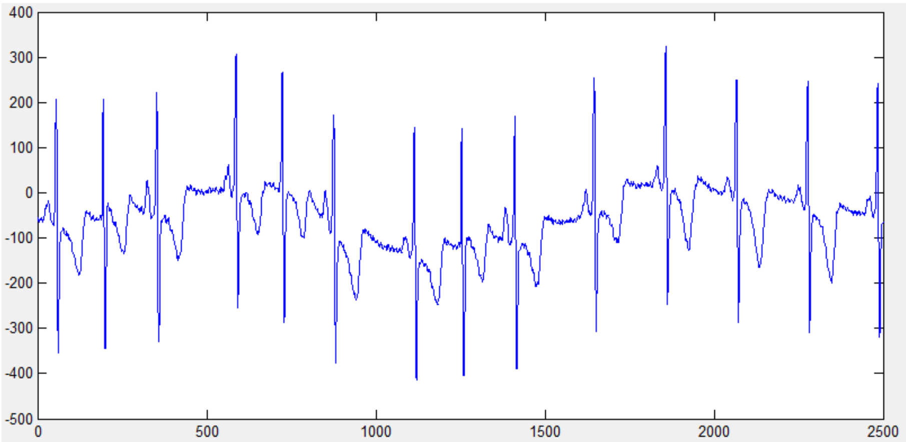




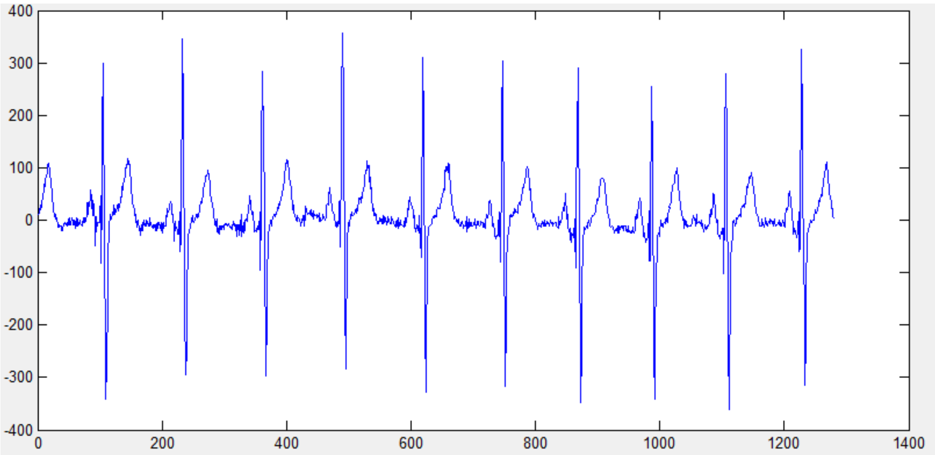
Normal Sinus Rhythm



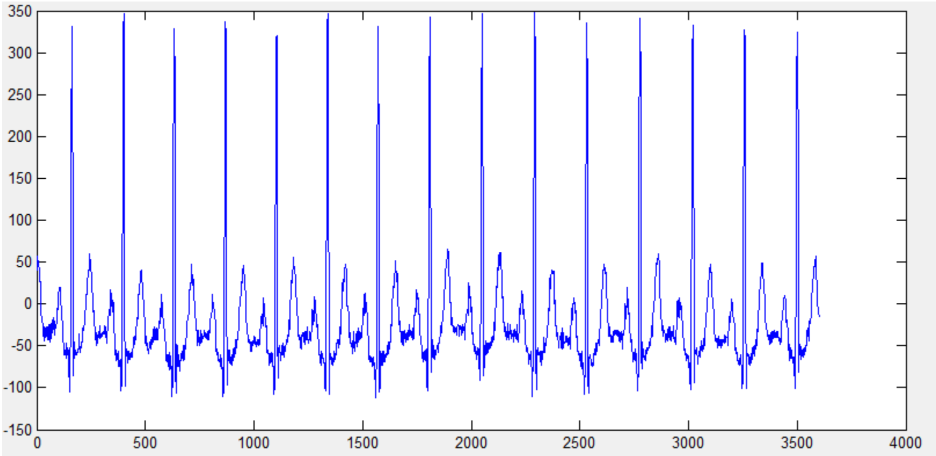
Arythmia



Atrial Fibrillation



Supraventricular Arythmia



S-T Change

7. Evaluation

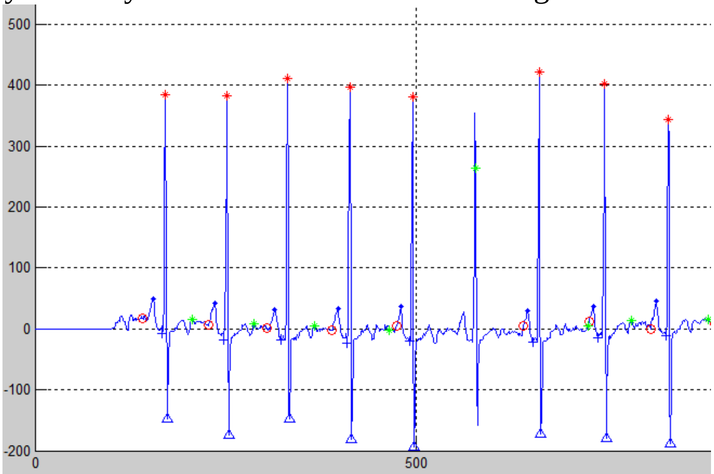
Evaluation of the project is divided into 3 sections which are described below:

7.1 Segmentation of ECG Beat

The proposed ECG beat segmentation method was tested on all Normal, Arythmia, Atrial Fibrillation, Supraventricular arythmia and S-T change from the MITDB.

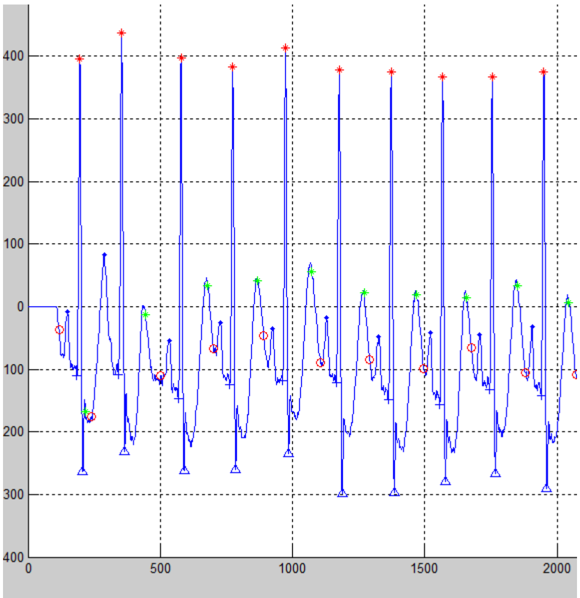
Normal Sinus Rhythm

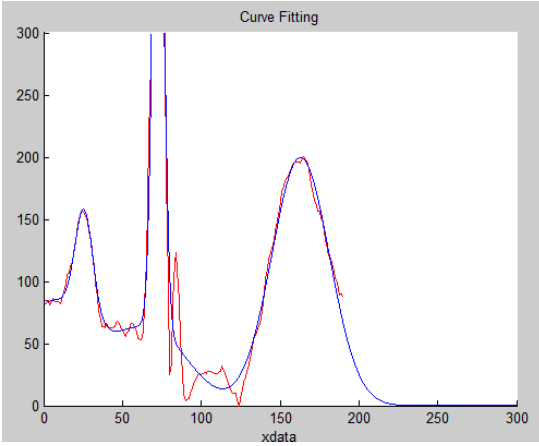
The algorithm concluded 91% of the beats are properly segmented. It detected all the 8 beats correctly and only 1 beat incorrect as shown in fig.



Arythmia

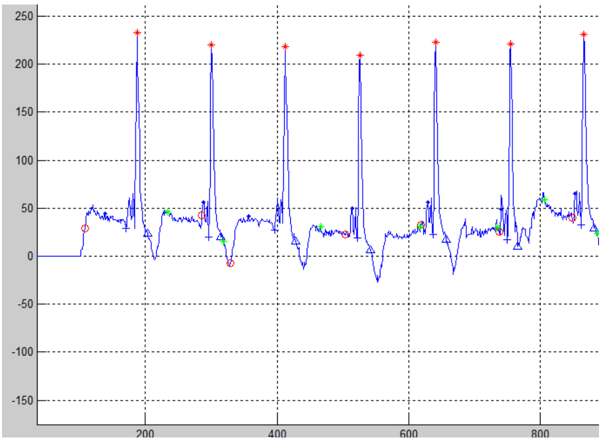
The algorithm concluded 90% of the beats are properly segmented as shown in fig. Though it detect Cut – Point sometimes wrong but due to curve fitting algorithm they were fixed as shown in fig.





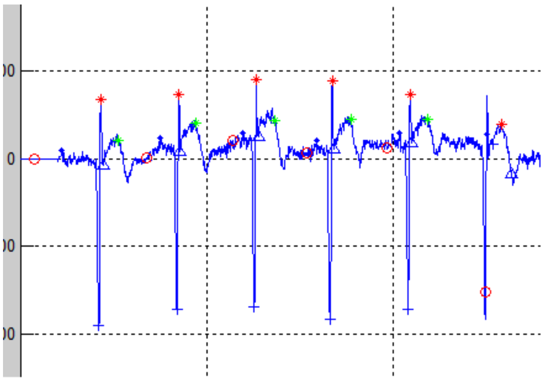
SupraVentricular Arythmia

The algorithm concluded 88% of the beats are properly segmented. It detected all the 7 R-peaks correctly but among 7 Cut – Points only 1 Cut-Point incorrect as shown in fig.



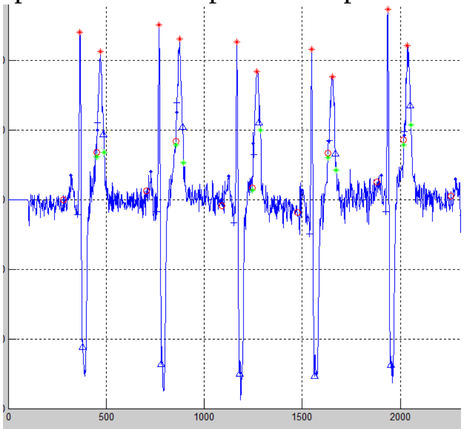
Atrial Fibrillation

The algorithm concluded 85% of the beats are properly segmented. It detected all 5 R-peaks correctly but 1 R-peak incorrect and among 6 Cut – Points, only 1 Cut-Point incorrect as shown in fig.



S-T Change

The algorithm concluded 70% of the beats are properly segmented. It detected all the T-peak of comparable amplitude with R-peak as R-peak as shown in fig



Segmentation of beat with their accuracy are summarized in the table.

RECORDS	ACCURACY (%)
Normal Sinus Rhythm	91
Arythmia	90
Atrial Fibrillation	85
Supraventricular Arythmia	88
S-T Change	70

7.2 Mathematical model for curve fitting

Calculating the test-statistic

The value of the test-statistic is

$$X^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

where

X^2 = Pearson's cumulative test statistic, which asymptotically approaches a χ^2 distribution.

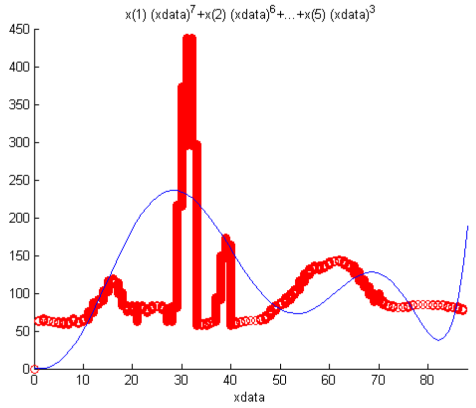
O_i = an observed (model) value

E_i = an expected (actual) value

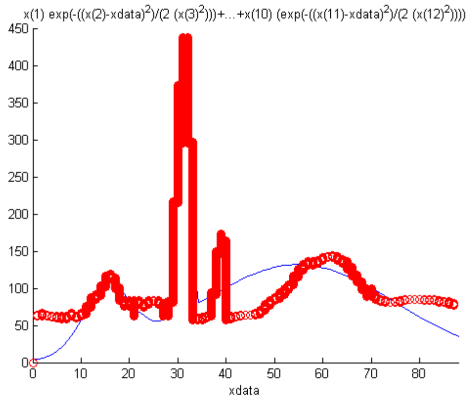
n = the number of data points in sample.

Model Function Used (for beat)	Average Chi Square Value (X2)
Polynomial (degree 7)	14.9
4 Gaussian Curves	8.7
5 Gaussian Curves	5.5
6 Gaussian Curves	11.3

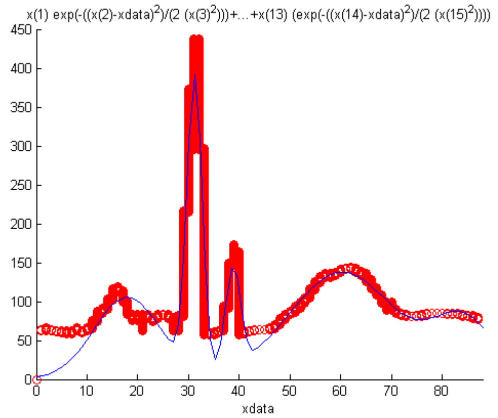
Curve fitting in various models are shown in fig



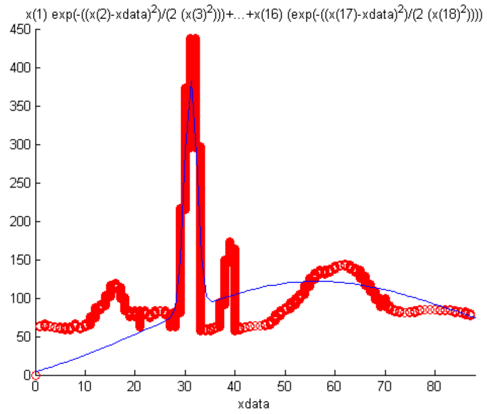
Polynomial(7 degree)



4 Gaussian Curves



5 Gaussian Curves



6 Gaussian Curves

7.3 Classification of Cardiac Diseases

The waveforms of five different ECG beats are classified in the present study. For the fine diagnostic classes (normal beat, arythmia, Supraventricular arythmia beat, atrial fibrillation beat, S-T change) training and test sets were formed by 170 vectors of 110 dimensions (extracted feature vectors).

RECORDS	**Training Set**
Normal Sinus Rhythm	25
Arythmia	25
Atrial Fibrillation	25
Supraventricular Arythmia	25
S-T Change	25

In classification, the aim is to assign the input patterns to one of several classes, usually represented by outputs restricted to lie in the range from 0 to 1, so that they represent the probability of class membership. While the classification is carried out, a specific pattern is assigned to a specific class according to the characteristic features selected for it. In this application, there were five classes: Normal Beat, Arythmia, Supraventricular Arythmia Beat, Atrial Fibrillation Beat, S-T Change. Classification results of the Support Vector Machine were displayed by a confusion matrix. The confusion matrix showing the classification results of the Support Vector Machine is given below.

Output/Desired	Normal	Arythmia	Atrial Fibrillation	Supraventricular Arythmia	S-T Change
Normal	14	1			
Arythmia		17		2	1
Atrial Fibrillation		2	13		
Supraventricular Arythmia				16	4
S-T Change		1		2	12

According to the confusion matrix, 1 normal beat was classified incorrectly by the Support Vector Machine as an Arythmia, 2 Arythmia beat was classified as a Supraventicular Arythmia beat and 1 beat as S-T change, 1 congestive heart failure beat was classified as a ventricular tachyarrhythmia beat, 2 Atrial Fibrillation beat was classified as an Arythmia beat, 4 Supraventicular Arythmia beats were classified as S-t Change beats, 2 S-T Change beats were classified as Supraventicular Arythmia beats and 1 Arythmia.

The accuracy for all the five classes are summarized in the table.

RECORDS	**Accuracy(%)**
Normal Sinus Rhythm	93.33
Arythmia	85
Atrial Fibrillation	86.67
Supraventricular Arythmia	80
S-T Change	80

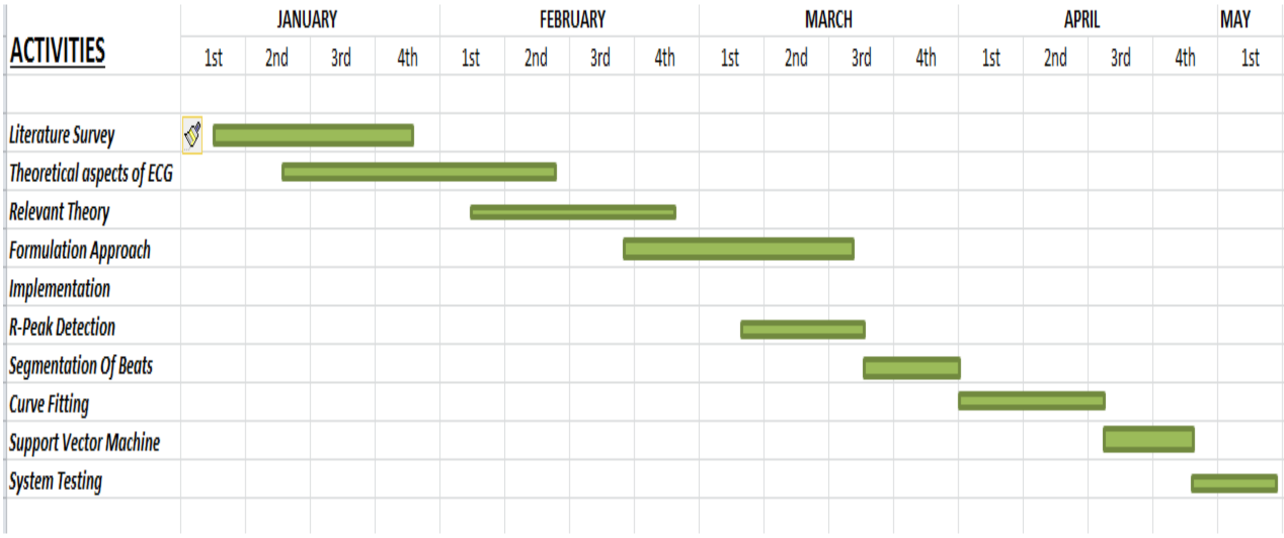
The classification accuracy which is defined as the percentage ratio of the number of beats correctly classified to the total number of beats considered for classification is **84.70%.**

8.Conclusion

Successfully developed “ECG Analysis And Diagnosis System” that takes :

- ECG data as input & conclude the result into five classes (Normal Sinus Rhythm, Artyhmia, Atrial Fibrillation, Supraventricular Arythmia, S-T Change).
- The system is able to solve about 80% of the Heart Problems.
- Segmentation of Each Beat And Curve Fitting Algorithm is never done before that is the main key point for the success of the system.
- The system is much more efficient as compared to another system.

9. Gantt Chart



10. Future Possibilities

1. Some of the Cardinal problems - Atrial Fibrillation, Ventricular Tachycardia , Ventricular Fibrillation, Third Degree block having irregular rhythm are left untouched .

2. Classification of each type of arrhythmia can be done separately.

3. Different type of classifier can be used for better accuracy.

Appendix (Source Code)

```
% Load original 1D signal.
clc;
clear all;
close all;
ELEVATED=[]
[fname path]=uigetfile('*.mat');
fname=strcat(path,fname);

        load(fname );
```

```
% Apply continous wavelet using db4 as mother wavelet
[c,l]=wavedec(s,4,'db4');
%'1st level reconstructed'
ca1=appcoef(c,l,'db4',1);
%'2nd level reconstructed'
ca2=appcoef(c,l,'db4',2);
```

```
%% ZERO CROSSING REMOVAL%%%%%%
base_corrected=ca2;
y=base_corrected-zc;
figure(4)
plot(y),grid on
title('base line corrected and smoothed signal')
```

```
%% DETECT R_PEAK
y1=y;
m1=max(y1)-max(y1)*.50;   %% Setting threshold values
P=find(y1>=m1);
P1=P;P2=[];
k=length(P1)-1;i=1;
while(i<=k)
   high=0;
   j=i;
   while(i<=k)
        if(P1(i+1)-P1(i)>15)
        break;
        end;
        i=i+1;
    end;
    last=P1(j);
    high=y1(P1(j));
    j=j+1;
    while(j<=i)
        if(y1(P1(j))>high)
        high=y1(P1(j));
        last=P1(j);
        end;
        if(j==k)
        break;
        end;
        j=j+1;
    end;
    P2=[P2 last];
    i=i+1;
end
if(P1(k+1)-P1(k)>25)
P2=[P2 P1(k+1)]
```

```
end;
Rt=y1(P2);
P3=P2*4;
Rloc=[];                        %%%  X-coordinates of position of R-peak
for( i=1:1:length(P3))
    range= [P3(i)-25:P3(i)+25];
    m=max(A(range));
    l=find(A(range)==m);
    pos=range(l);
    Rloc=[Rloc pos(1)];
end
Ramp=A(Rloc);                   %%% Amplitude values of R peak


figure(6)
plot(A),grid on,hold on
plot(Rloc,Ramp,'*');
title('Detected R peak in actual Signal')

 %%Q Peak Detection
    rn=(Rloc(1,2)-Rloc(1,1))/10;
    a=floor((Rloc(i,j)-5)-rn):Rloc(i,j)-1;
    m=min(y1(a));
    b=find(y1(a)==m);
    b=b(1);
    b=a(b);
    Qloc(i,j)=b;  %%%  X-coordinates of position of Q-peak
    Qamp(i,j)=m;  %%% Amplitude values of Q peak
    %%%%% ONSET
    fnd=0;
    for k=floor(b-(5+rn)):+1:(b-1)
        if((y1(k)<=0) && (y1(k-1)>0))
        qon1=k;
        fnd=1;
        break
        end
    end
    if(fnd==0)
    Qrange=floor(b-(5+rn)):+1:b;
    qon1=find(y1(Qrange)==max(y1(Qrange)));
    qon1=Qrange(qon1);
    end
    QON(i,j)=qon1(1);
    fnd;
```

```
%%%%% OFFSET
for k=b+1:+1:floor(b+(rn-1))
    if((y1(k)>=0) && (y1(k-1)<=0))
        qon1=k;fnd=1;
    break
    end
end
if(fnd==0)
Qrange=b+1:+1:b+(rn-1);
qon1=find(y1(Qrange)==max(y1(Qrange)));
qon1=Qrange(qon1);
end
QOF(i,j)=qon1(1);
```

```
%%P Peak Detection

    rn=floor((Rloc(1,2)-Rloc(1,1))/2);
    a=Rloc(i,j)-rn:QON(i,j)-1;

m=max(y1(a));
b=find(y1(a)==m);
b=b(1);
b=a(b);
Ploc(i,j)=b;
Pamp(i,j)=m;

F=[F (Ploc(i,j)-(QON(i,j)-Ploc(i,j)))];
if(((QON(i,j)-Ploc(i,j)))>20)
Cloc(i,j)=(Ploc(i,j)-(QON(i,j)-Ploc(i,j)));  %% Starting of each beat
Camp(i,j)=A(Cloc(i,j));
else
Cloc(i,j)=(Ploc(i,j)-(2*(QON(i,j)-Ploc(i,j))));
Camp(i,j)=A(Cloc(i,j));
end;
```

```
    %% S  Detection
    rn=floor((Rloc(1,2)-Rloc(1,1))/10);
    a=Rloc(i,j)+1:Rloc(i,j)+(rn+5);
    m=min(y1(a));
    b=find(y1(a)==m);
    b=b(1);
    b=a(b);
    Sloc(i,j)=b;
    Samp(i,j)=m;
    %%%% onset off
    fnd=0;
for k=Rloc(i,j)+1:+1:b
    if((y1(k)<=0) && (y1(k-1)>0))
        qon1=k;
        fnd=1;
      break
  end
end
if(fnd==0)
Qrange=Rloc(i,j)+1:+1:b;
qon1=find(y1(Qrange)==max(y1(Qrange)));
qon1=Qrange(qon1);
end
SON(i,j)=qon1(1);
fnd=0;
for k=b:+1:b+(rn+5)
    if((y1(k)>=0) && (y1(k-1)<0))
        qon1=k;
        fnd=1;
      break
  end
end

if(fnd==0)
Qrange=b:+1:b+(rn+5);
qon1=find(y1(Qrange)==max(y1(Qrange)));
qon1=Qrange(qon1);
end
SOFF(i,j)=qon1(1);
end;
end;
```

```
% T - peak
sd=7;
Tloc=[];
sd=100;
for(m=1:+1:length(Cloc(1,:))-1)
m
a=y1(SOFF(1,m):Cloc(1,m+1));
[c,l]=wavedec(a,4,'db4');      %% Again cwt is used
  ca2=appcoef(c,l,'db4',2);
  y1t=ca2;

sd=sd+1;
  max(y1t)
  if(max(y1t)<0)
m1=max(y1t)+max(y1t)*.40;
    else
    m1=max(y1t)-max(y1t)*.60;
    end;
    m1
P=find(y1t>=m1);
P1=P;
P2=[];
k=length(P1);
k=k-1;
i=1;
while(i<=k)
   high=0;
   j=i;
   while(i<=k)
        if(P1(i+1)-P1(i)>10)
        break;
        end;
        i=i+1;
```

```
    if(P3-15<=SOFF(1,m))
    ton=SOFF(1,m)+3;
    else
    ton= P3-15;
    end;
    if(P3+15>=Cloc(1,m+1))
    tof=Cloc(1,m+1)-3;
    else
    tof=P3+15;
    end;
    if(ton<tof)
    range= [ton:tof];
    else
    range=[tof:ton];
    end;
    n=max(y1(range));
    l=find(y1(range)==n);
    l=l(1);
    pos=range(l);
    if(pos>=Cloc(1,m+1))
    pos=Cloc(1,m+1)-1;
    end;
    Tloc=[Tloc pos];
end;
Tamp=y1(Tloc);

figure(7)
plot(y1),grid on,hold on
plot(Tloc,Tamp,'*');
title('Detected T peak in actual Signal')
```

```
%% sigma detection


sigma=[];
mean=[];
amplitude=[];
%p-peak
Ploc(ij)-Cloc(ij)
Pmidamp=Y(Ploc(ij)-Cloc(ij))/2;
Pmidval=find(Y>=Pmidamp);
temp = [];
for pk=1:+1:length(Pmidval)
if(0<=Pmidval(pk))
if(QON(ij)-Cloc(ij)>=Pmidval(pk))
temp= [temp Pmidval(pk)];
end
end
end
z=length(temp);
op= temp(z)-temp(1);
if(op==0)
op=1;
end;
sigma = [sigma op];
mean=[mean (Ploc(ij)-Cloc(ij))];
amplitude=[amplitude Y(Ploc(ij)-Cloc(ij))];

%Q-peak
Qloc(ij)-Cloc(ij)
Qmidamp=Y(Qloc(ij)-Cloc(ij))/2;
Qmidval=find(Y>=Qmidamp);
temp = [];
for pk=1:+1:length(Qmidval)
if(QON(ij)-Cloc(ij)<=Qmidval(pk))
if(QOF(ij)-Cloc(ij)>=Qmidval(pk))
temp= [temp Qmidval(pk)];
end
end
end
z=length(temp);
op= temp(z)-temp(1);
if(op==0)
op=1;
end;
sigma = [sigma op];
mean=[mean (Qloc(ij)-Cloc(ij))];
amplitude=[amplitude Y(Qloc(ij)-Cloc(ij))];
```

```
%S-peak
Sloc(ij)-Cloc(ij)
Smidamp=Y(Sloc(ij)-Cloc(ij))/2;
Smidval=find(Y>=Smidamp);
temp = [];
for pk=1:+1:length(Smidval)
if(SON(ij)-Cloc(ij)<=Smidval(pk))
if(SOFF(ij)-Cloc(ij)>=Smidval(pk))
temp= [temp Smidval(pk)];
end
end
end
z=length(temp);
op= temp(z)-temp(1);
if(op==0)
op=1;
end;
sigma = [sigma op];
mean=[mean (Sloc(ij)-Cloc(ij))];
amplitude=[amplitude Y(Sloc(ij)-Cloc(ij))];
```

```
%r-peak
Rloc(ij)-Cloc(ij)
Rmidamp=Y(Rloc(ij)-Cloc(ij))/2;
Rmidval=find(Y>=Rmidamp);
temp = [];
for pk=1:+1:length(Rmidval)
if(Qloc(ij)-Cloc(ij)<=Rmidval(pk))
if(Sloc(ij)-Cloc(ij)>=Rmidval(pk))
temp= [temp Rmidval(pk)];
end
end
end
z=length(temp);
op= temp(z)-temp(1);
if(op==0)
op=1;
end;
sigma = [sigma op];
mean=[mean (Rloc(ij)-Cloc(ij))];
amplitude=[amplitude Y(Rloc(ij)-Cloc(ij))];
```

```
%T-peak
Tloc(ij)-Cloc(ij)
Tmidamp=Y(Tloc(ij)-Cloc(ij))/2;
Tmidval=find(Y>=Tmidamp);
temp = [];
for pk=1:+1:length(Tmidval)
if(SOFF(ij)-Cloc(ij)<=Tmidval(pk))
if(Cloc(ij+1)-Cloc(ij)>=Tmidval(pk))
temp= [temp Tmidval(pk)];
end
end
end
z=length(temp);
op= temp(z)-temp(1);
if(op==0)
op=1;
end;
sigma = [sigma op];
mean=[mean (Tloc(ij)-Cloc(ij))];
amplitude=[amplitude Y(Tloc(ij)-Cloc(ij))];
```

```
%%% Apply Curve fitting %%%
x0 = [amplitude(1) mean(1) sigma(1) amplitude(2)
mean(2) sigma(2) amplitude(3) mean(3) sigma(3)
amplitude(4) mean(4) sigma(4) amplitude(5) mean(5) sigma(5)];
x(1) = amplitude(1);
x(2) = mean(1);
x(3) = sigma(1);
x(4)=amplitude(2);
x(5)=mean(2);
x(6)=sigma(2);
x(7)=amplitude(3);
x(8)=mean(3);
x(9)=sigma(3);
x(10)=amplitude(4);
x(11) = mean(4);
x(12) = sigma(4);
x(13) = amplitude(5);
x(14)=mean(5);
x(15)=sigma(5);


F = @(x,xdata)x(1)*exp(-((x(2)-xdata).^2)/(2*(x(3).^2)))
+ x(4)*(exp(-((x(5)-xdata).^2)/(2*(x(6).^2))))+
x(7)*(exp(-((x(8)-xdata).^2)/(2*(x(9).^2))))+
x(10)*(exp(-((x(11)-xdata).^2)/(2*(x(12).^2))))+
x(13)*(exp(-((x(14)-xdata).^2)/(2*(x(15).^2))));
options=optimset('Display','on','Algorithm','levenberg-marquardt'
,'ScaleProblem','Jacobian','TolFun',1e-12,'TolX',1e-10);
 [x,resnorm,~,exitflag,output] = lsqcurvefit(F,x0,t,y,[],[],options)

   F = @(xdata)x(1)*exp(-((x(2)-xdata).^2)/(2*(x(3).^2))) +
   x(4)*(exp(-((x(5)-xdata).^2)/(2*(x(6).^2))))+
   x(7)*(exp(-((x(8)-xdata).^2)/(2*(x(9).^2))))+
   x(10)*(exp(-((x(11)-xdata).^2)/(2*(x(12).^2))))+
   x(13)*(exp(-((x(14)-xdata).^2)/(2*(x(15).^2))));
   error1=0;
   for(i=1:+1:length(data))
   error1=error1+abs(y(i)-F(i));
   end;
   error
   if(error1<error)
   xmin=data;
   val=x;
   error=error1;
   error
   end;
```

```
%% using correlation coefficients
CR=zeros(15,15);
for u=1:+1:15
for v=1:+1:15
    Col1=D(:,u);
    Col2=D(:,v);
    Cor=corrcoef(Col1,Col2);
    CR(u,v)=Cor(1,2);
end;
end;
rd=[];
for i=2:+1:15
for j=1:+1:i-1
 rd=[rd CR(i,j)];
end;
end;
```

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Suggestion Of Board Members