Sudan University of Science and Technolog

College of Graduate Studies

Heart Beat Rate Variability Analysis Using Statistical Methods

تحليل معدل التغير في ضربات القلب باستخدام الطرائق الاحصائية

A thesis Submitted in Partial Fulfillment for the Requirement of

the Degree of MSC in Biomedical Engineering

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الآيـــــة

قال تعالي

(قَالَ رَبِّ اشْرَحْ لِي صَدْرِي ﴿25﴾ وَيَسِّرْ لِي أَمْرِي ﴿26﴾ وَاحْلُلْ عُقْدَةً مِنْ لِسَانِي ﴿27﴾ يَفْقَهُوا قَوْلِي ﴿28﴾) **صدق الله العظيم**

سورة طه الايه (25-28)

Dedication

To my Mother,

God bless her

To the soul of my father with love and respect

To my brother

To my kind husband

To my sweetly daughter sadeem

To my warm family and my all friends

Acknowledgment

I would like to thanks all those whom assist me to complete this work
Special thanks to Dr.mohammed yagoob who supervised this project to his support and efforts

ABSTRACT

Heart Rate Variability (HRV) Represent one of the most promising markers which represent anon invasive way of measuring autonomic nervous system(ANS), it describes the variation over time of both instantaneous heart rate and the interval between consecutive heart beats.

Previously traditional methods had been used for calculating heart beat as using hand with time , and after the appearance of the new method and devices those depend on computer program the HRV analysis become more easier and more accurate, thus this is the primary purpose of use the statistical methods to analyze HRV using Mat lab program. New method has been proposed to analyze HRV using statistical methods by using the matlab program. HRV analysis was divided into four phases ,in the first phase a pre processing was done to remove power line interference and the base line wander using second order IIR notch filter "pole-zero placement" and fourth order chebyshev band pass filter "bilinear transformation" respectively. Secondly, discrete wavelet transformation was applied on ECG signals as one of the robust features ,which were subsequently used for next phase. The third phase detection of R peak and RR interval were calculated from the wavelet vector, different statistical features were calculated as an input for classification phase. Finally, classifier was designed to differentiate between normality and abnormality. Results obtained from this work are acceptable when compare it with previous studies results and result in the same data base, the accuracy of this work represent 95% .

المستخلص

معدل التغير في ضربات القلب تمثل واحدة من العلامات الواعدة التي تمثل الطريقة اللااختراقية (الغير مباشرة) لقياس الجهاز العصبي اللاإرادي (ANS) ، فهو يصف التغير مع مرور الوقت لكل من معدل ضربات القلب اللحظية والفترة الفاصلة بين دقات القلب المتتالية.فيما سبق كان يتم حساب ضربات القلب بالطرق التقليدية كحسابها باليد مع الزمن، ومع ظهور الطرق الحديثة المعتمدة علي الأجهزة المبرمجة بلغات الحاسوب أصبح حساب معدل التغيير في ضربات القلب أكثر سهولة ودقة ولذا فان هذا يمثل الغرض الاساسي من استخدام الطرائق الاحصائية لتحليل معدل التغير في ضربات القلب باستخدام برنامج الماتلاب .طريقة جديدة مقترحة لتحليل معدل التغير في ضربات القلب باستخدام الطرائق الاحصائية ويتم تطبيقيها على أربعة مراحل ، في المرحلة الأولى أجريت معالجة أولية لإزالة التداخل الناتج من خط الكهرباء والحدة من الخط الاساسى باستخدام مرشحات رقمية second order IIR notch filter "pole-zero placement" and fourth order chebyshev band pass filter "bilinear transformation" بالتتابع. ثانيا تم تطبيق تحول المويجات المنفصلة على إشارات ECG باعتبارها واحدة من الميزات القوية التي تستخدم في المرحلة المقبلة. المرحلة الثالثة هي الكشف عن الذروة R و RR الفاصلة من متجه المويجات ، حسبت الميزات الإحصائية المختلفة كمدخل لمرحلة التصنيف. وأخيرا تم تصميم المصنف للتفريق بين الطبيعي و الشاذ .النتائج المتحصل عليها مقبولة مقارنة مع الدراسات السابقة ومع النتائج في قاعدة البيانات.والدقة المتحصل عليها كانت بنسبة 95%.

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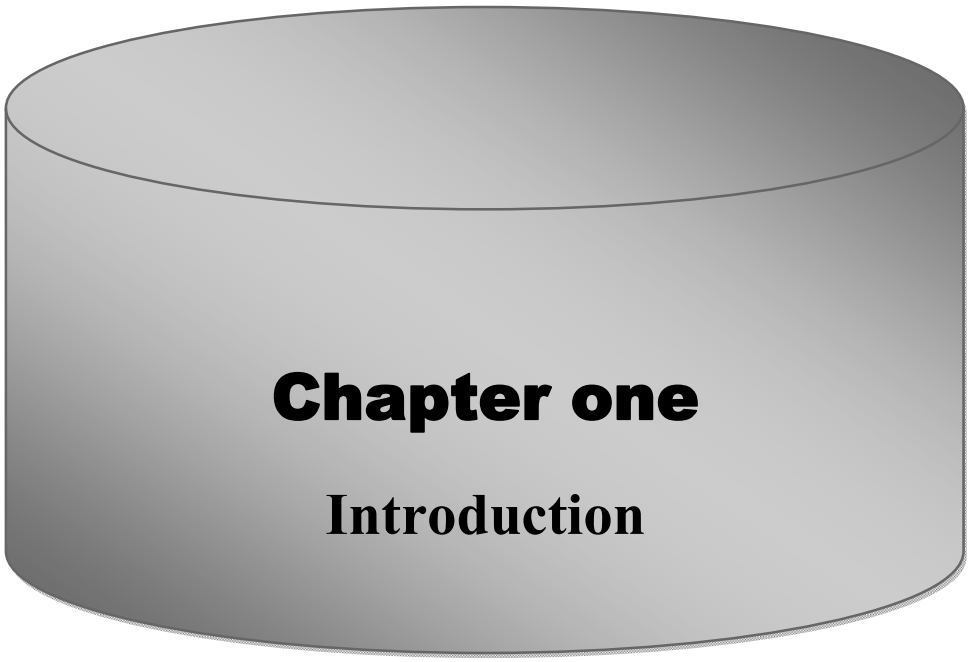
Abbreviations

Abbreviation	Meaning
HRV	Heart Rate Variability
SA	Sino Atrial
ANV	Autonomic Nervous System
ECG	Electro Cardio Gram
MIT _BIH	Masschusetts Institute of Technology Beth Israel Hospital database
AAMI	Association for the Advancement of Medical Instrumentation
VEBs	Ventricular Ectopic Beats
SVEBs	Supra Ventricular Ectopic Beats
STFT	Short Time Fourier Transform
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
STD	Standard Deviation
RMS	Roots Mean Squirts
VI	Virtual Instrument
FC	Filling Cystometry
FSF	First Sensation of fling
FDV	First Desire to Void



Chapter one

Introduction

Chapter one

Introduction

1.1 Introduction

HRV represent one of the most promising markers, which represent a non invasive way of measuring autonomic nervous system. HRV computed by analyzing beat-to-beat interval time series derived from an electrocardiogram (ECG).

1.1.1 Heart Rate Variability (HRV)

Heart rate variability (HRV) represents one of the most promising such markers, HRV is computed by analyzing beat-to-beat interval time series derived from an electrocardiogram (ECG), an arterial pressure tracing, or a plethysmographic pulse wave signal. A variety of metrics have been proposed for measuring HRV. These metrics can broadly be classified into time [1], frequency [2], fractal [3], and nonlinear [4] domain measures of HRV.

Heart rate variability is non invasive way of measuring autonomic nervous system dynamics as influenced by ones emotional state by studding beat to beat variation [5]. it describe the variation over time of both instantaneous heart rate and the interval between consecutive heart beats ,the rhythm of the heart is modulated by SA node which is largely influenced by both the sympathetic and Para sympathetic branches of the ANS as shown in figure(1.1) bellow [6] :

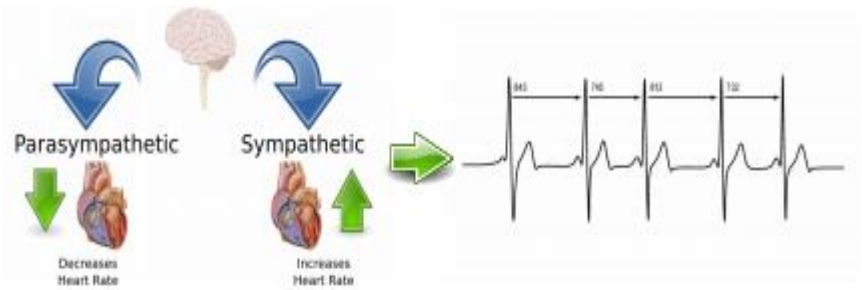


Figure 1.1 autonomic regulation of heart result in HRV

Heart rate variability (HRV) analysis is an important application with many research and clinical use, which give information about the autonomic heart modulation mechanism [7], the normal one-cycle of electrocardiogram (ECG) signal consists of several waves, as shown in Figure(1.2).

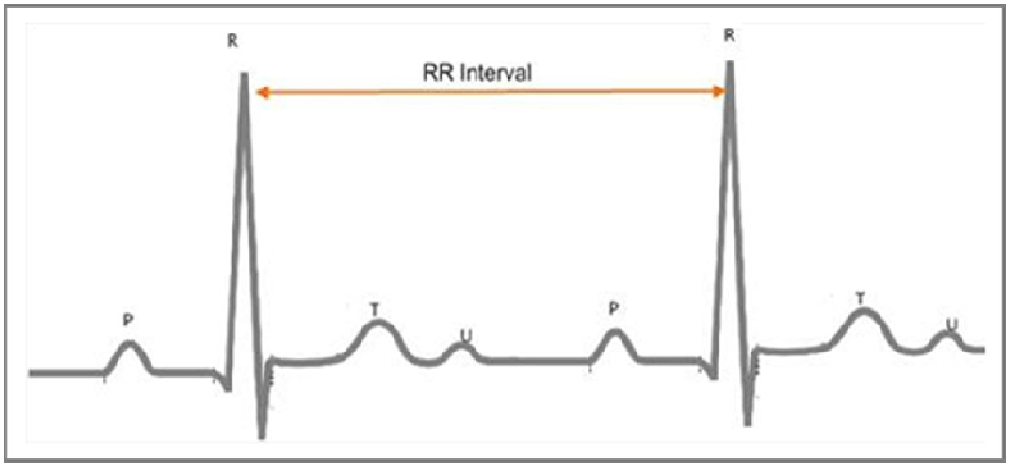


Figure 1. 2 R Peaks and RR Intervals of an ECG Signal

Figure (1.2) illustrate that the wave with the highest amplitude is the R wave, An RR interval is the time elapsed between two successive R waves, The waves with the lower amplitudes are the P wave, the T wave and the U wave [8].

1.1.2 Introduction to Electrocardiography (ECG)

The various propagating action potentials within the heart produce a current flow, which generates an electrical field that can be detected, in significantly attenuated form, at the body surface, via a differential voltage measurement system. The resulting measurement, when taken with electrodes in standardized locations, is known as the electrocardiogram (ECG), Electrocardiogram , an electrical recording of the heart and is used in the investigation of heart disease [9].

An electrocardiogram (ECG) is a graph produced by an electro cardio graph that provides information about an individual cardiac health [7]. it is diagnosis tool that reported the electrical activity of heart recorded by skin electrode, the morphology

and heart rate reflects the cardiac health of human heart beat, it is anon invasive technique that means this Signal is measured on the surface of human body, which is used in identification of heart disease [10].anther definition of the noninvasive technique meaning that this signal can be measured without entering the body at all. Electrodes are placed on the user's skin to detect the bioelectric potentials given off by the heart that reach the skins surface. The ECG detection which shows the information of the heart and cardiovascular condition is essential to enhance the patient living quality and appropriate treatment. It is valuable and an important tool in the diagnosing the condition of the heart diseases [11]. Any disorder of heart rate or rhythm or Change in the morphological pattern is an indication of cardiac arrhythmia which could be detected by analysis of the recorded ECG wave form and duration of the P-QRS-T wave contains useful information about the nature of disease afflicting the heart [10].

The electrical wave is due to the depolarization and re polarization of Na and k ions in the blood as shown in figure bellow [10].

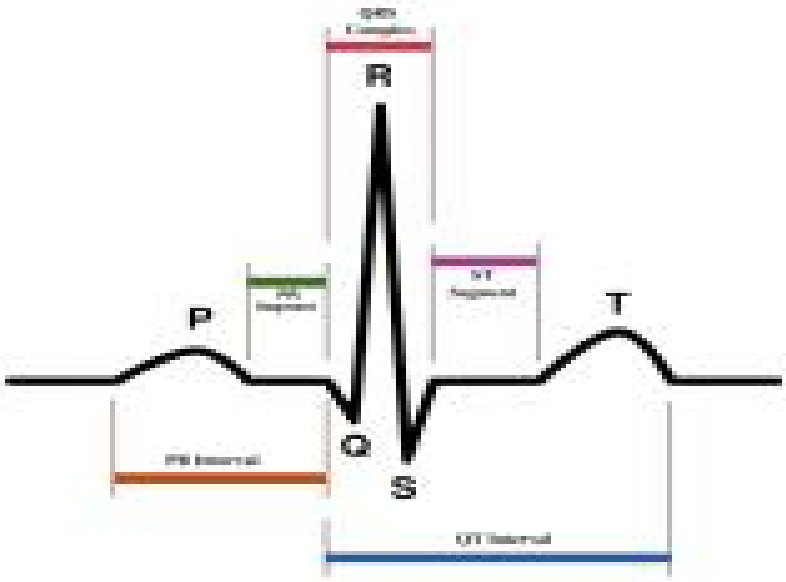


Figure 1.3 Peaks in ECG signal

The importance of HRV is to detect the healthy subject and it use in clinical cases such as myocardial infarction, hypertension, chronic obstructive pulmonary disease, diabetic neuropathy and apnea [12].

Signal analysis technique help in obtain information which completely change the way in diagnosis disease, when it is not possible to imagine

Situation related to the heart without obtain information from bio electrical signal delivered from the heart.

1.2 Problem Statement:

Heart rate variability is a more sensitive tool to detect abnormalities of the heart, it establish itself as a non-invasive methods and clinical tool for indirectly investigating both cardiac and autonomic system function in both normal and abnormal.

1.3 Objectives:

The general objective of the research is:

1- To evaluate the usefulness of analysis of heart rate variability (HRV) to be a useful method of assessing cardiovascular autonomic control, between normal and abnormal .

2- To evaluate the sensitivity of HRV to detect diagnosis information in different cases between normal and abnormal.

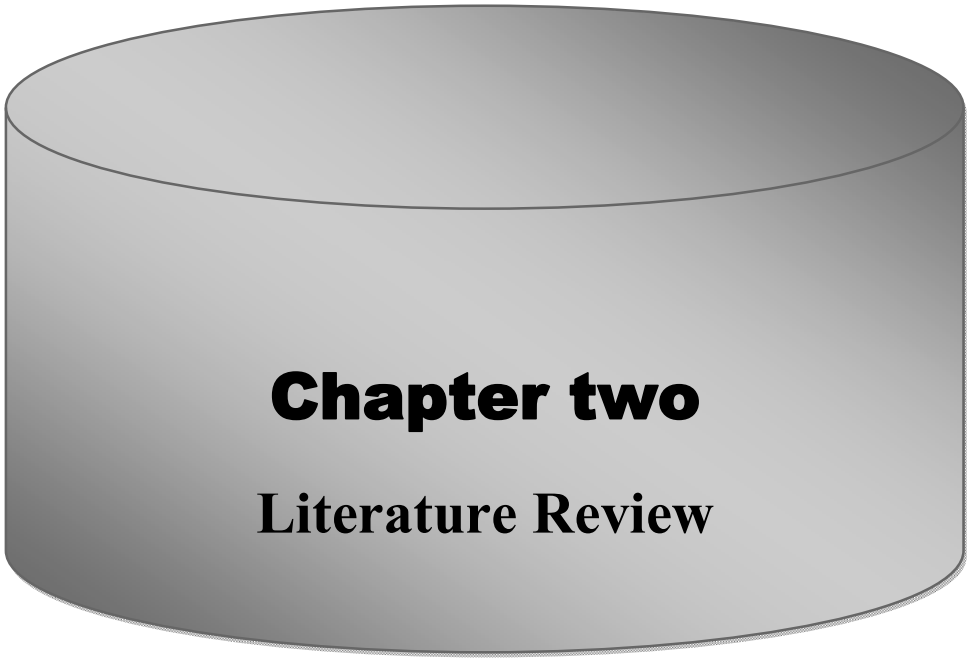
The specific objective:

1- To propose a new method ECG analysis by features extraction (using wavelet transform).

2- To use accuracy means of methods for analysis heart rate variability (using statistical methods).

1.4 Organization of the thesis:

the thesis contain in chapter one introduction to heart rate variability ,chapter two literature reviews ,chapter there analysis for (HRV) using statistical methods, chapter four result and discussions, chapter five conclusion and recommendation and finally Reference and Appendix.


Chapter two
Literature Review

Chapter Two

Literature review

2.1 Theoretical Background

Study of heart rate variability is being used to identify the relationship between autonomic nervous system and heart , but direct gathering information is not available , in contrast most researcher depend on data provided from ECG measuring system. This system proposed to study HRV is composed of the following component parts.

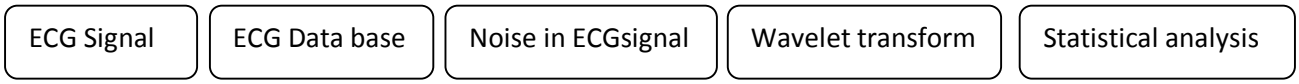
1- ECG Signal

2-ECG database

3- Noise in ECG signal

4-Wavelet transform

5-Statistical analysis



2.1.1 ECG Signal

ECG signal is an electrical signal that obtained from the heart by surface electrodes ,the standard ECG has 12 leads which include 3 bipolar leads ,3 unipolar leads and cheats leads(precordial),a lead is pair of electrodes (+positiveve & - negative) placed on the body in designated anatomical location and connected to an ECG record [13].

A normal ECG recorded by the electrode consist of p wave ,QRS complex and T waves .the QRS complex include three separate waves Q,R&S all these are generated when the cardiac impulse goes through the ventricles .in the ECG signal waves Q and S are generally significantly less prominent than the wave lengths of p and sometimes may be missing ,the P wave depends on electrical

current generated when the atria depolarize before contraction and the QRS complex is produced by currents arising when the ventricles depolarize prior to contract .there for P wave as well as component of the QRS complex corresponded to depolarization ,the T wave which is caused by current arising when the ventricles recover from the depolarization state is known as the repolarization wave. in essence ,the ECG signal is composed of wave of depolarization and repolarization as show in figure (2.2) and (2.3) .QRS complex are present in most of heart beats that are associated with ventricular electrical activity and contain important clinical information so it is signal to noise ratio is the highest among all waves present in the ECG signal . The P wave reflects the depolarization of the right and left atria. Its amplitude is normally less than 300 μV, and its duration is less than 120 ms. The QRS complex reflects depolarization of the right and left ventricles. Its duration is normally about 70-110 ms. it has the largest amplitude of the ECG waveforms, sometimes reaching 2-3 mV. The T wave reflects ventricular re polarization and extends about 300 ms [13] . QRS complex corresponds to the current that causes contraction of the left and right ventricles [5],the figure (2.1) below shown the QRS complex.

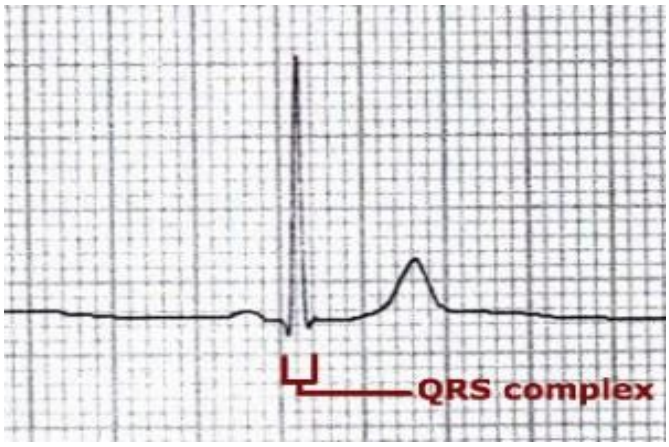


Figure 2.1 QRS complex [14]

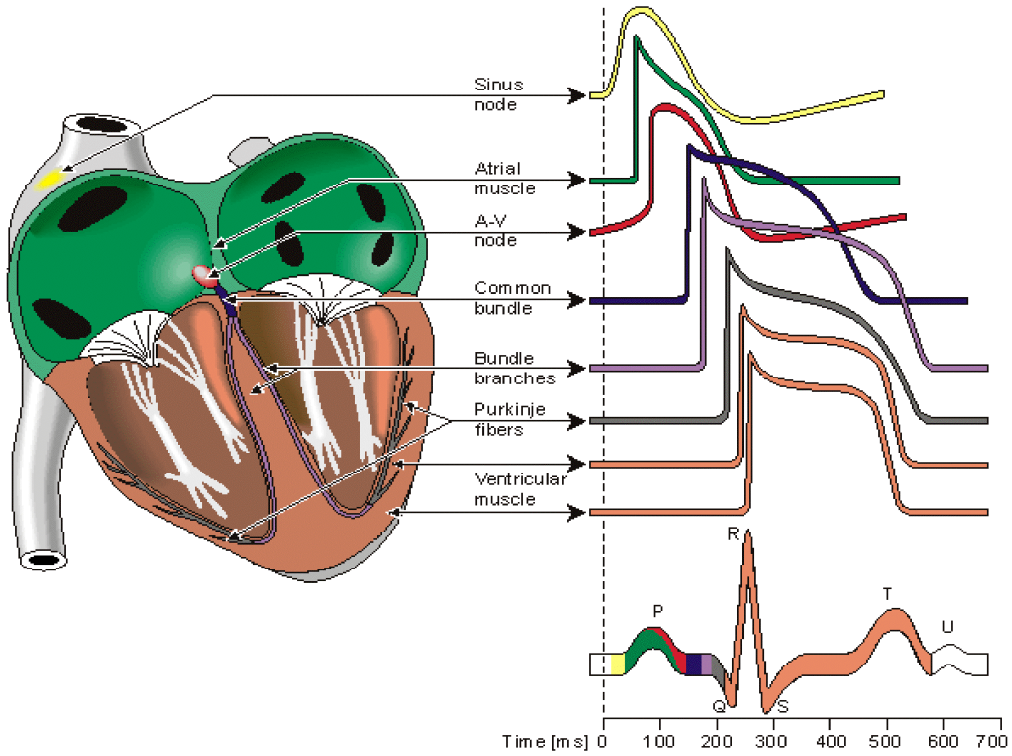


Figure 2.2 Electrical activity of the heart [13

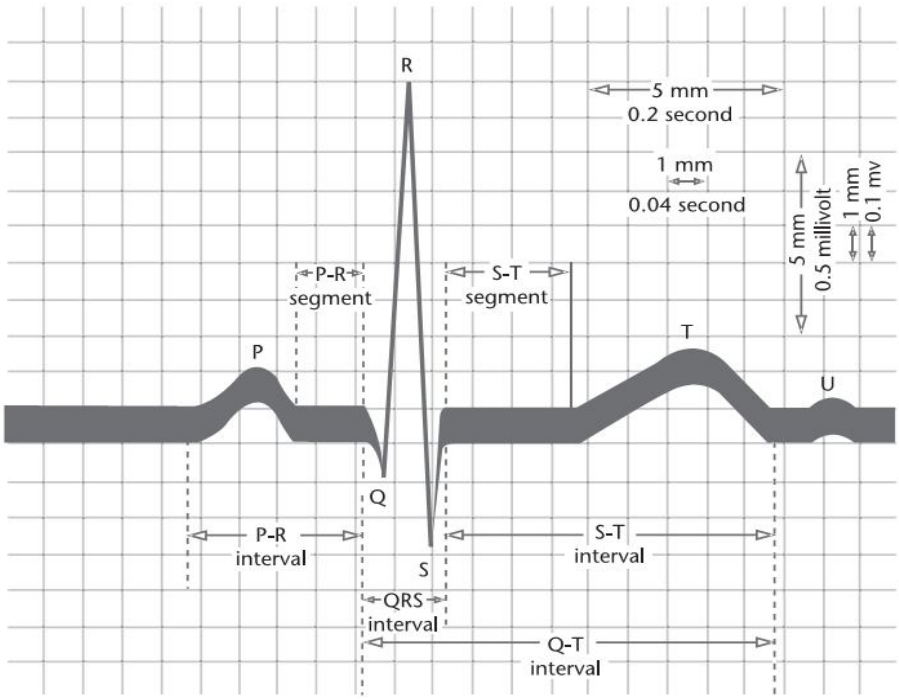


Figure 2.3 The normal ECG signal [13]

The interpretation of the ECG signal is an application of pattern recognition. The purpose of pattern recognition is to automatically categories a system into one of a number of different classes. An experienced cardiologist can easily diagnose various heart diseases just by looking at the ECG waveforms printout. In some specific cases, sophisticated ECG analyzers achieve a higher degree of accuracy than that of cardiologist [15].

2.1.2 Masschusetts Institute of Technology Beth Israel Hospital Arrhythmias database (MIT-BIH)

The MIT/BIH arrhythmia database is used in the study for performance evaluation. The database contains 48 records, each containing two-channel ECG signals for 30 min duration selected from 24-hr recordings of 47 individuals there are 116,137 numbers of QRS complexes in the database .The subjects were taken from, 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years and the records 201and 202 came from the same male subject. Each recording includes two leads; the modified limb lead II and one of the modified leads V1, V2,V4 or V5. Continuous ECG signals are band pass-filtered at 0.1–100 Hz and then digitized at 360 Hz. Twenty-three of the recordings (numbered in the range of 100–124) are intended to serve as a representative sample of routine clinical recordings and 25 recordings (numbered in the range of 200–234) contain complex ventricular, junctional, and supraventricular arrhythmias. And another kind of record contain 18 records as rythmia ECG signal.

The database contains annotation for both timing information and beat class information verified by independent experts.

MIT-BIH heartbeat types are combined according to Association for the Advancement of Medical Instrumentation (AAMI) recommendation of classifying ventricular ectopic beats (VEBs) from the non-ventricular ectopic beats . AAMI also recommends that each ECG beat can be classified into the following five heartbeat type as shown in the table (2.1)

Each class includes heartbeats of one or more types. Class N contains normal and bundle branch block beat types and escape Beat, class S contains supraventricular ectopic beats (SVEBs), class V contain Premature ventricular contraction beats and ventricular Escape beat, class F contains beats that result from fusing normal and VEBs, and class Q contains unknown beats including paced beats [12].

Table 2.1 Mapping the MIT-BIH arrhythmia database heart beat types to the AAMI heartbeat classes .

AAMI heartbeat	Description	MIT/BIH heartbeat types
Group of arrhythmias N	Normal signal	Normal (N),Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Atrial Escape (AE), Nodal (junctional) escape beat(NE)
Group of arrhythmias type Sv	Supraventricular ectopic beat	Atrial Premature (AP), Aberrated Atrial Premature (aAP), Nodal (junctional) Premature (NP), Supraventricular Premature (SP),
Group of arrhythmias V	Ventricular ectopic beat	Premature Ventricular Contraction (PVC),

		Ventricular escape (VE)
Group of arrhythmias F	Fusion beat	Fusion of ventricular and normal (fVN), Fusion of paced and normal beat (fPN)
Group of arrhythmias Q	Unknown beat	Paced (P), Unclassified (Q)

To download ECG signals from the data base go to WWW.PhysioNet.org, After that PhysioBank / Signal Archives/ ECG/ MIT-BIH Arrhythmia Database. To read all ECG signals files(.atr annotation files, .dat binary signal files, .hea header files) used matlab code.

2.1.3 Noise in ECG signal

ECG signal is often contaminated by different types of noises and artifacts that can be within the frequency band of ECG signal, which may change the characteristics of ECG signal.

The corruption of ECG signal is due to following major noises:

2.1.3.1 Power line interferences

Power line interferences contains 60 Hz pickup. It is indicated as an impulse or spike at 60 Hz/50 Hz harmonics, and will appear as additional spikes at integral multiples of the fundamental frequency. Its frequency content is 60 Hz/50 Hz and its harmonics, amplitude is up to 50 percent of peak-to-peak ECG signal amplitude.

Naturally precautions should be taken to keep power lines as far as possible or shield and ground them, but this is not always possible [12] .

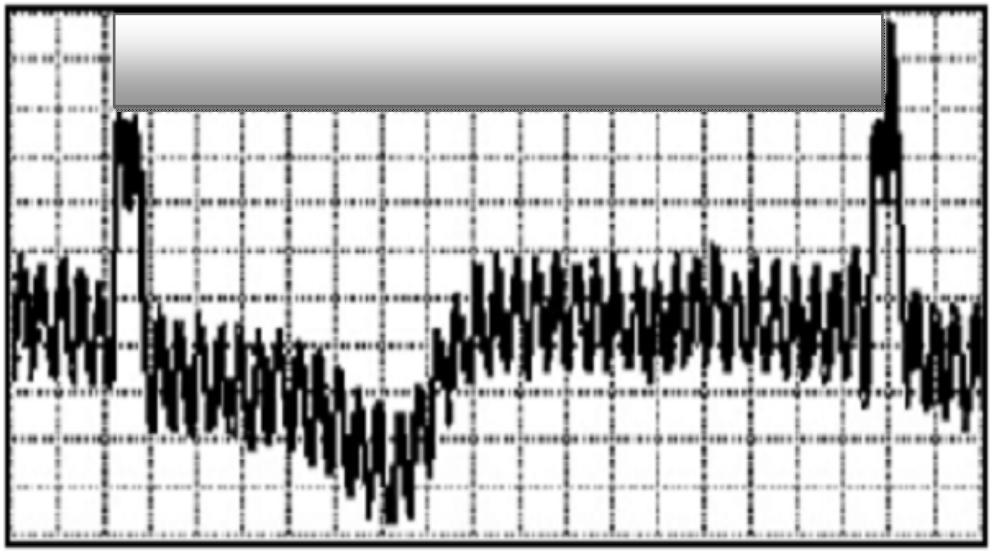


Figure 2.4 Electrocardiographic mixed with 60Hz powerline interference.

2.1.3.2 Baseline wander

Base-line drift may be caused in chest-lead ECG signals by coughing or breathing with large movement of the chest, or when an arm or leg is moved in the case of limb-lead ECG acquisition. Base-line wander can sometimes caused by variations in temperature and bias in the instrumentation and amplifiers.

The variation of the baseline with respiration can be represented as a sinusoidal component and the frequency of respiration added to the ECG signal. The variation could be reproduced by amplitude modulation of the ECG by the sinusoidal component that is added to the base line.

The magnitude of the undesired wander may exceed the amplitude of the QRS complex by several times. Its spectral content is usually confined to an interval well below 1 Hz. but it may contain higher frequencies. Removal of baseline wander is required in order to minimize changes in beat morphology This is especially important when unnoticeable changes in the "low-frequency" ST-T segment are analyzed for the diagnosis of ischemia. The baseline wander in ECG causes problems in detection peaks [12].

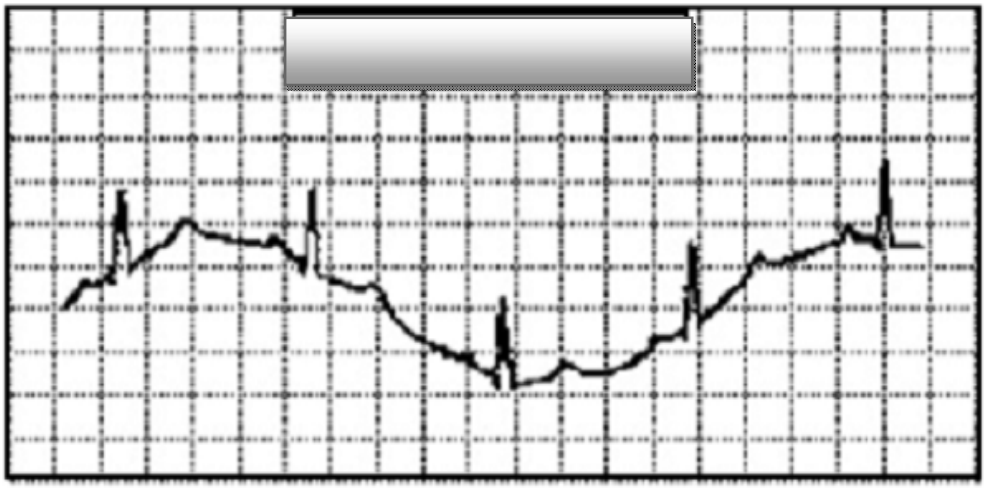


Figure 2.5 ECG with baseline wander.

2.1.3.3 Motion artifact

Motion artifacts are transient base line changes in the electrode skin impedance with electrode motion. The shape of the base line disturbance caused by the motion artifacts can be assumed to be a biphasic signal resembling one cycle of a sine wave. The peak amplitude and duration of the artifacts are variables. The duration of this kind of noise signal is 100–500ms with amplitude of 500% peak-to-peak ECG amplitude [12].

2.1.4 The Wavelet Transform

Most signals are represented in the time domain. More information about the time signals can be obtained by applying signal analysis, the time signals are transformed using an analysis function. The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal.

The Fourier transform is only able to retrieve the global frequency content of a signal, the time information is lost. This is overcome by the short time Fourier transform (STFT) which calculates the Fourier transform of a windowed part of the signal and shifts the window over the signal. The short time Fourier transform gives the time-frequency content of a signal with a constant

frequency and time resolution due to the fixed window length. For low frequencies often a good frequency resolution is required over a good time resolution. For high frequencies, the time resolution is more important.

A multi-resolution analysis becomes possible by using wavelet analysis ,The wavelet transform (WT) is designed to address the problem of non-stationary ECG signals. It derived from a single generating function called the mother wavelet by translation and dilation operations. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, that is leading to an optimal time-frequency resolution in all frequency ranges. The WT of a signal is the decomposition of the signal over a set of functions obtained after dilation and translation of an analyzing wavelet [11]**,** The first step of wavelet decomposition is to select an appropriate wavelet for the signal to be analyzed. Appropriate wavelets should have a wave shape, which is close to the analyzed or filtered signal. Convolving the wavelet function with the original signal produces the equivalent of a high-pass filter (or a low-pass filter), resulting in the details (or the approximation) of the signal. figure(2.6) shows the wavelet decomposition for each level of decomposition the signal is filtered into approximate information of the signals (lower frequencycomponent) and detail information (higher frequency component). If this procedure is repeated N times, a filter bank is created with N filters.

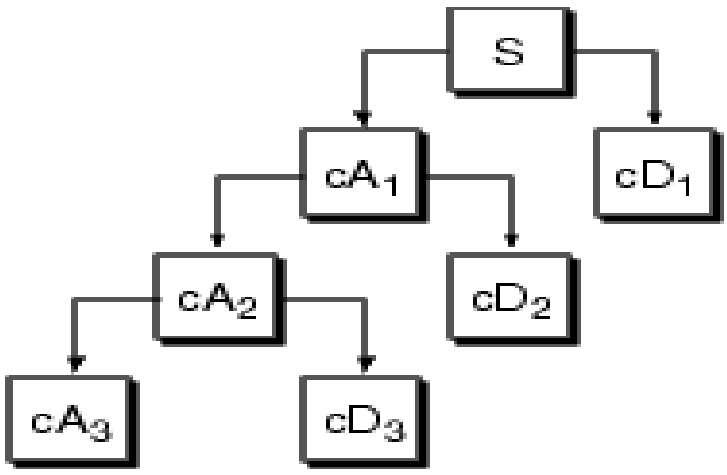


Figure 2.6 Wavelet Decomposition

2.1.4.1 The Types of Wavelet

2.1.4.1.1 The Continuous Wavelet Transform(CWT)

The continuous wavelet transform is calculated analogous to the Fourier transform, by the convolution between the signal and analysis function. However the trigonometric analysis functions are replaced by a wavelet function. Time information is obtained by shifting the wavelet over the signal. The frequencies are changed by contraction and dilatation of the wavelet function. The continuous wavelet transform retrieves the time-frequency content information with an improved resolution compared to the STFT.

2.1.4.1.2 The Discrete Wavelet Transform (DWT)

The discrete wavelet transform (DWT) is uses filter banks to perform the wavelet analysis. The discrete wavelet transform decomposes the signal into wavelet coefficients from which the original signal can be reconstructed again. The wavelet coefficients represent the signal in various frequency bands.

The DWT is sufficient for most practical applications and for the reconstruction of the signal. The DWT provides enough information, and offers a significant reduction in the computation time. Here, we have discrete function f (n) and the definition of DWT is given by:

$$W(a,b)=c(j,k)=\sum_{n=z} f(n)\Psi j,k(n) \quad (1)$$

Where $\Psi j,k(n)$ is a discrete wavelet defined as:

$$\Psi j,k(n)=2^{-j}*\Psi(2^{-j}\, n-k) \quad (2)$$

Equations (1), (2) from [16].

In the DWT analyses, the signal at different frequency bands and at different resolutions is decomposed into a 'coarse approximation' and 'detailed information'. Two sets of functions are employed by the DWT, the scaling functions (associated with the low pass filter) and the wavelet functions (associated with the high pass filter). The signal is filtered by passing it through

successive high pass and low pass filters to obtain versions of the signal in different frequency bands.

The fundamental idea behind wavelets is to analyze according to scale. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large window, we would notice gross features. Similarly, if we look at a signal with a small window, we would notice small features. The result in wavelet analysis is to see both the forest and the trees, so to speak.

DWT has different families such as Haar Wavelet, Daubechies Wavelets, Symlets Wavelets, Coiflets Wavelets, Biorthogonal Wavelets, Meyer Wavelet, Mexican Hat Wavelet and so on.

In this work we used Daubechies Wavelet (db4) which it looks like ECG signal. In dbN, N is the order ,Some authors use 2N instead of N [17].

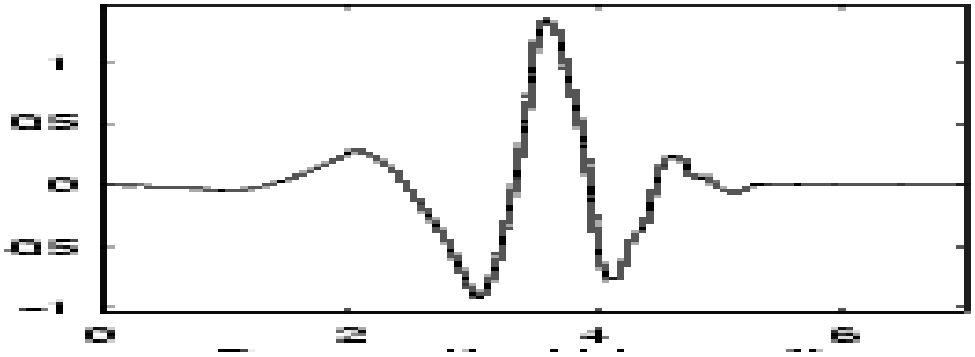


Figure 2.7 Daubechies (db4) [17]

2.1.5 Statistical analysis

In this last point we use the statistical methods such as mean (Mi) ,standard deviation (Std) and roots mean squirts (RMS) to evaluate the result.

2.2 Previous studies

The auther of this paper (using lab view for heart rate variability analysis) using time series analysis, time-domain measurements, They extract many

measurements from the original RR interval signals to show changes in the autonomic nervous system (ANS). The Biomedical Toolkit contains the HRV Statistics VI and the HRV Histogram VI. They use these two VIs to extract several commonly used measurements, as shown in table (2.2).

Table 2.2 Time-Domain Measurements of Heart Rate Variability

Variable	**Unit**	**Description**
Statistical Measurements		
RR Mean & Std	S	Mean and standard deviation of all RR intervals.
HR Mean & Std	1/min	Mean and standard deviation of all heart rates.
RMSSD	Ms	Square root of the mean of the sum of squares of differences between adjacent RR intervals.
NN50 Count	N/A	Number of pairs of adjacent RR intervals differing by more than 50 ms in all the measurements.
pNN50	%	NN50 count divided by the total number of all RR intervals.
Geometric Measurements		
HRV Triangular Index	N/A	Total number of all RR intervals divided by the height of the histogram of all RR intervals.
TINN	Ms	Baseline width of the minimum square difference triangular interpolation of the highest peak of the histogram of all RR intervals measured on a discrete scale with bins of 7·8125 ms (1/128 s).

They found in the result that the proposed technique heart Rate Variability Analyzer application to acquire these measurements. Figure(2.5) illustrate RR interval in HRV signal [8].

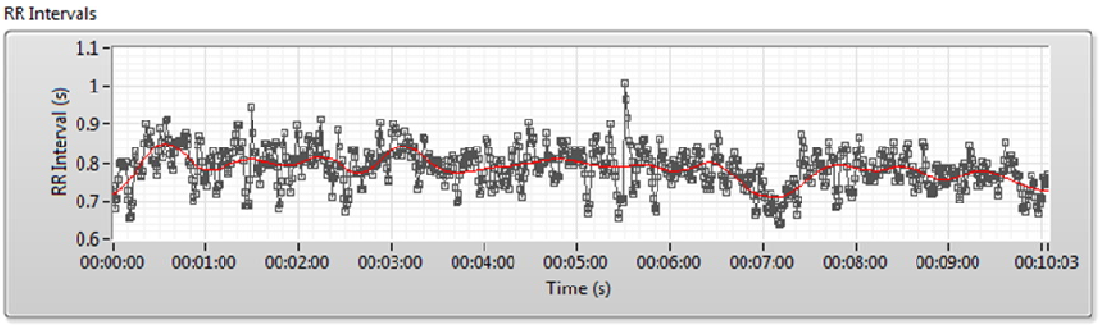


Figure 2.8 Detraining process for RR interval signal in HRV

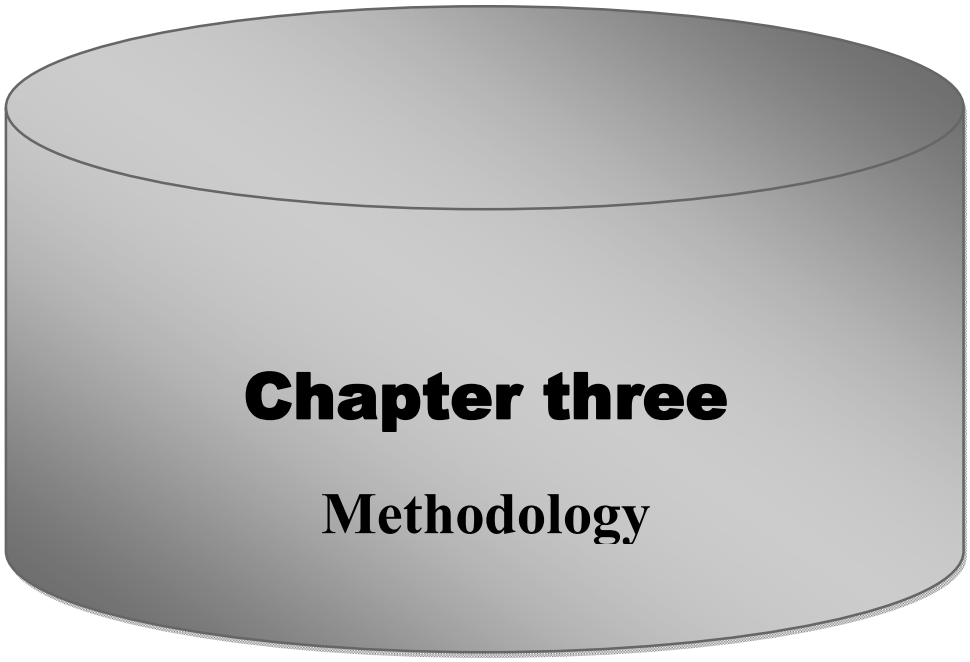
Ulrich Mehnert,* Peter A. Knapp, Nicole Mueller, Andre´ Reitz, and Brigitte Schurch, discuss an objective measure of autonomic activity and bladder sensations during urodynamics using heart rate variability. They use a volunteer sample of healthy female subjects a standard FC at 25 ml/min was performed using an 8 Fr micro tip catheter with integrated pressure transducers. During FC, subjects had to indicate first Sensation of fling (FSF), first desire to void (FDV) and strong desire to void (SDV). A 3-lead electrocardiogram was continually recorded ,continuously recorded. After 5 h all measurements were repeated. Power spectrum analysis was used to analyze HRV, to obtain low frequency (LF) and high frequency (HF) parameters, from which the LF/HF ratio was derived. finally they found 12 subjects with a mean age of 23.3 2.3 years could be included. 11 of 12 subjects completed both measurement sessions. One subjects had to be excluded, due to irritating urethral discomfort following cathe- terisation. The LF/HF ratio showed a reproducible activation pattern in the healthy subjects with a stable sympathovagal balance until FDV Before SDV was indicated the sympathovagal balance started to shift towards sympathetic activation and caused a significant increase in LF/HF [18].

Szi-Wen Chen discuss A Wavelet-Based Heart Rate Variability Analysis for the Study of No sustained Ventricular Tachycardia, they proposed work investigated Wavelet analysis methods. These methods represent the temporal characteristics of a signal by its spectral components in the frequency domain, and the next step they describe Analysis Scheme which use WT-based analysis

scheme for short-time HRV assessments. and suggested that the proposed technique could effectively extract features, which differentiate between the types of heart diseases analyzed and also for normal heart signal their test results [19].

P. Sasikala, Dr. R.S.D. Wahidabanu, Salem, discuss the robust R Peak and QRS detection in Electrocardiogram using Wavelet Transform by using matlab program for preprocessing and feature extraction using digital filters in pre processing and wavelet transform in feature extraction. they found on their result the information about the R Peak and QRS complex obtained is very useful for ECG classification, analysis, diagnosis, authentication and identification performance. The QRS complex is also used for beat detection and the determination of heart rate through R-R interval estimation. This information can also serve as an input to a system that allows automatic cardiac diagnosis [16].

R. Harikumar, S.N. Shivappriya, discuss Analysis of QRS Detection Algorithm for Cardiac Abnormalities they use in their methods The ECG Beat Classification will consist of 5 modules. ECG (ventricular arrhythmia) signals used for the research were obtained from the Physionet Database (Physio Bank)]. A set of programs from the Physionet website were used to import ECG records each signal component consists of data file, attribute file and header file written in Ma lab code. Mat lab and its Wavelet Toolbox were used for ECG signal processing and analysis. The five module for HRV signal are:Preprocessin Module,Feature Extraction Module,Feature Reduction, Classifier and Optimizer Module and the Output module which gives the performance metrics of the of Analyzer and diagnosis result [20].



Chapter three

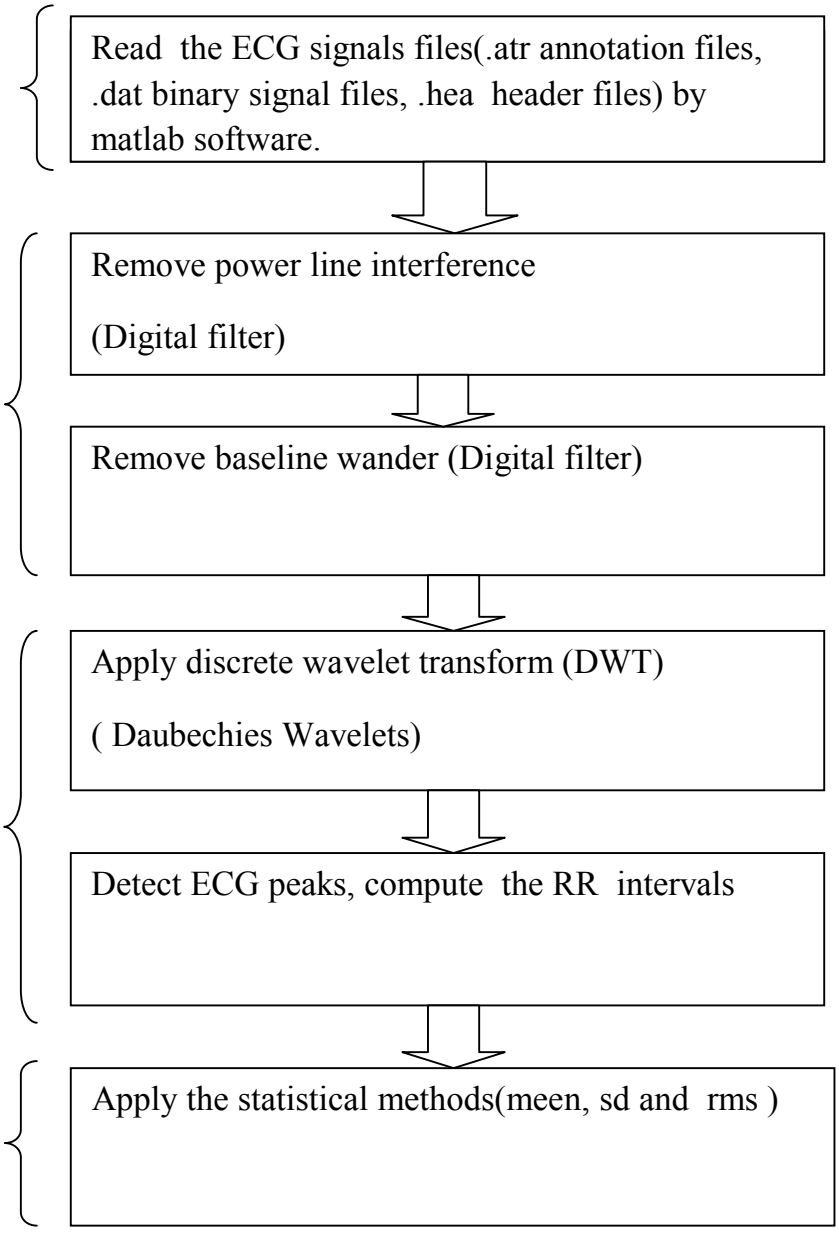
Methodology

Chapter Three

Methodology

3.1Methodology

The HRV analysis represent four steps as shown in this block diagram below which describe the ECG pre-processing, ECG feature extraction and the statistical methods.



3.2 Read ECG Signals

We are read ECG signals from MIT-BIH database by using matlab code .

20 ECG signals were used, they have normal and abnormal signals**.**

Table(3.1):The ECG Signal Read

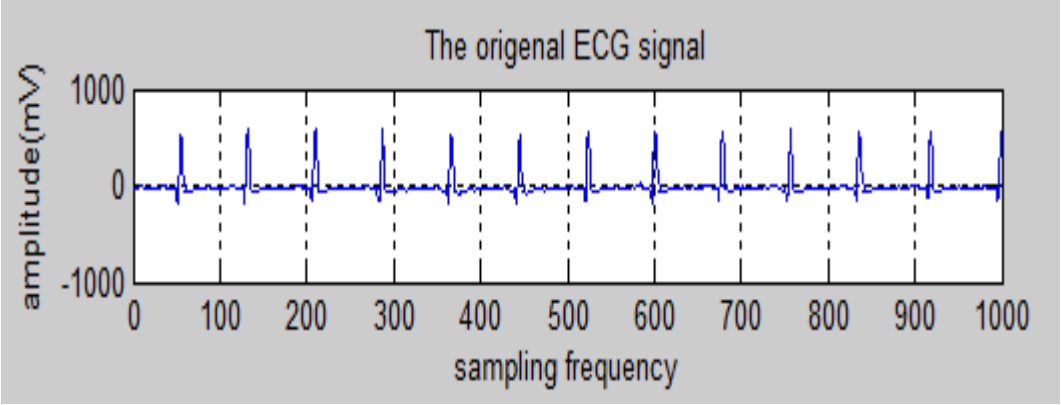


Figure 3.1 The reading of racord16265

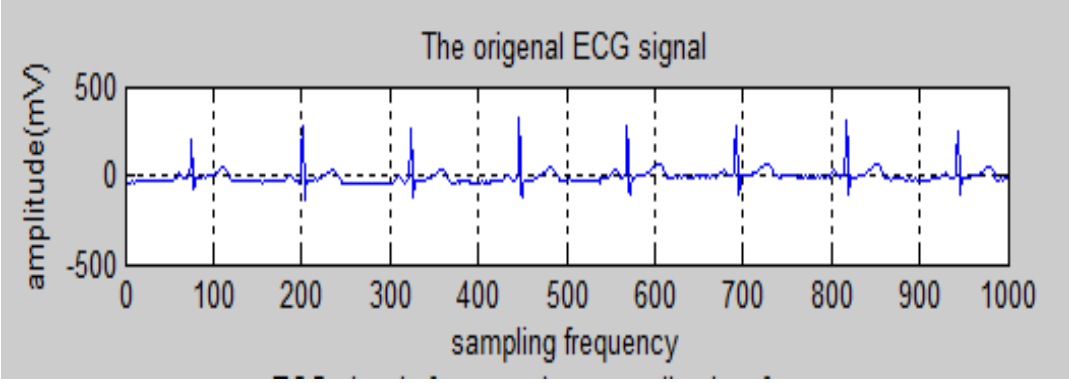


Figure 3.2 The reading of racord16272

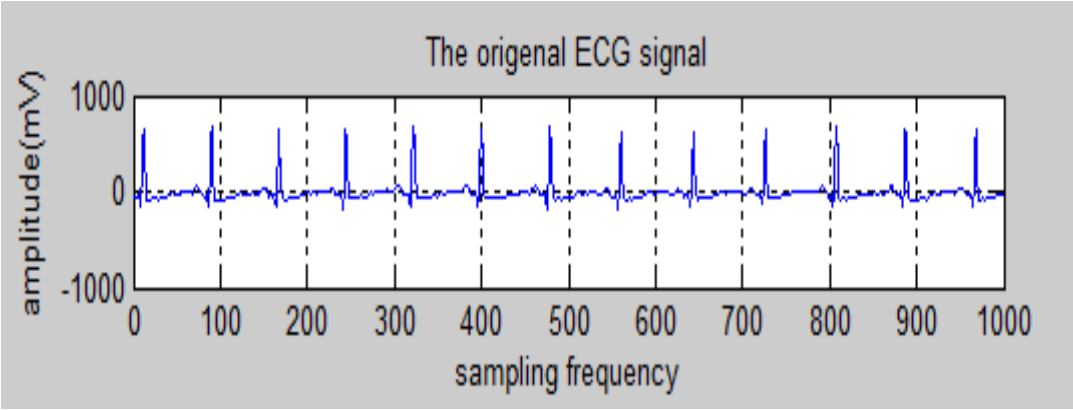


Figure 3.3 The reading of racord16273

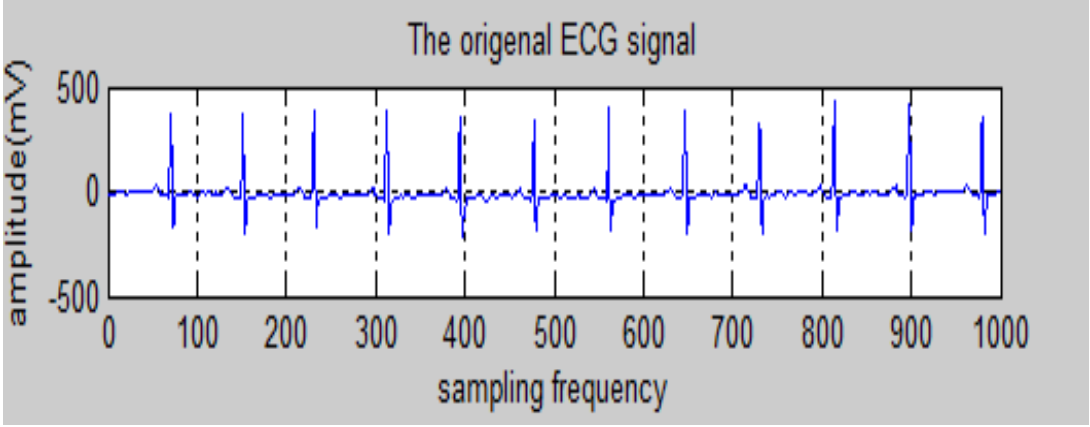


Figure 3.4 The reading of racord16420

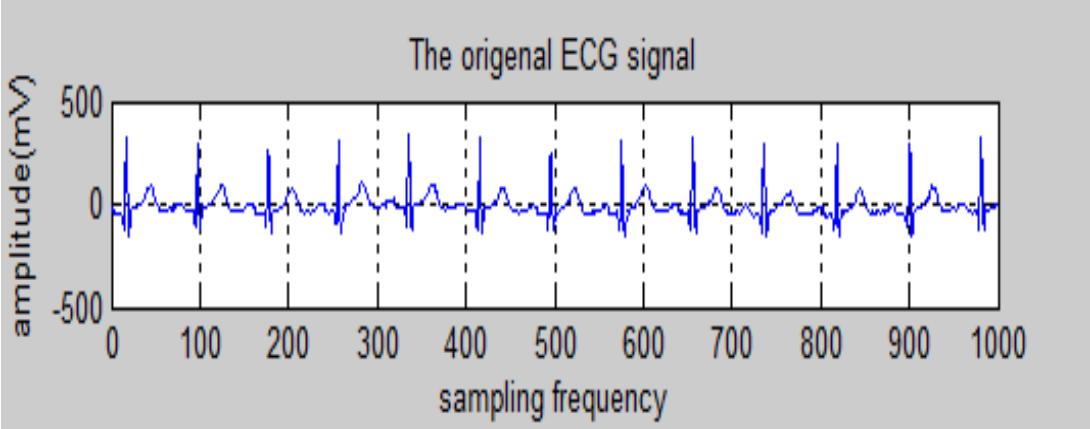


Figure 3.5 The reading of racord16483

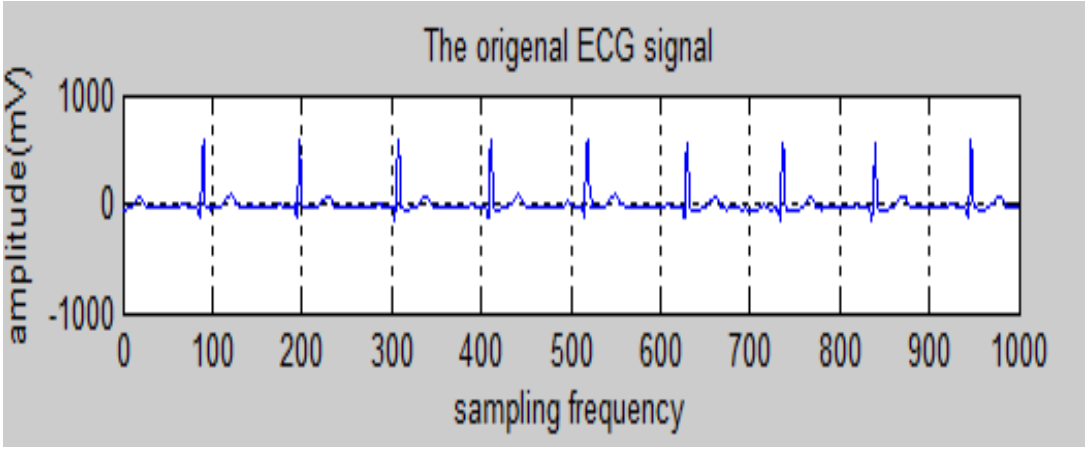


Figure 3.6 The reading of racord16786

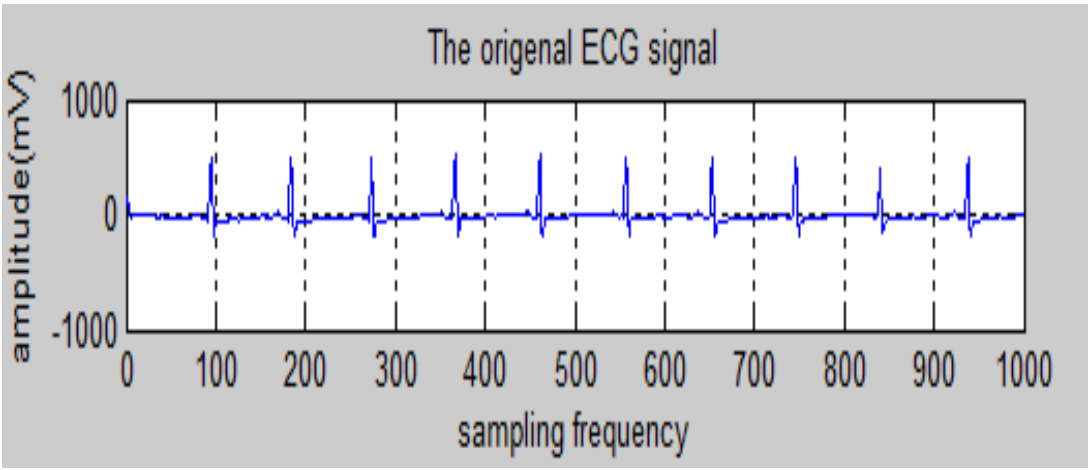


Figure 3.7 The reading of racord17453

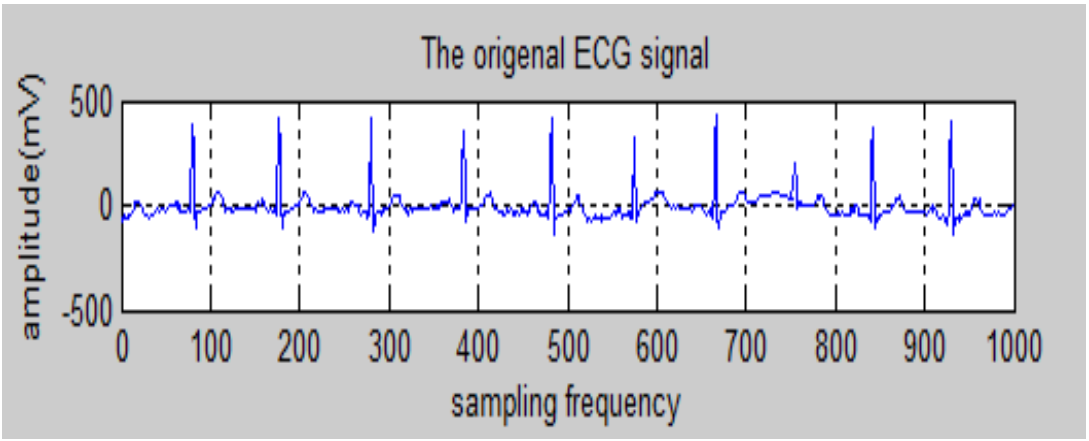


Figure 3.8 The reading of racord18184

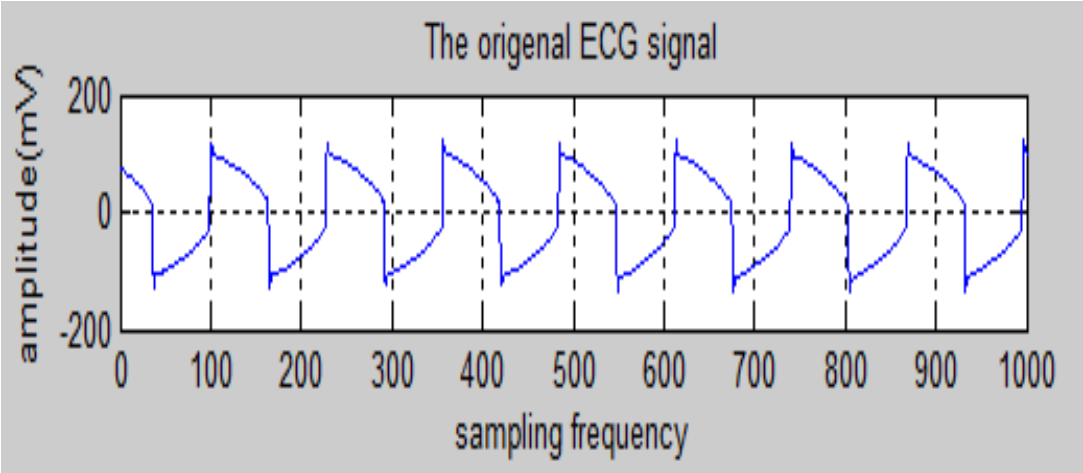


Figure 3.9 The reading of racord19088

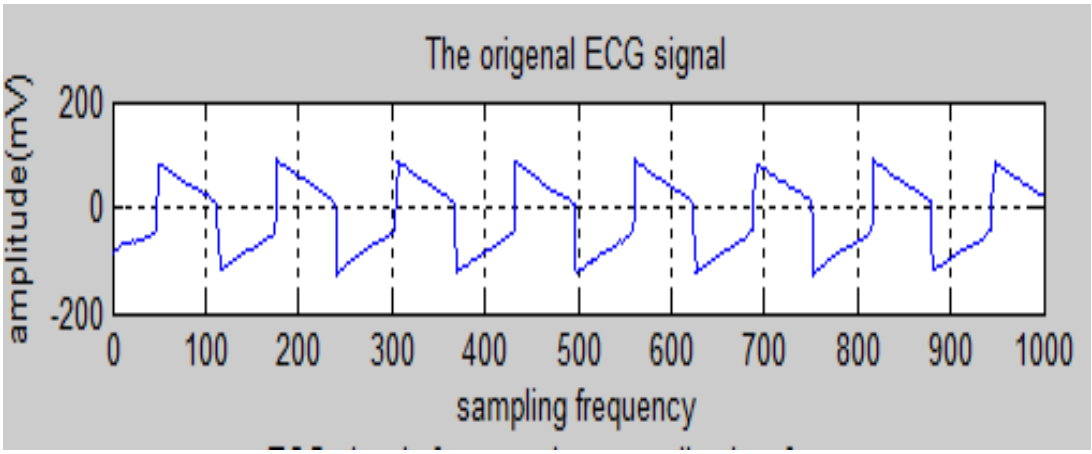


Figure 3.10 The reading of racord19830

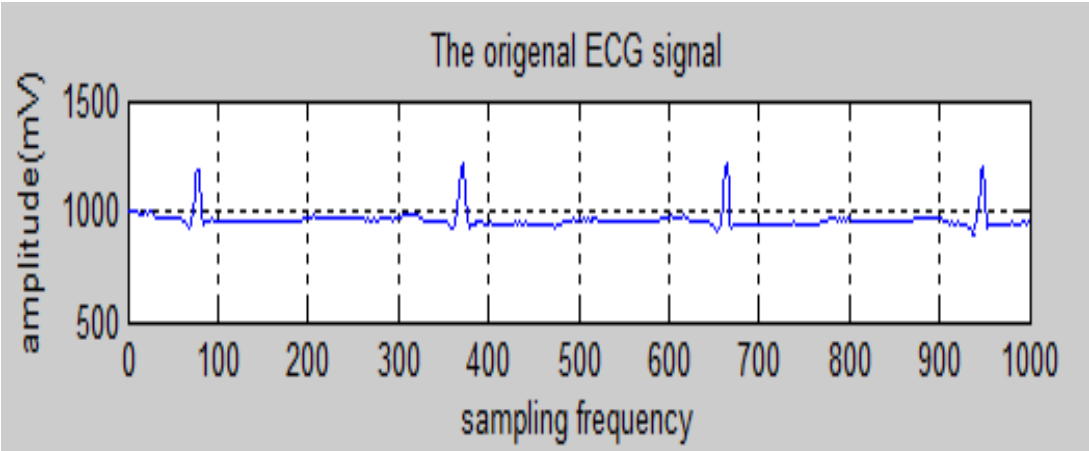


Figure 3.11 The reading of racord100

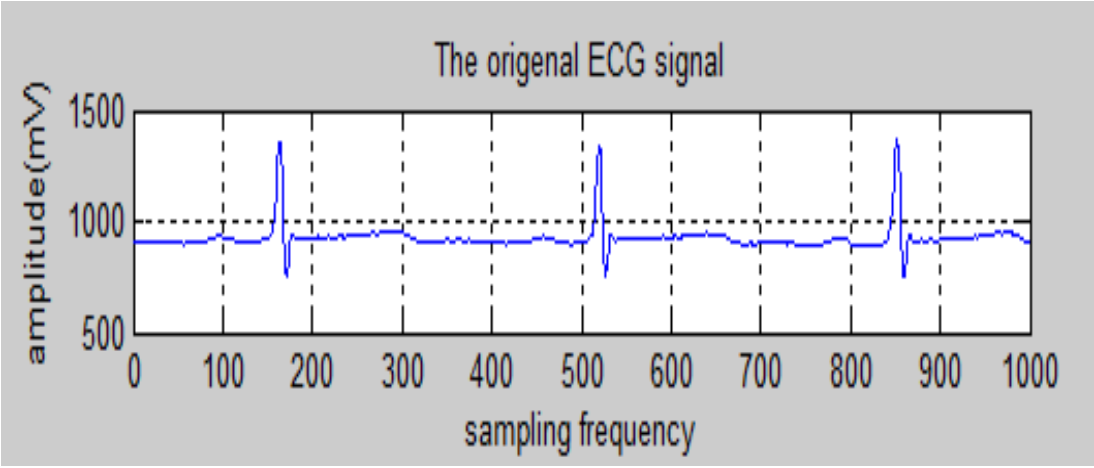


Figure 3.12 The reading of racord115

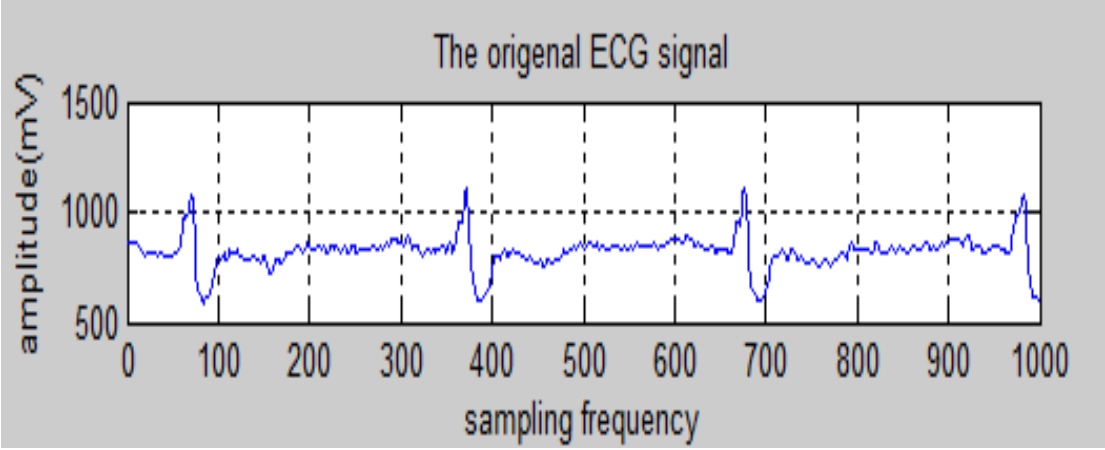


Figure 3.13 The reading of racord118

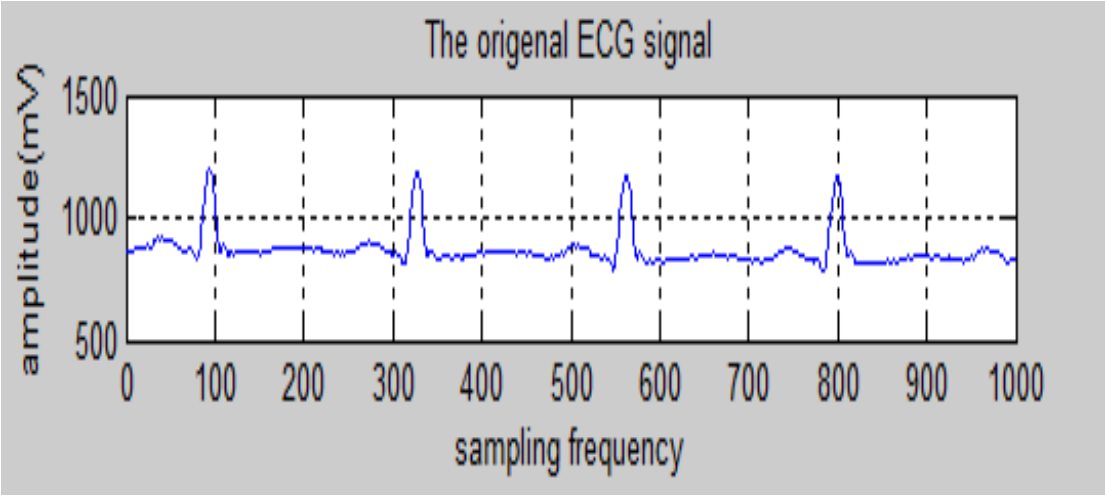


Figure 3.14 The reading of racord122

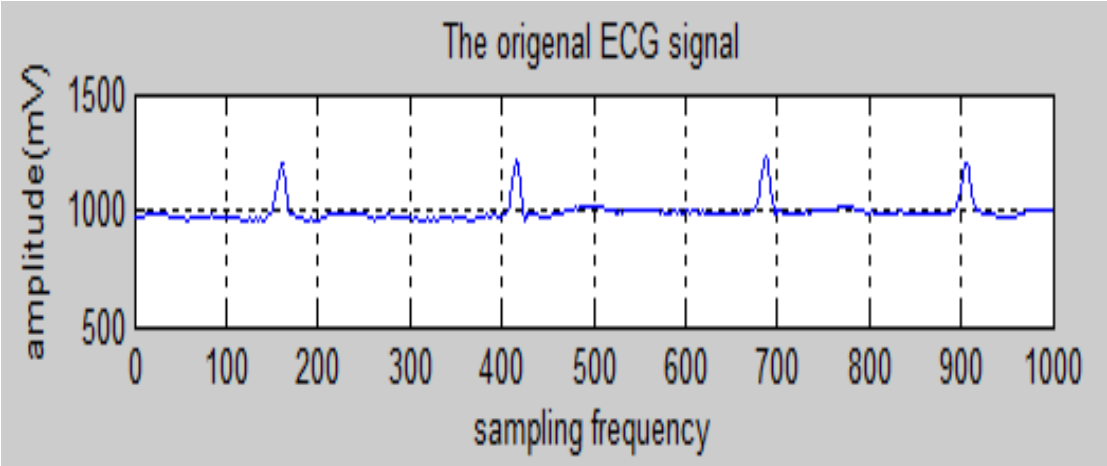


Figure 3.15 The reading of racord201

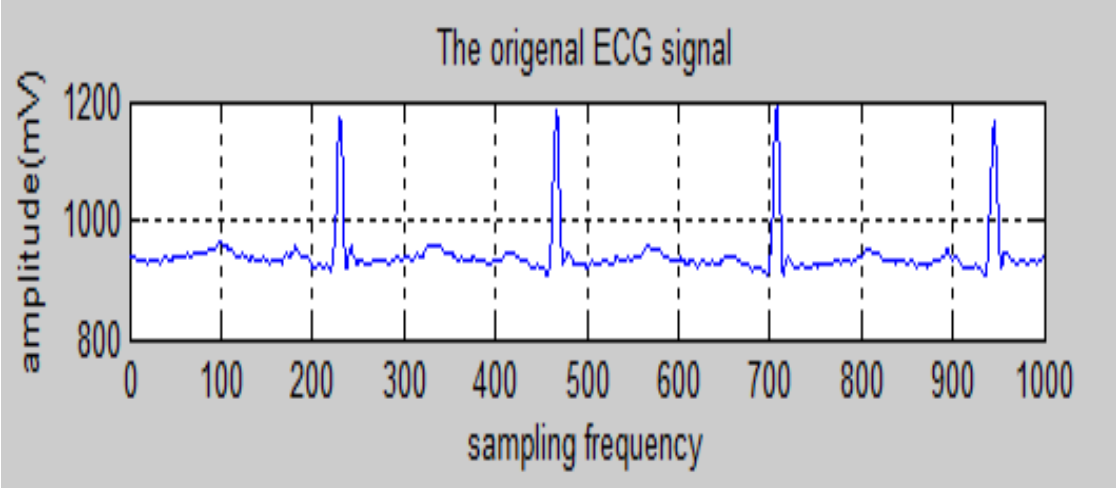


Figure 3.16 The reading of racord205

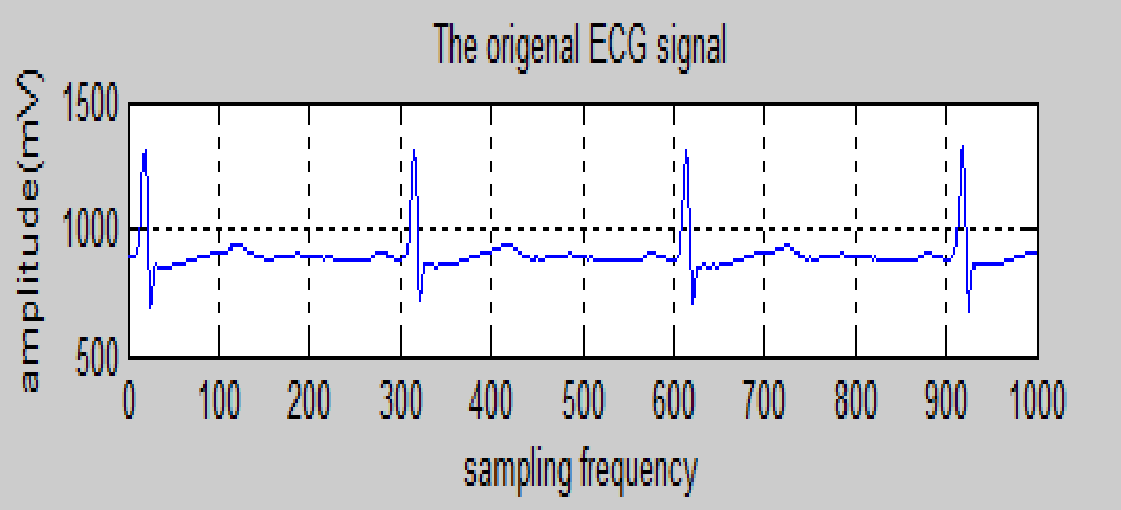


Figure 3.17 The reading of racord220

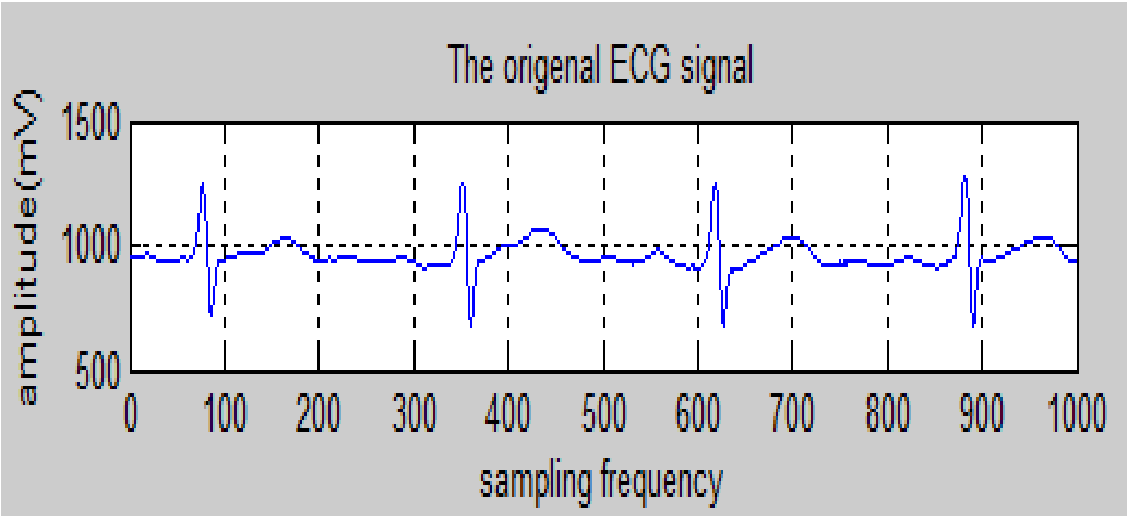


Figure 3.18 The reading of racord230

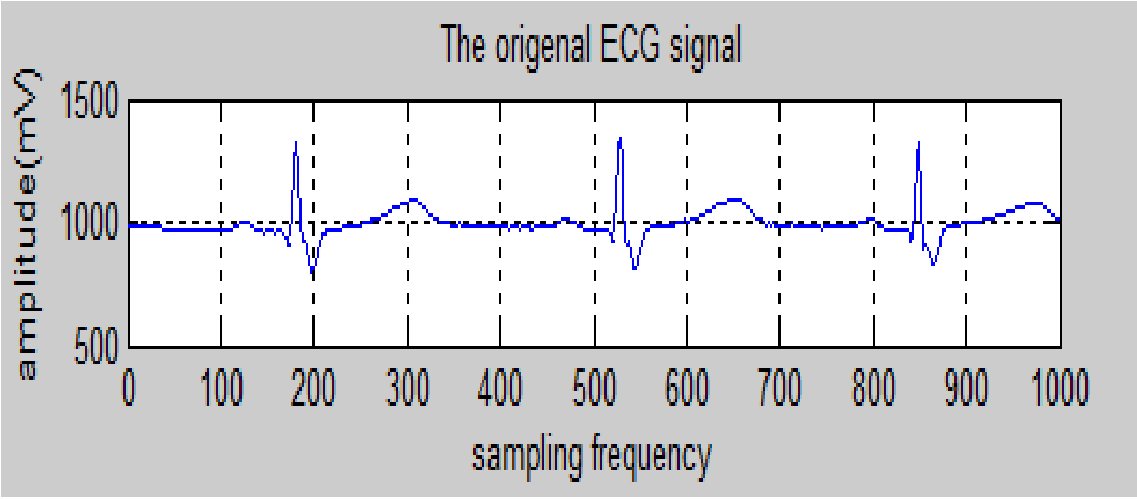


Figure 3.19 The reading of racord231

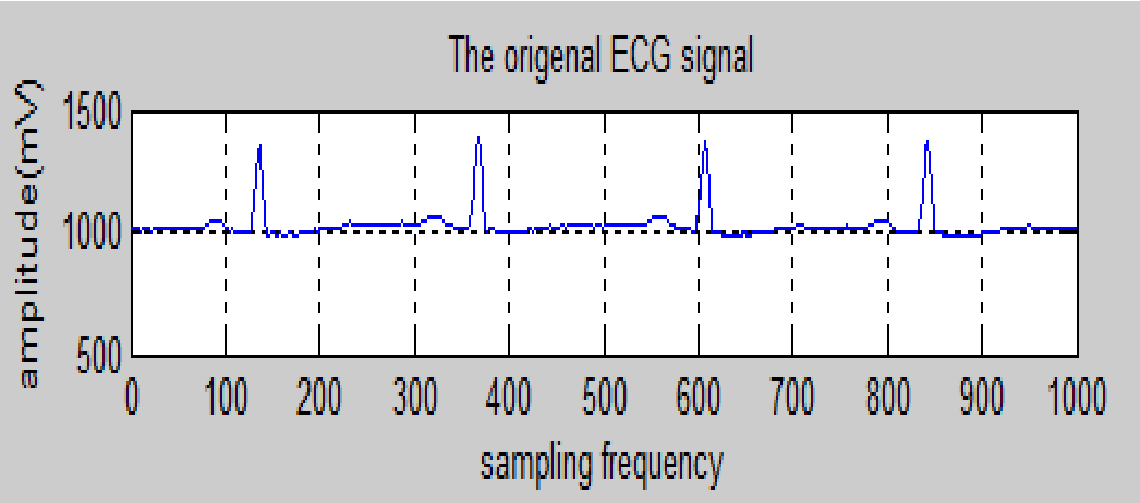


Figure 3.20 The reading of racord234

3.3 Preprocessing

3.3.1 (ECG Filtering)

HRV depend on ECG signal which a major diagnostic tool for the cardiologists and ECG signal provides almost all the information about electrical activity of the heart. So care should be taken while doing the ECG filtering.

3.3.1.1 Powerline Interference

Powerline Interference at ECG signals from MIT-BIH database is (60 Hz),to reduction it there were Designed a band stop (notch) filter second order IIR with the following specification using the pole-zero placement

- Sampling rate(fs) 600 Hz.
- 3dB band width BW Hz.
- Centred of pass band (narrow) fo

The design formulas for band stop filters are given in the following equation:

$$r \approx 1-(BW_{3db}/f_s)*\pi \quad (3)$$

$$\text{for } 0.9 \leq r < 1$$

which is the required magnitude of the poles.

$$\theta = (f_0/f_s)*360^o \quad (4)$$

We use the center frequency to obtain the angle of the pole location in(3.2) above.

Then we calculate the scale factor to adjust the band stop filter to have a unit pass band gain given by:

$$k=(1-2r\cos\theta+r2)/(2-2\cos\theta) \quad (5)$$

finally we obtain the transfer function as follows:

$$H(z)=(z2 - 2z\cos\theta+1)/(z2 - 2rz\cos\theta+r2) \quad (6)$$

All equations of power line interference from [21]

Figure show the remove of power line interference

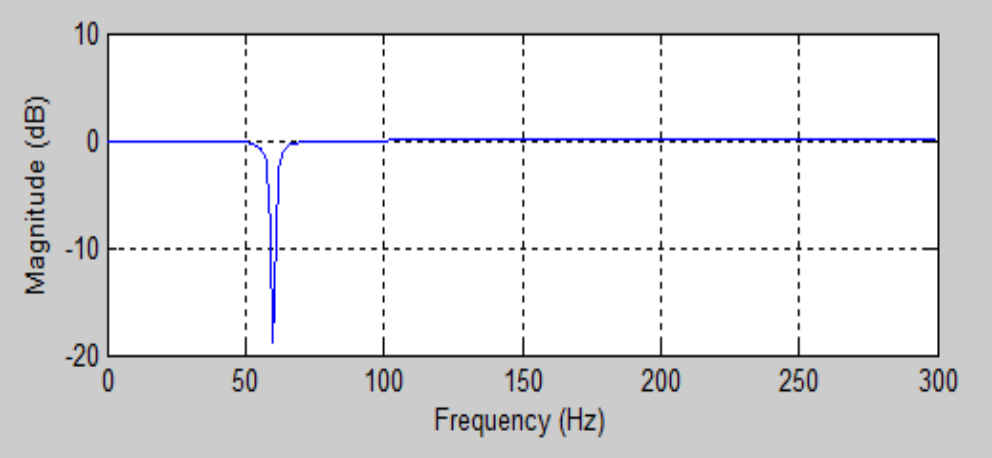


Figure 3.21(a) A second order IIR band stop (notch) filter frequency response of 60Hz(magnitude).

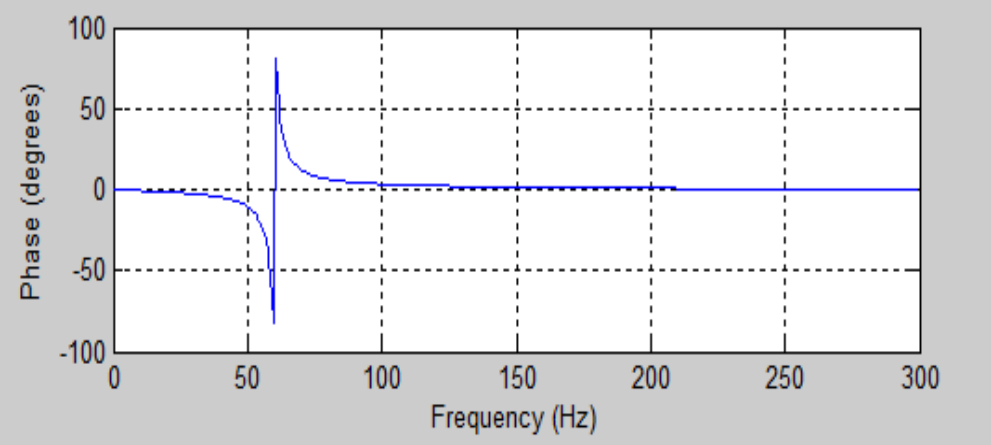


Figure 3.21(b) A second order IIR band stop (notch) filter frequency response of 60Hz (phase).

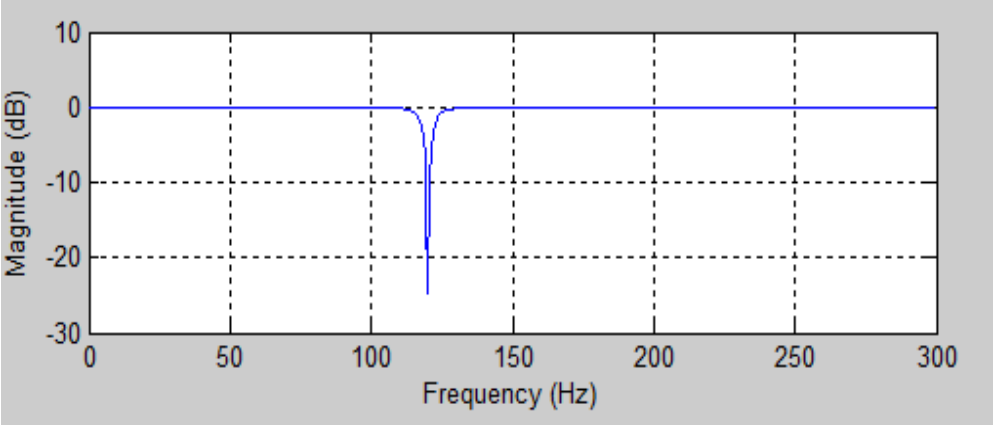


Figure 3.22(a) A second order IIR band stop (notch) filter frequency response of 120Hz(magnitude).

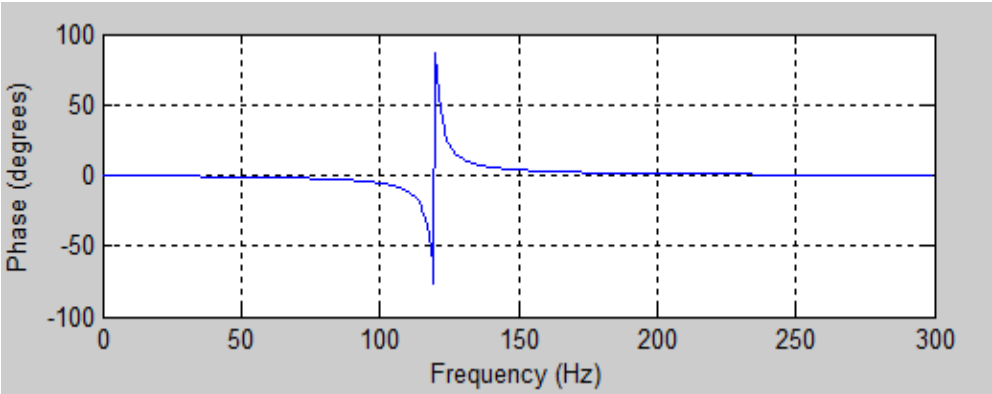


Figure 3.22(b) A second order IIR band stop (notch) filter frequency response of 120Hz(phase).

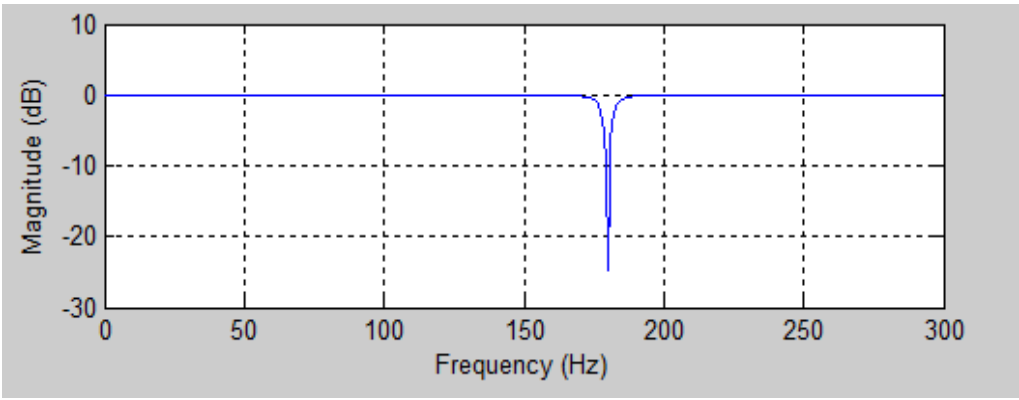


Figure 3.23(a) A second order IIR band stop (notch) filter frequency response of 180Hz(magnitude).

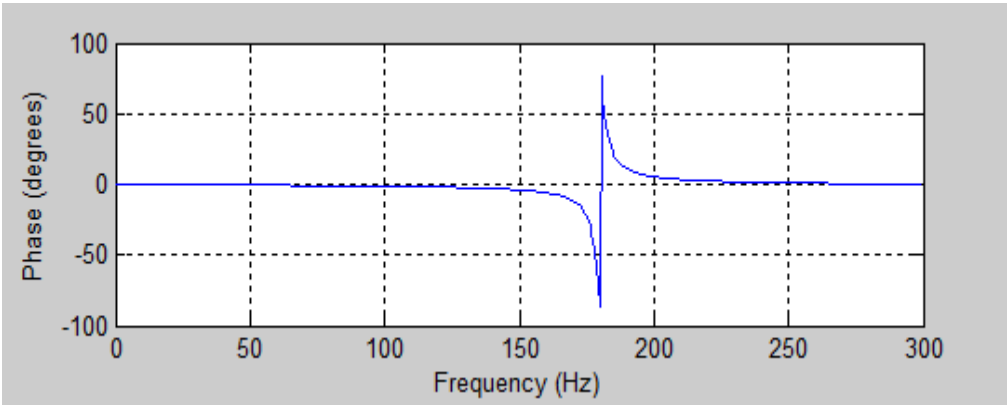


Figure 3.23(b) A second order IIR band stop (notch) filter frequency response of 180Hz(phase).

3.3.1. 2 Baseline wander

We need to remove DC drift and to filter muscle noise which may occur at approximately 40Hz or more, if we consider the lowest heart rate as 30 beats per minute the corresponding frequency is 30/60 which equal 0.5Hz [21].

Now we use the band pass fourth order chebyshev filter using the bilinear transformation which is the best methods in HRV [21].

There are three steps to design the filter:

- Given the digital filter frequency specification, pre warp the digital

$$\omega_a = \frac{2}{T} \tan \frac{(\omega_d T)}{2} \quad (7)$$

$$\omega_d = \frac{2}{T} \tan^{-1} \frac{(\omega_a T)}{2} \quad (8)$$

The tow equassion above for low pass and high pass filter, and for band pass and band stop filter we use:

$$\omega_{al} = \frac{2}{T} \tan \frac{(\omega_l T)}{2} \quad (9)$$

$$\omega_{ah} = \frac{2}{T} \tan \frac{(\omega_h T)}{2} \quad (10)$$

Where

$$\omega_0 = \sqrt{\omega_{al}\omega_{ah}} \quad (11)$$

And

$$W = \omega_{ah} - \omega_{al} \quad (12)$$

- Perform the prototype transformation using the low pass prototype Hp(s).

From low pass to band pass:

$$H(s)=Hp(s)\,|_{s=}\quad \frac{(s2+\omega 02)}{sW} \qquad (13)$$

Where the first-order lowpass prototype filter given by:

$$Hp(s)=\quad \frac{1}{(s+1)} \qquad (14)$$

- Substitute the BLT to obtain the digital filter:

$$H(z)=H(s)|_{s=}\quad \frac{2}{T}\quad \frac{z-1}{z+1} \qquad (15)$$

All equations of DC drift from [21].

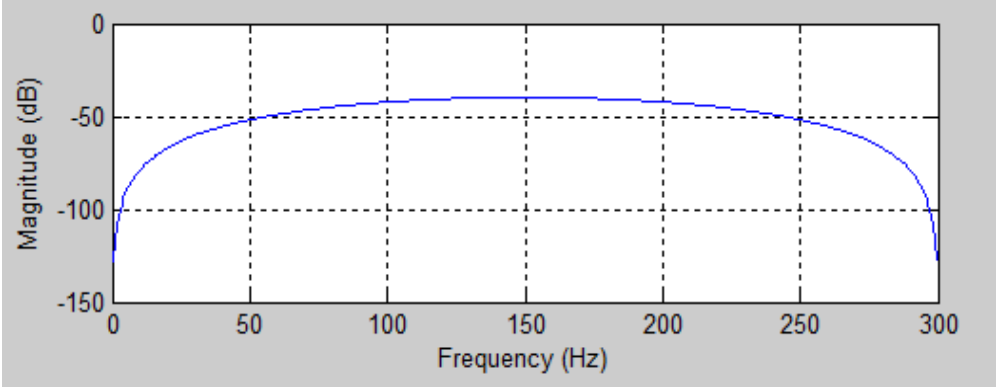


Figure 3.24(a) A band pass fourth order chebyshev filter frequency response(magnitude).

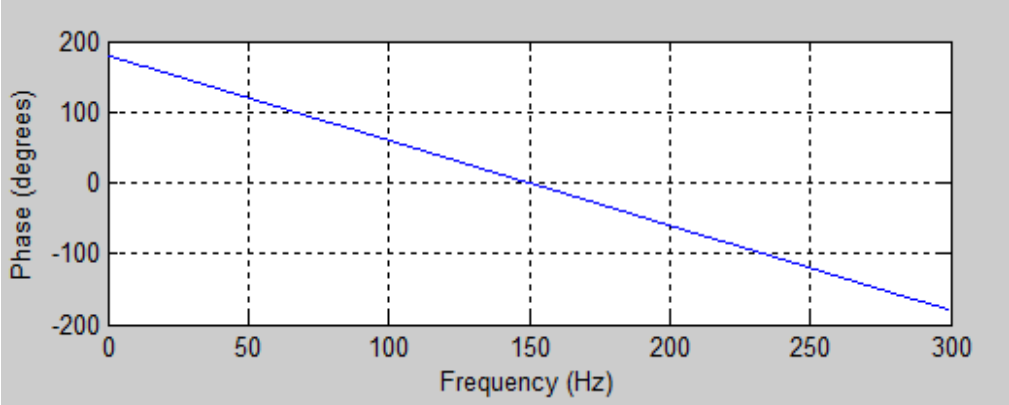


Figure 3.24 (b) A band pass fourth order chebyshev filter frequency response(phase).

3.4 ECG Feature Extraction

ECG wave commonly change their statistical properties over time, tending to be non stationary. For analyzing this kind of signal wavelet transforms are a powerful tool. The main tasks in ECG signal analysis are the detection of QRS complex , and estimation of another peaks potions.

Wavelet transform provide simultaneous time and frequency information. The wavelet transform decomposes the Electrocardiogram (ECG) signal into a set of frequency band. In the wavelet based algorithm, the ECG signal has been denoised by removing the corresponding wavelet coefficients at higher scales. The analysis has been done on ECG data files of the MIT-BIH Arrhythmia and Rhythmia Database.

3.4.1 Daubechies Wavelets

Wavelets classified into two classes: (a) orthogonal and
(b) biorthogonal. Based on the application, either of them can be used

Features of orthogonal wavelet filter banks

The coefficients of orthogonal filters are real numbers. The filters are of the same length and are not symmetric. The low pass filter, G_0 and the high pass filter, H_0 are related to each other by

$$H_0(z)=z^{-N} G_0(-Z^{-1}) \qquad (16)$$

Orthogonal filters offer a high number of vanishing moments. This property is useful in many signal and image processing applications. They have regular structure which leads to easy implementation and scalable architecture.

Daubechies represents a family of orthogonal wavelets characterized by a maximal number of vanishing moments for some given support's length.The elements of the Daubechies' family most used in practice are db2-db20. The index refers to the number of vanishing moments. The number of vanishing moments is equal with half of the length of the support in the case of Daubechies family of mother wavelets. For example, db1 (the Haar wavelet)

has one vanishing moment, db2 has two, etc. The Daubechies mother wavelets are not symmetric.

Table (3.1): General characteristics for Daubechies

Short name	Db
Order N	N strictly positive integer
Orthogonal	Yes
Biorthogonal	Yes
Compact support	Yes
DWT	Possible
CWT	Possible
Support width	2N-1
Filters length	2N
Regularity	about 0.2 N for large N
Symmetry	far from
Number of vanishing moments for psi	N

3.4.2 Feature description

By Matlab code Q R S peaks were detected and then then RR intervals were computed .

3.5 Statistical methods

The Matlab code were used and then calculate the statistical parameter such as the mean (Mi) ,standard deviation (Std) and roots mean squirts (RMS) to evaluate the HRV between normal and abnormal cases.

Chapter Four

The Results and Discussions

Chapter Four

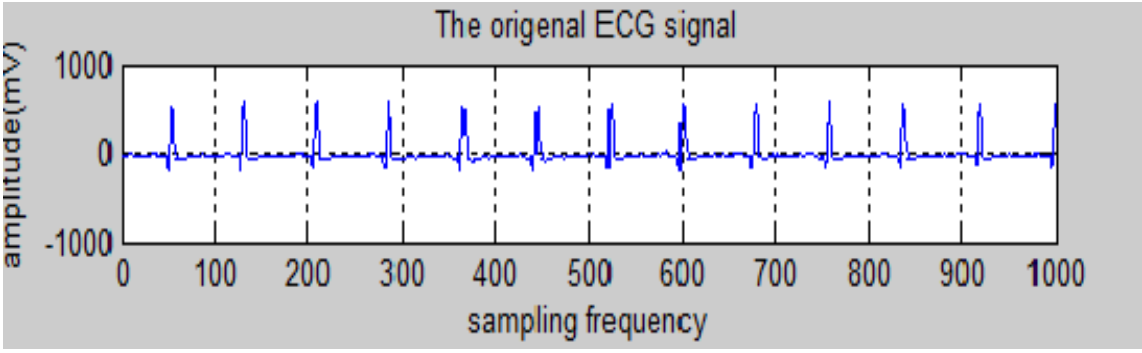
The Results and Discussions

The ECG signals from MIT-BIH database ,the beats were selected from the recordings of 20 patients which correspond to the following files:100,115,118,122,201,205,220,230,231,234,16265,16272,16273,16420,16483,16786,17453,18184,19088 and 19830. In this chapter the results of each steps of analysis for different signals were shown , after that the analysis of HRV by using the statistical methods were evaluations.

4.1 The Signal Pre processing Results

Two filters designed to remove the noises, A band stop (notch) filter second order IIR filter designed and implemented to remove the power line interference with a cut off frequency fc 60 Hz and its harmonic, The filter design showed in chapter 3 section (3.3.1) and the frequency response displayed in figure (3.1),(3.2) and (3.3), The anther filter is the band pass fourth order chebyshev filter designed and implemented to remove the baseline wander from signals, The filter design showed in chapter 3 section (3.3.2) and its frequency response displayed in figure (3.4).The results of two filters were shown at record 16265,16272,115 and 205 for examples.

Date No (1) - (16265)



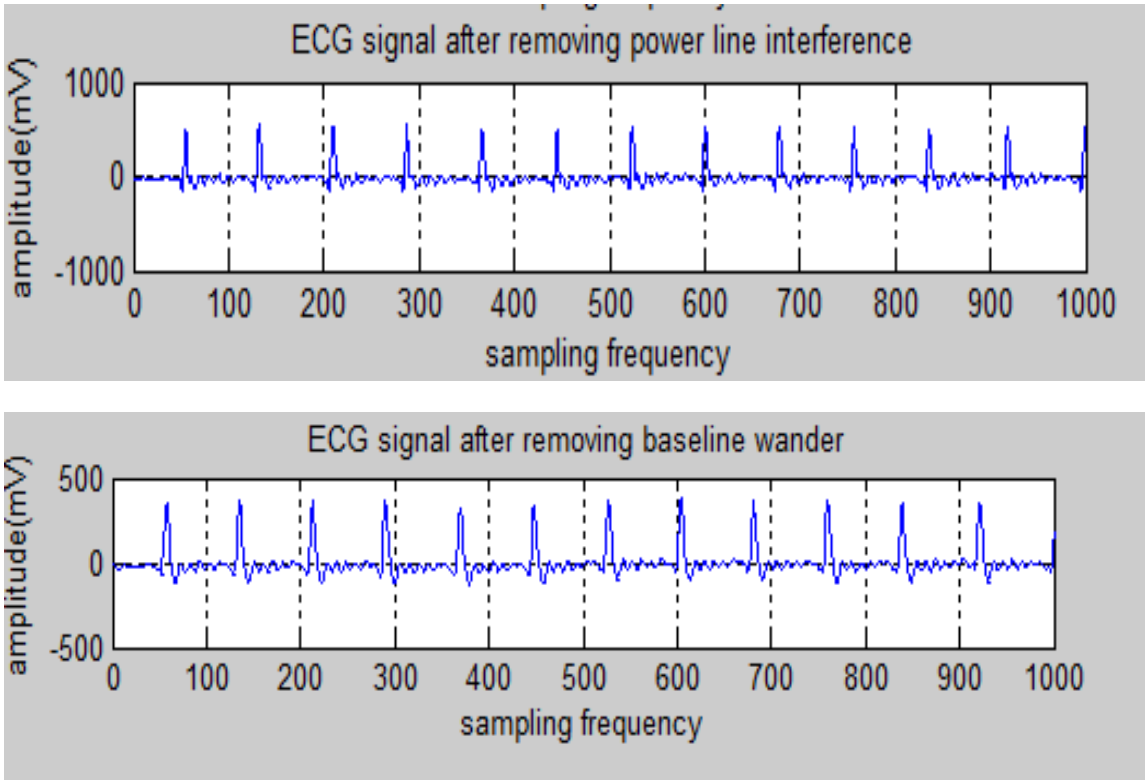


Figure 4.1 Apply the pre processing filters at record 16265

Date No (2) - (16272)

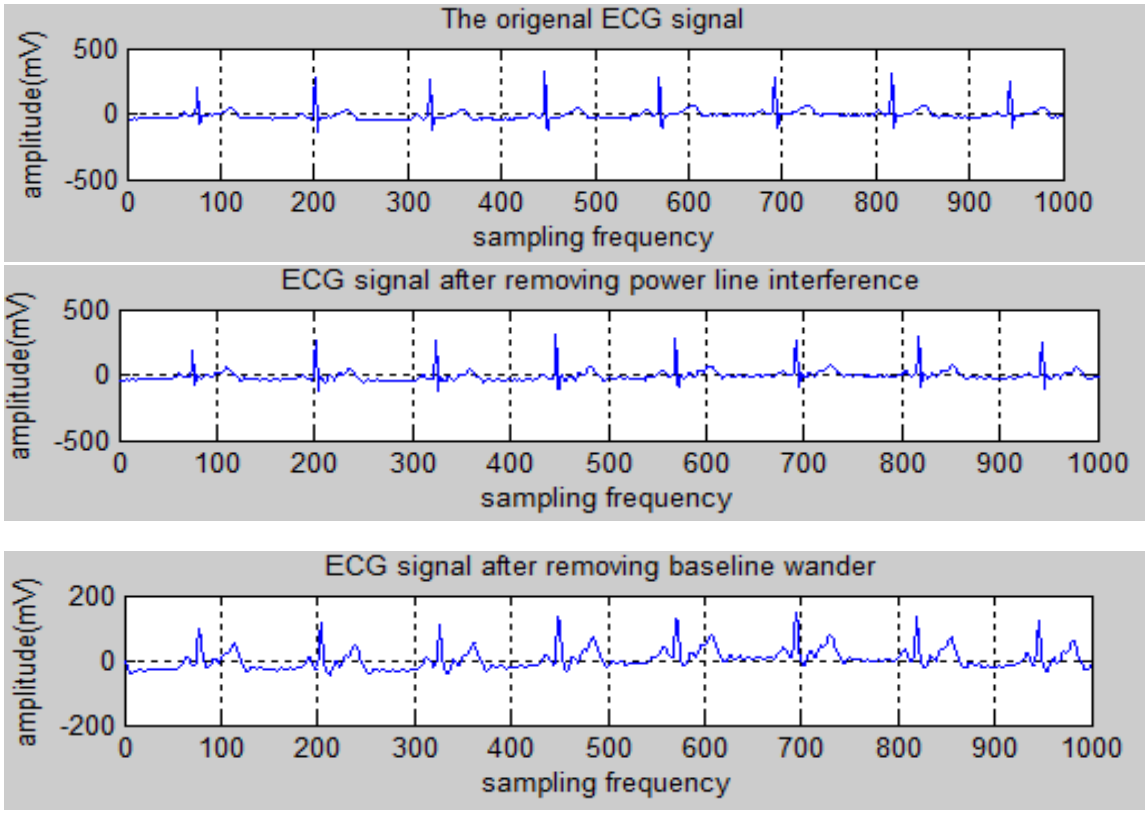


Figure 4.2 Apply the pre processing at record 16272

Date No (3) - (115)

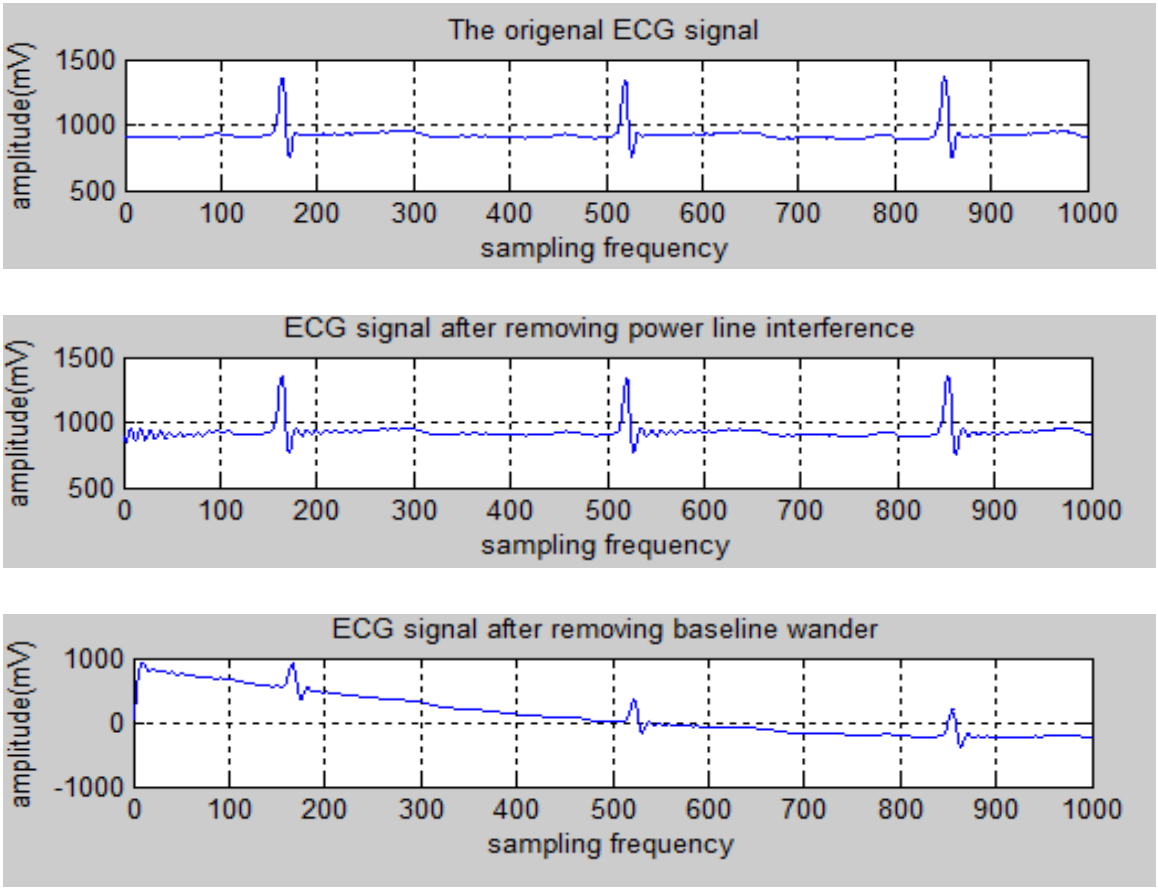
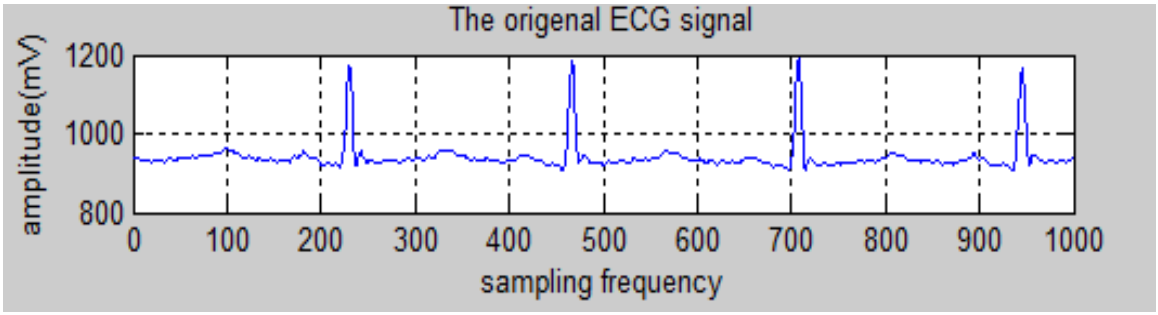


Figure 4.3 Apply the pre processing at record 115

Date No (4) - (205)



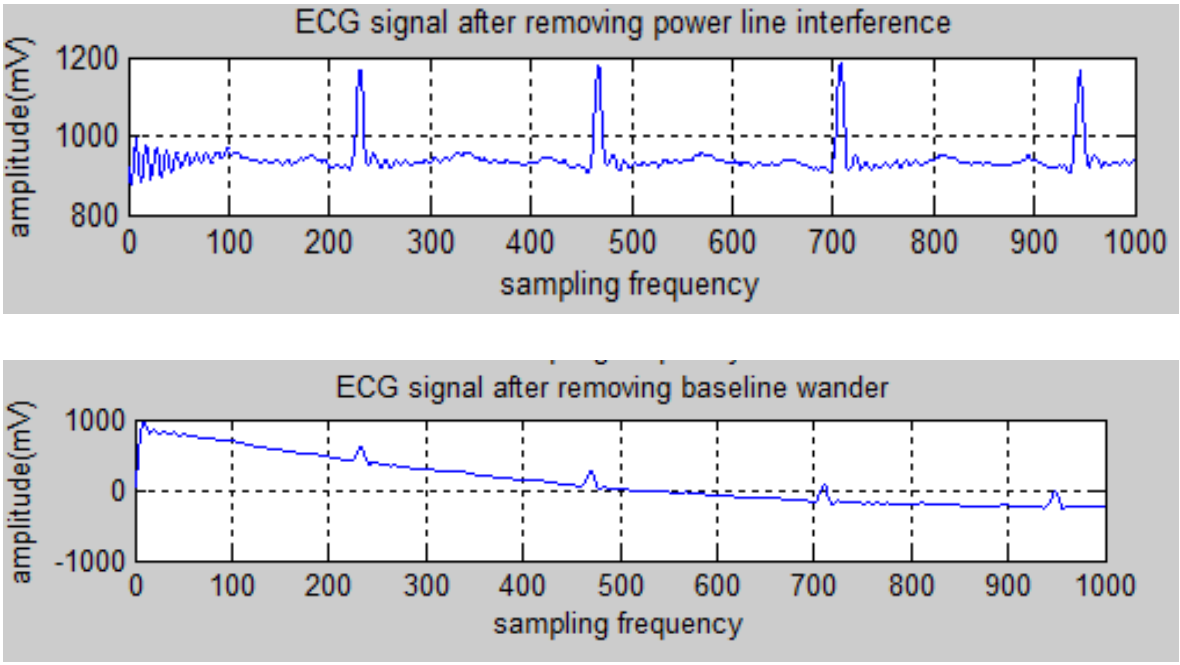


Figure 4.4 Apply the pre processing at record 205

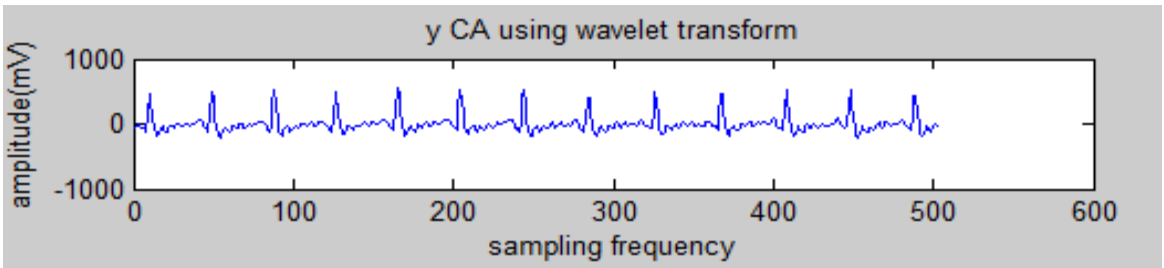
In figures (4.1),(4.2),(4.3) and (4.4).A second-order IIR band stop filter are used to remove the power line interference 60Hz, and A fourth-order band pass chebyshev filter designed to remove the baseline wander.

4.2 ECG Feature Extraction Results

Discrete wavelet transform DWT (Daubechies Wavelets "db4") was applied at filtered signals to detect the QRS peaks from ECG signals, compute or detect the RR intervals, the choose of db4 depend on the previous studies. The results of 16273,18184 ,100 and 231 records were presented.

4.2.1 Results of Daubechies 4 at filtered signals

Date No (5) - (16273)



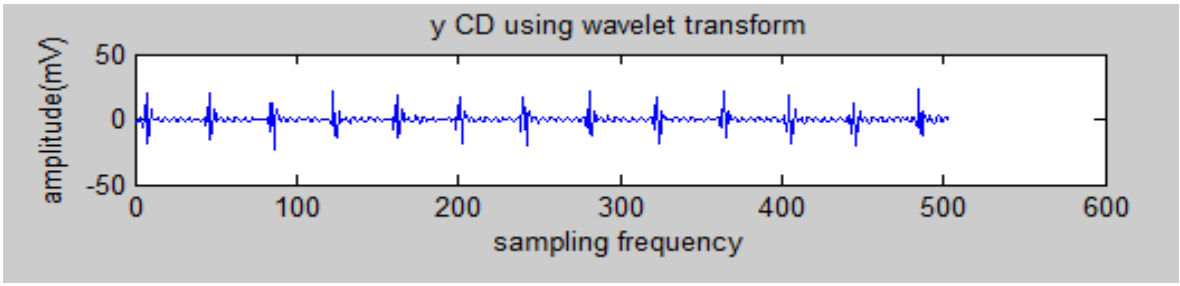


Figure 4.5 Db4 at record 16273 and extracted the coefficients (y CD,y CA)

The detail and approximation as shown below

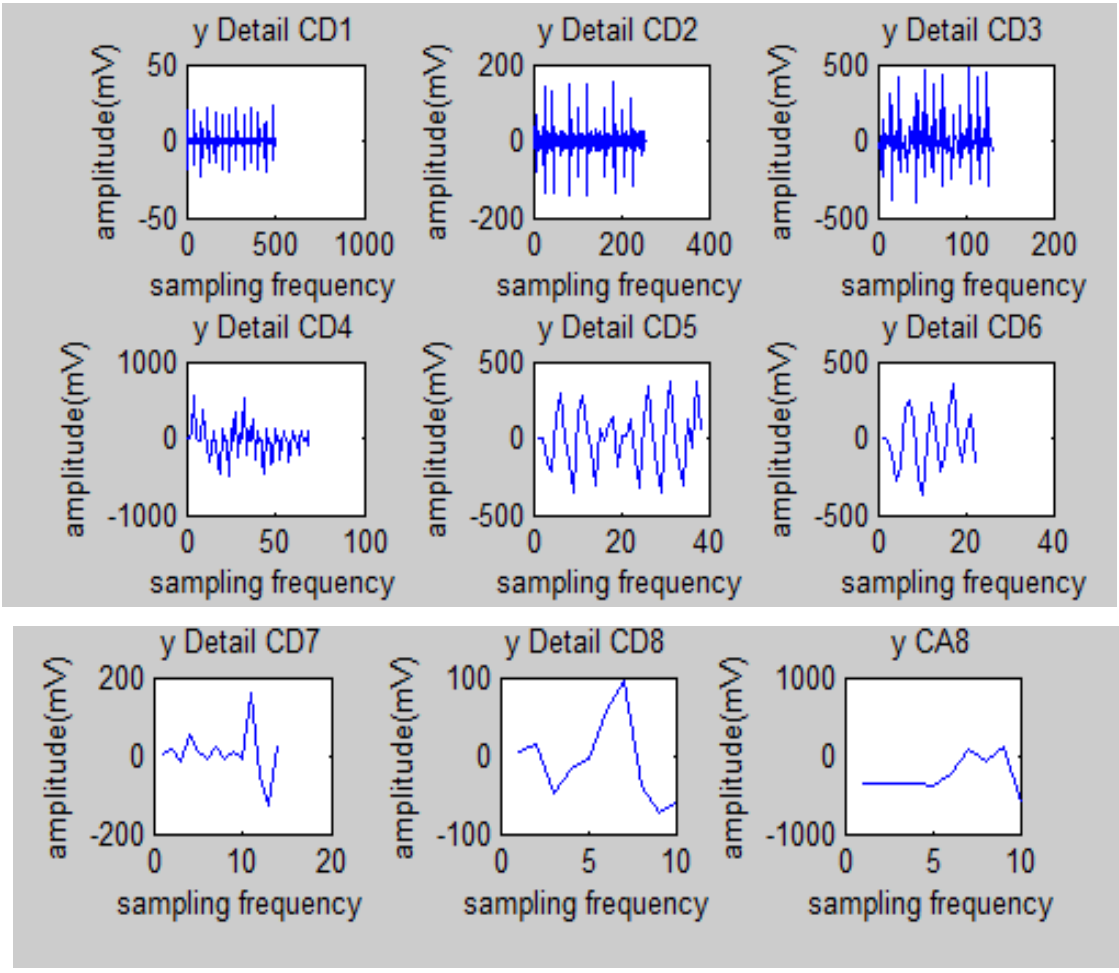


Figure 4.6 Detail and approximation depends on db4 at record 16273

Then computes the vector of reconstructed coefficients, based on the wavelet decomposition structure as shown below

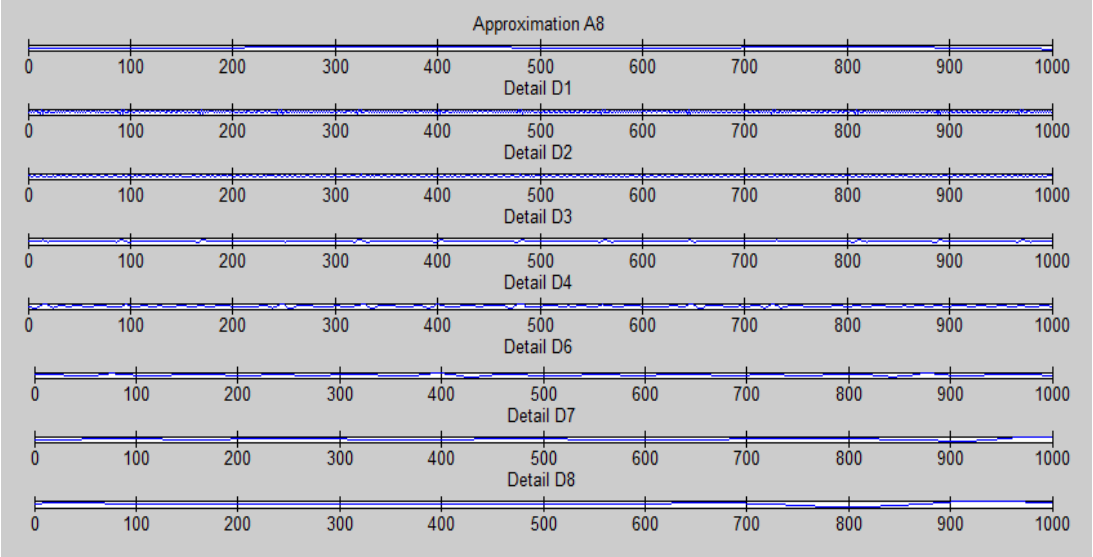


Figure 4.7 The approximation A8 at record 16273

Date No (6) – (18184)

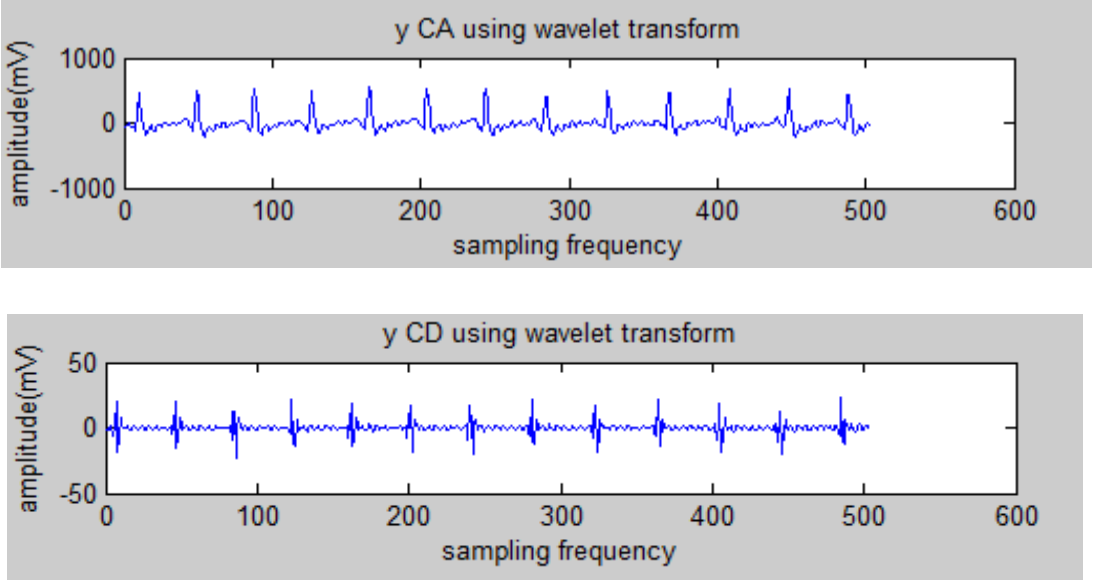
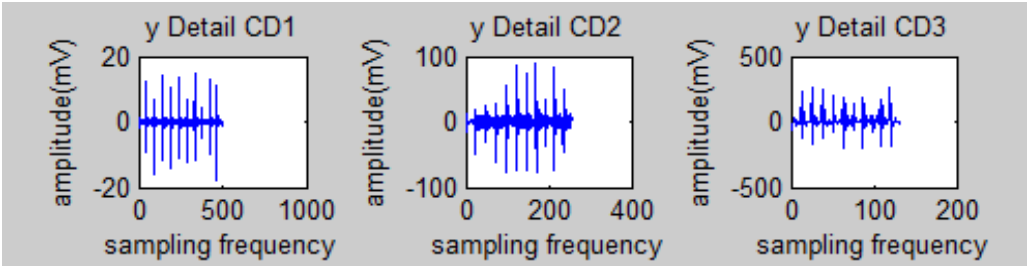


Figure 4.8 Db4 at record 18184 and extracted the coefficients (y CD,y CA)

The detail and approximation as shown below



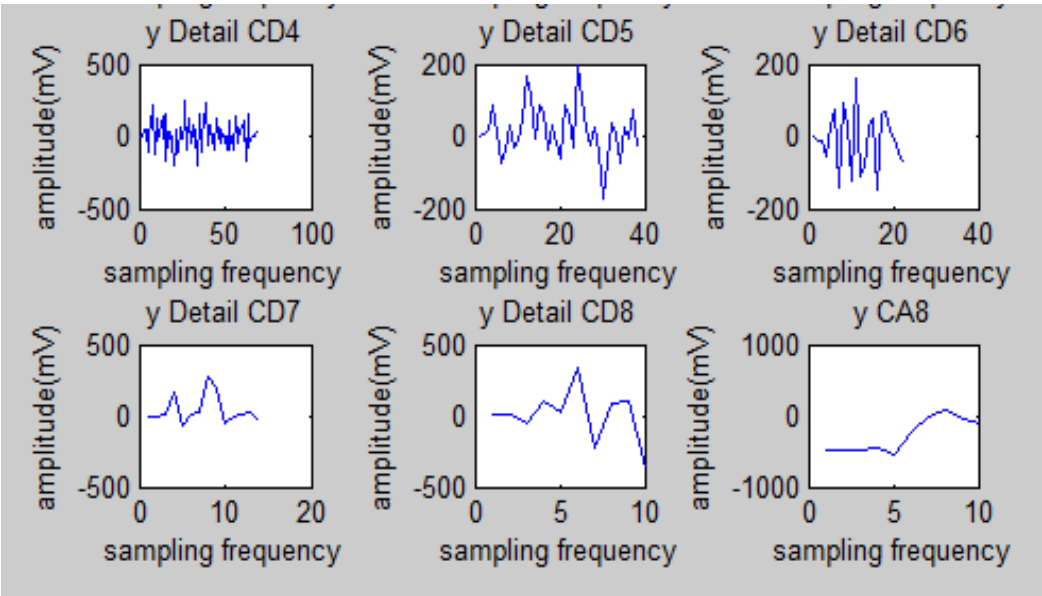


Figure 4.9 Detail and approximation depends on db4 at record 18184

Then computes the vector of reconstructed coefficients, based on the wavelet decomposition structure as shown below

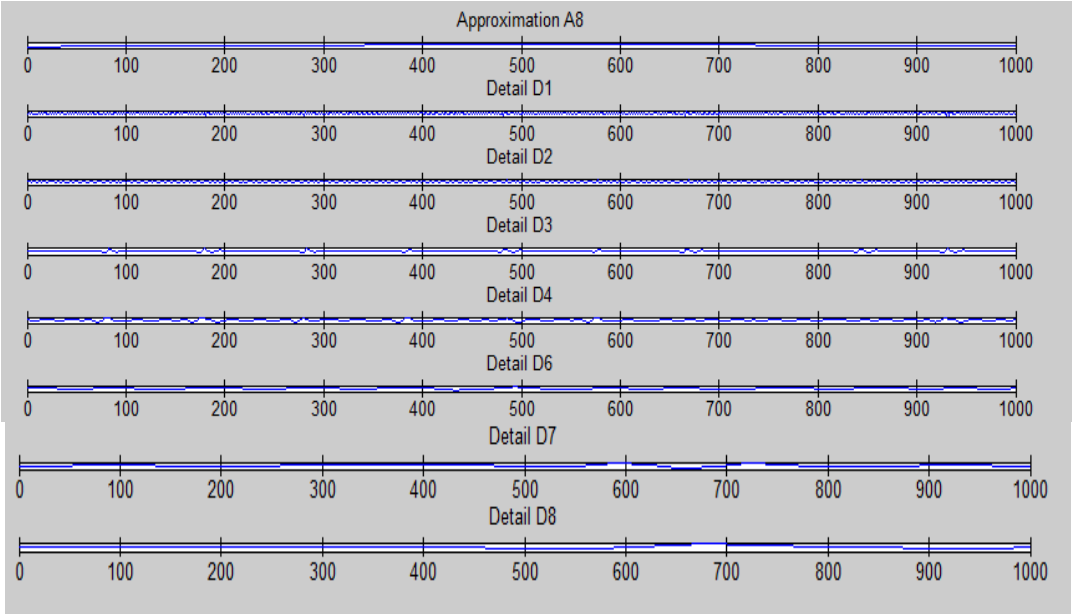


Figure 4.10 The approximation A8 at record 18184

Date No (7) - (100)

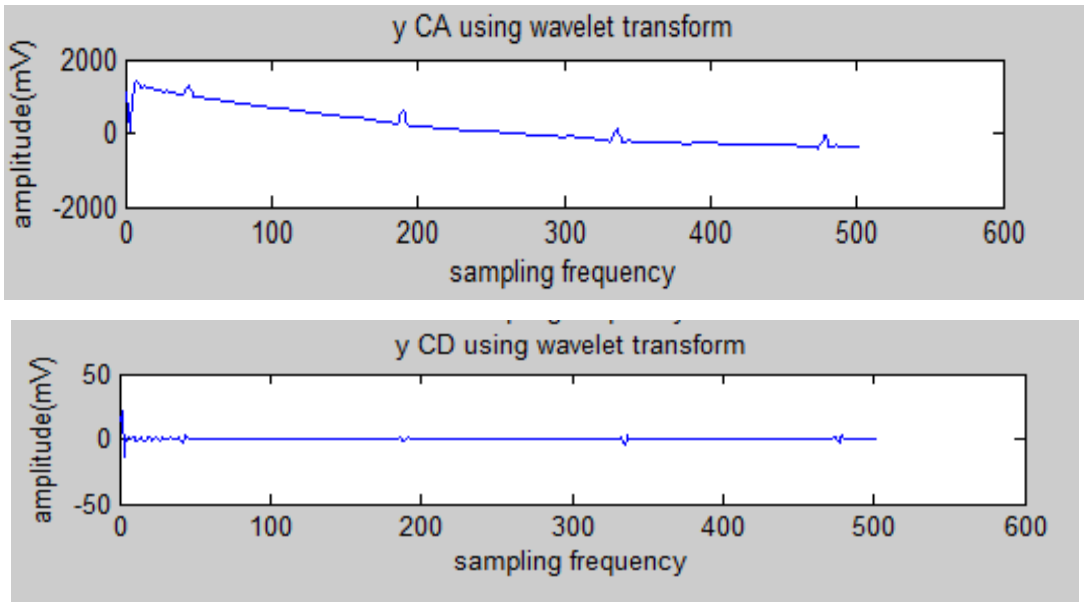


Figure 4.11 Db4 at record 100 and extracted the coefficients (y CD,y CA)

The detail and approximation as shown below

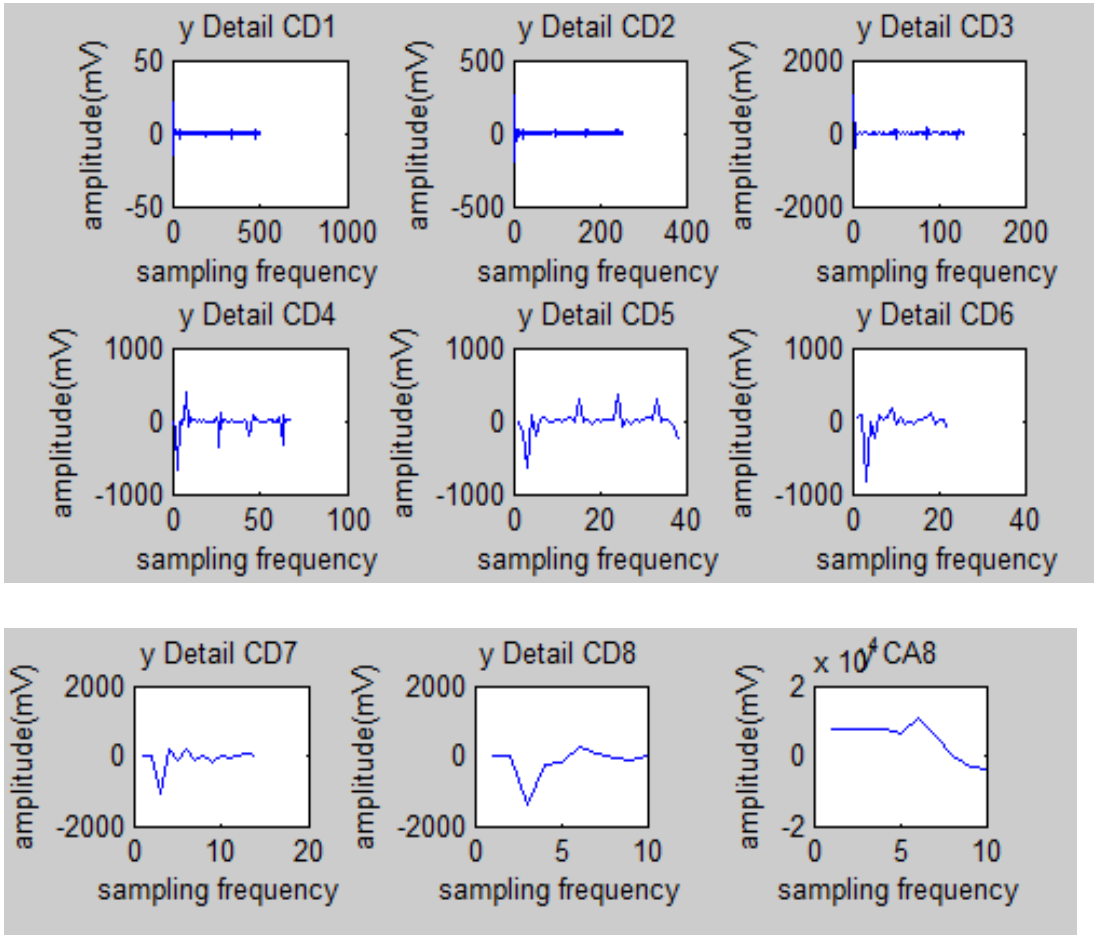


Figure 4.12 Detail and approximation depends on db4 at record 100

Then computes the vector of reconstructed coefficients, based on the wavelet decomposition structure as shown below

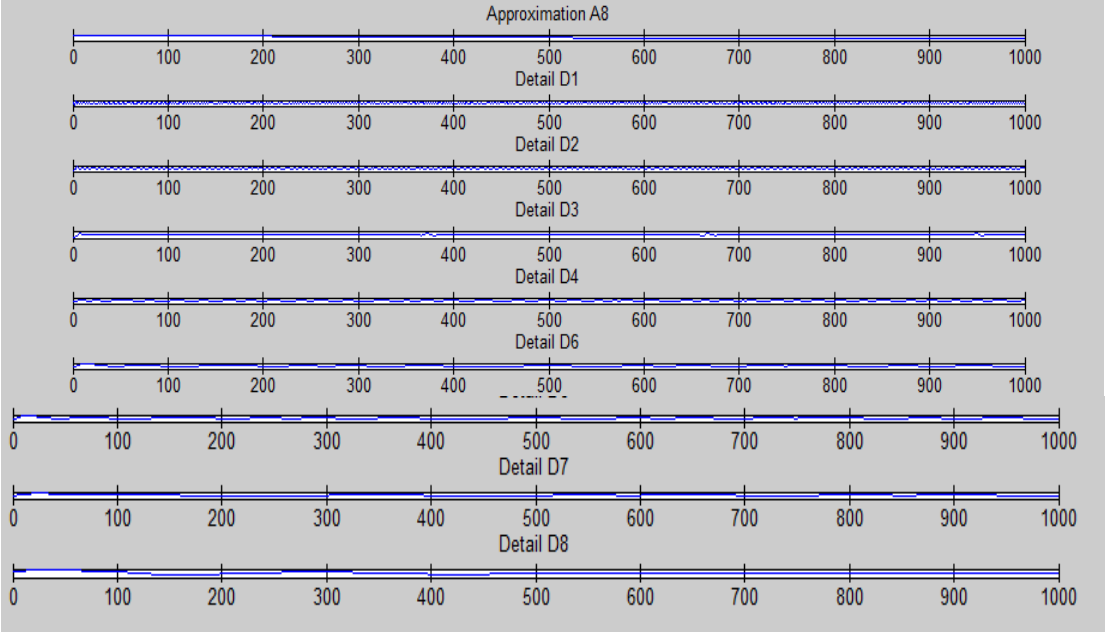


Figure 4.13 The approximation A8 at record 100

Date No (8) - (231)

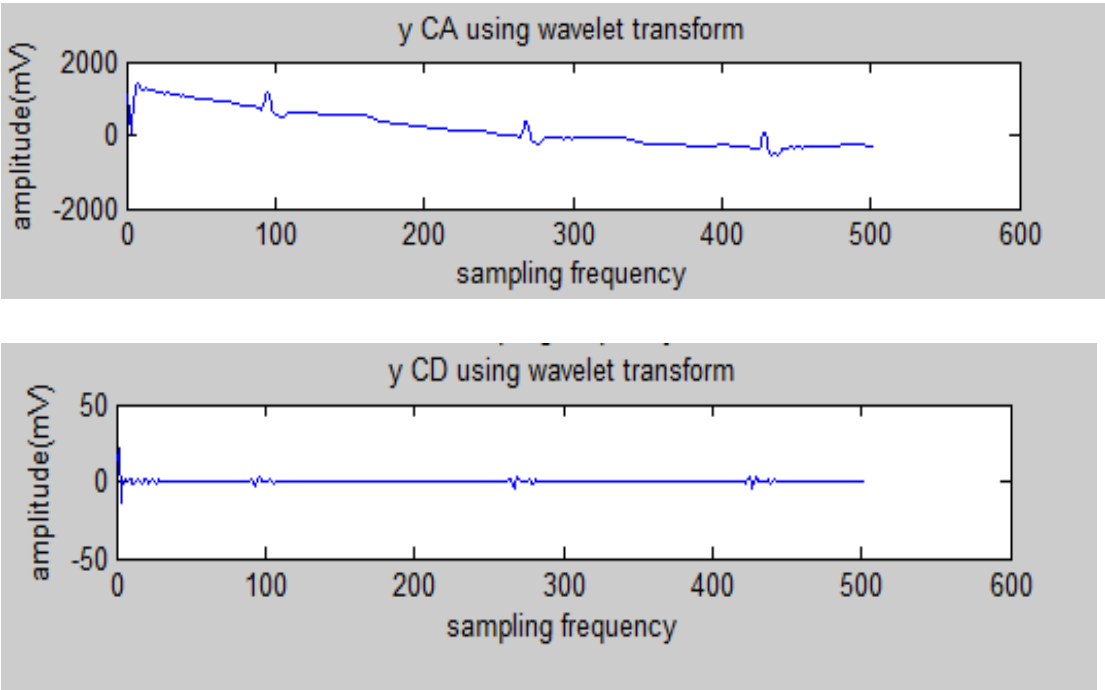


Figure 4.14 Db4 at record 231 and extracted the coefficients (y CD,y CA)

The detail and approximation as shown below

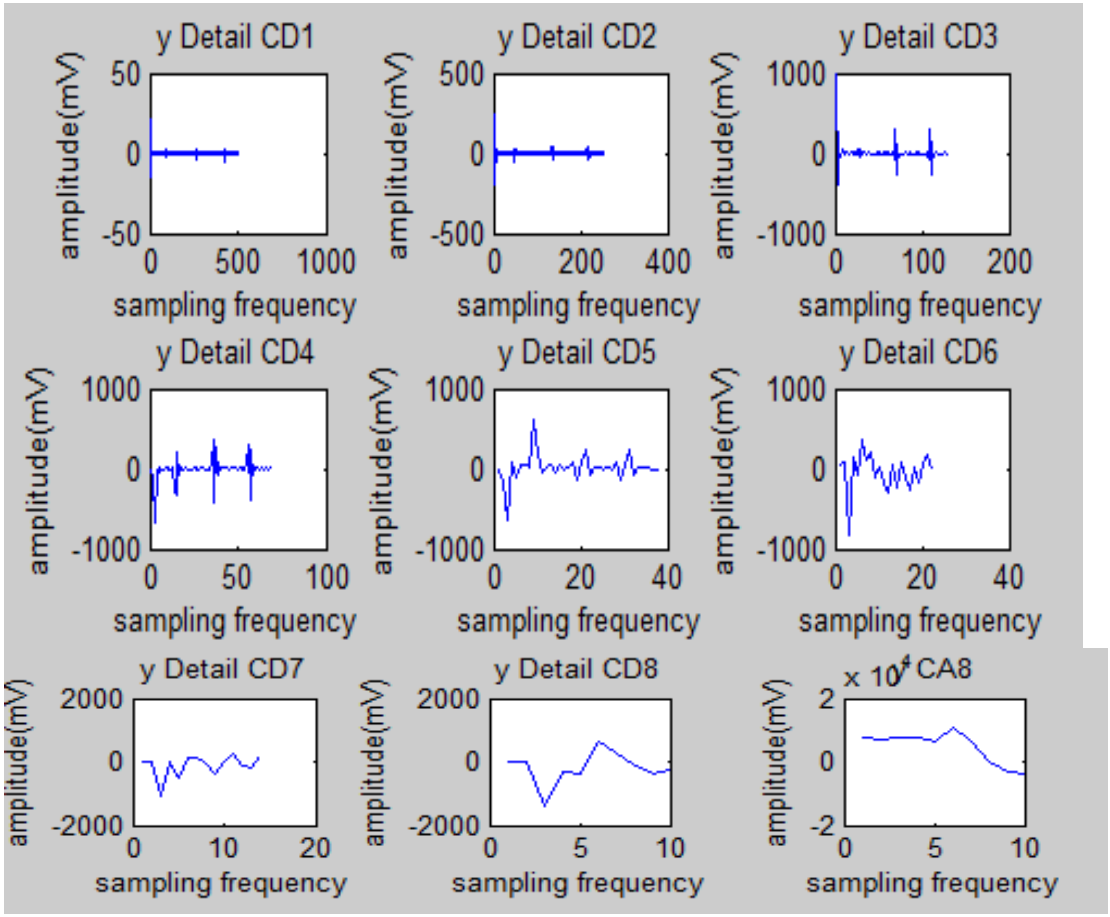


Figure 4.15 Detail and approximation depends on db4 at record 231

Then computes the vector of reconstructed coefficients, based on the wavelet decomposition structure as shown below

Figure 4.16 The approximation A8 at record 231

In figures (4.5), (4.6) ,(4.7) ,(4.8),(4.9),(4.10),(4.11),(4.12),(4.13),(4.14).(4.15) and (4.16) Daubechies Wavelets “bd4” was applied at filtered signals. The output signals are decomposed depend on(D3,D4 and D5). Therefore details are reduced and QRS complex is preserved, and extracted the Coefficients after the transform.

4.2.2 Results of Peaks Detection

The R peaks were detected at the decomposed signals .The values which are greater than 60% of the max value of the actual signal are represent R peaks, depended on R peaks in MATLAB software. the result illustrated in record 16273,18184,100 and 231 as example as shown in figures below.

Date No (9) – (16273)

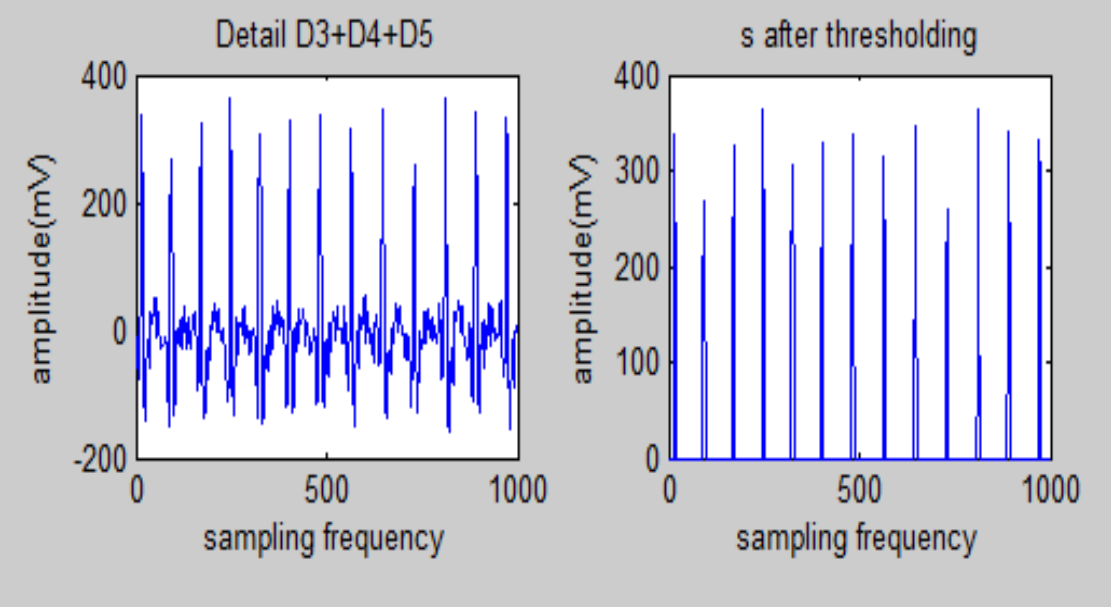


Figure 4.17 The QRS Complex Detection in record 16273

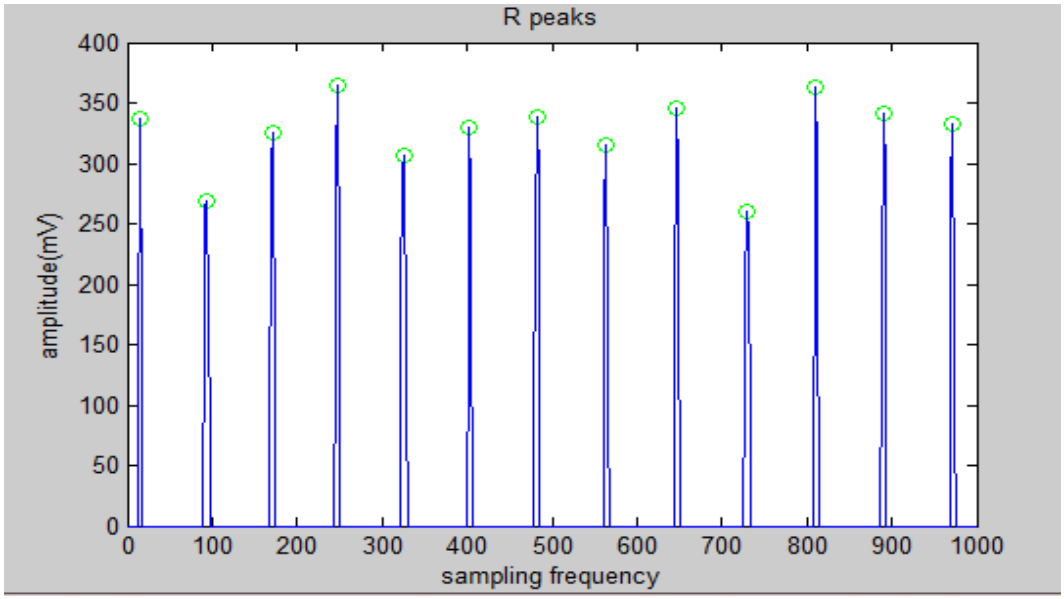


Figure 4.18 The R peaks in record 16273

Date No (10) – (18184)

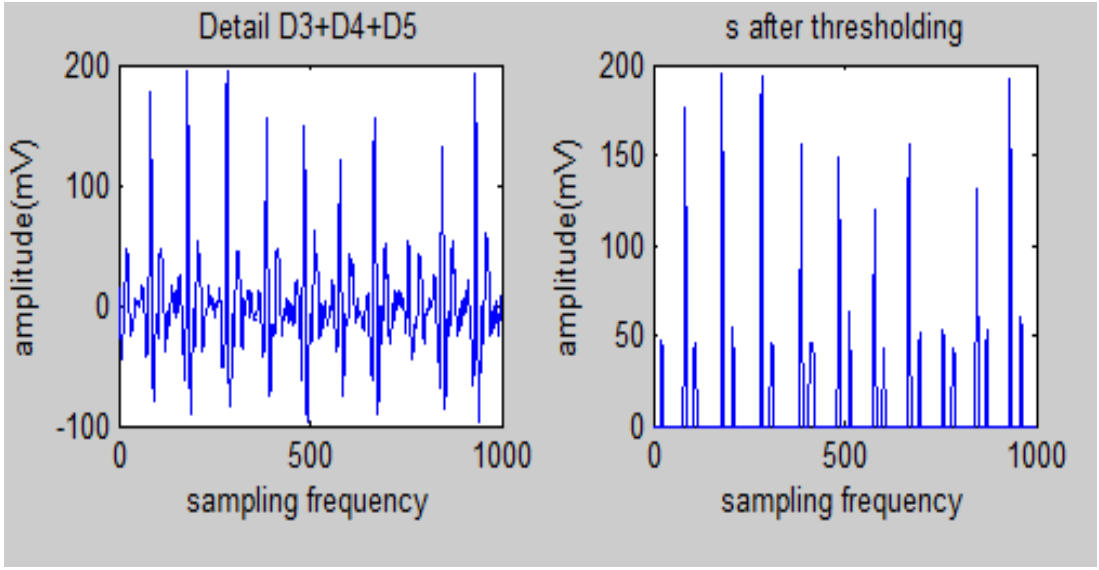


Figure 4.19 The QRS Complex Detection in record 18184

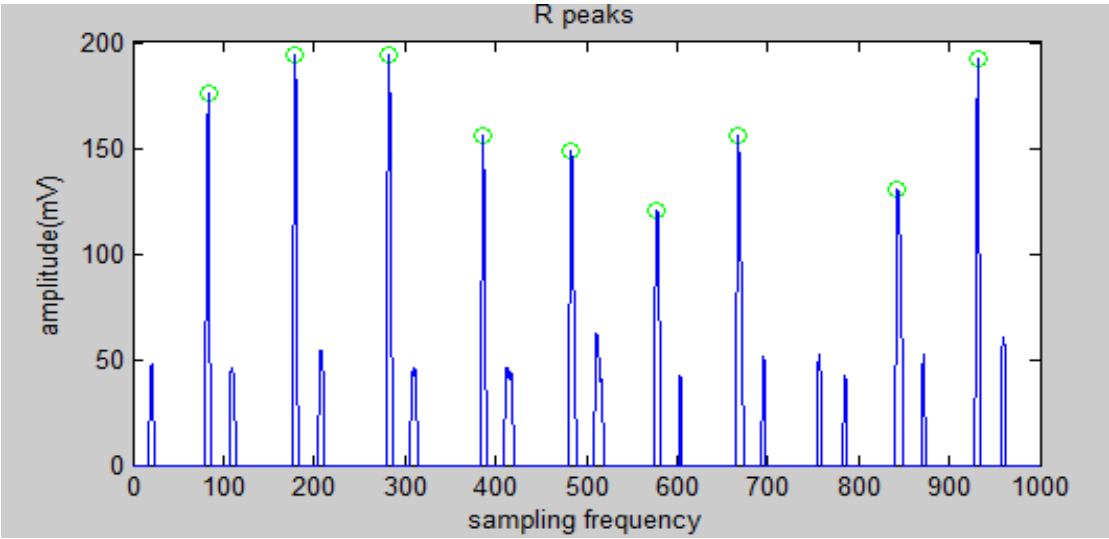


Figure 4.20 The R peaks in record 18184

Date No (11) – (100)

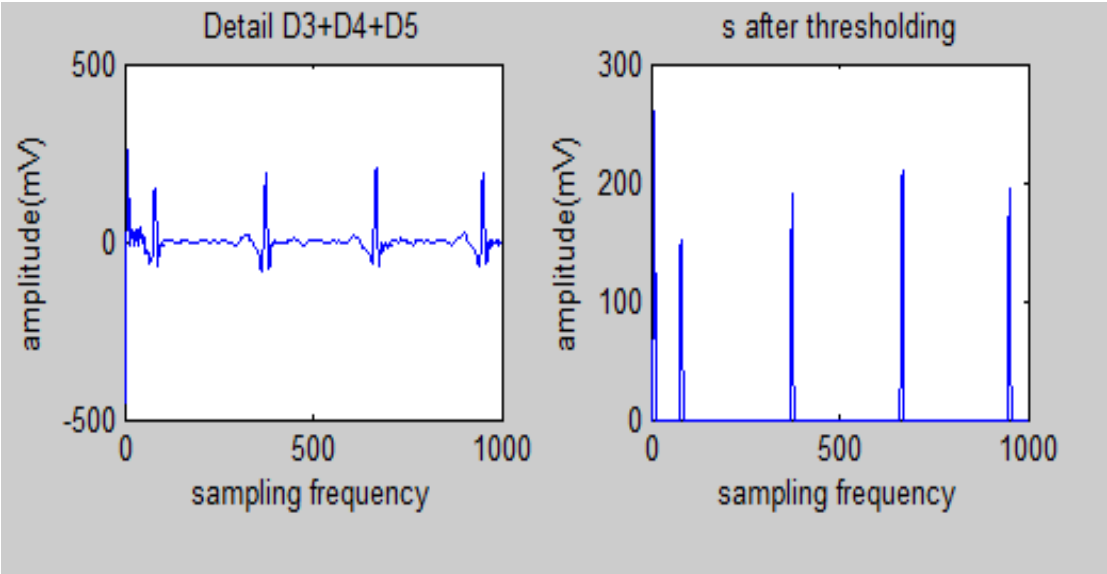


Figure 4.21 The QRS Complex Detection in record 100

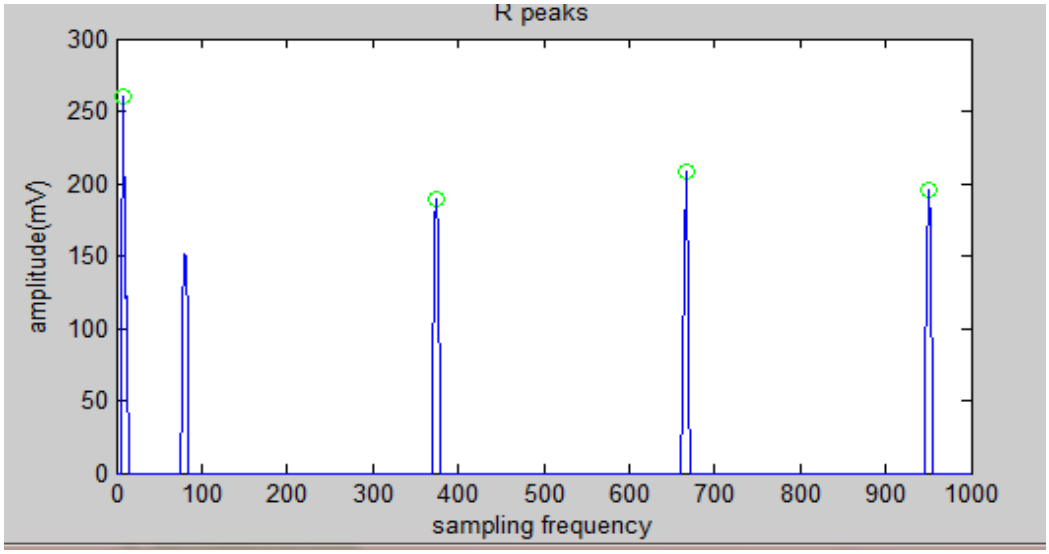


Figure 4.22 The R peaks in record 100

Date No (12) –(231)

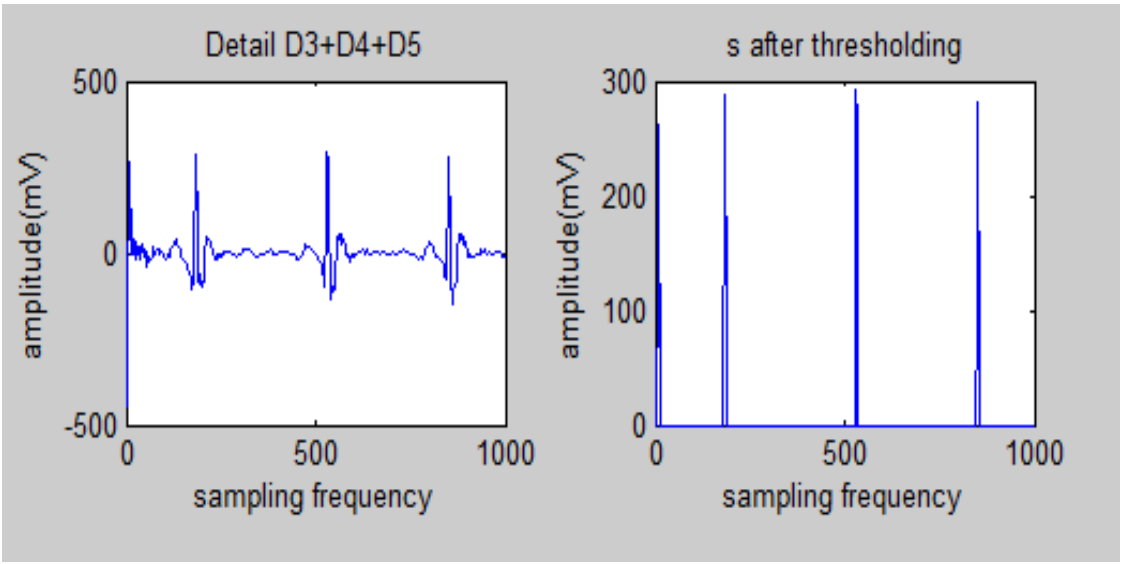


Figure 4.23 The QRS Complex Detection in record 231

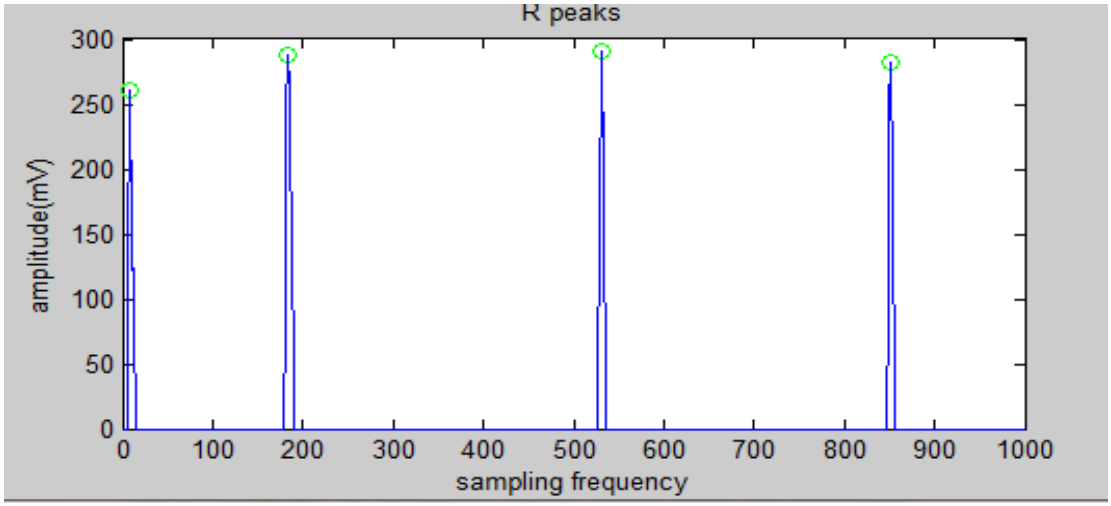


Figure 4.24 The R peaks in record 231

4.3 Result of statistical methods

The result of applying the statistical method well be illustrated in the table below:

Table(4.1):Result of Analysis for HRV depend on RR Interval in ECG signal.

Number	Record	Mi(s)	Std(s)	RMS(s)	HRV(bpm)
1	16265	0.6633	0.25	0.6633	90.45
2	16272	0.8433	0.40	0.8433	71.14
3	16273	0.6738	0.25	0.6738	89.04
4	16420	0.9200	0.27	0.9200	65.21
5	16483	0.5670	0.25	0.5670	105.82
6	16786	0.7900	0.32	0.7900	75.94
7	17453	0.7323	0.27	0.7323	81.93
8	18184	0.7929	0.37	0.7929	75.69
9	19088	0.6076	0.13	0.6076	98.74
10	19830	0.4983	0.28	0.4983	120.40
11	100	1.0688	0.99	1.0688	56.13
12	115	1.0155	0.94	1.0155	59.08
13	118	0.9572	1.00	0.9572	62.68
14	122	0.5844	0.86	0.5844	102.66

15	**201**	**0.7644**	**0.98**	**0.7644**	**78.49**
16	**205**	**1.0577**	**1.34**	**1.0577**	**56.72**
17	**220**	**1.0344**	**1.22**	**1.0344**	**58.00**
18	**230**	**1.0222**	**1.12**	**1.0222**	**58.69**
19	**231**	**1.1500**	**1.25**	**1.1500**	**52.17**
20	**234**	**1.0000**	**1.03**	**1.0000**	**60.00**

4.4 Discussions

The result in section 4.3 above illustrate the sensitive of HRV, and the MATLAB code used illustrate this sensitivity of the HRV.

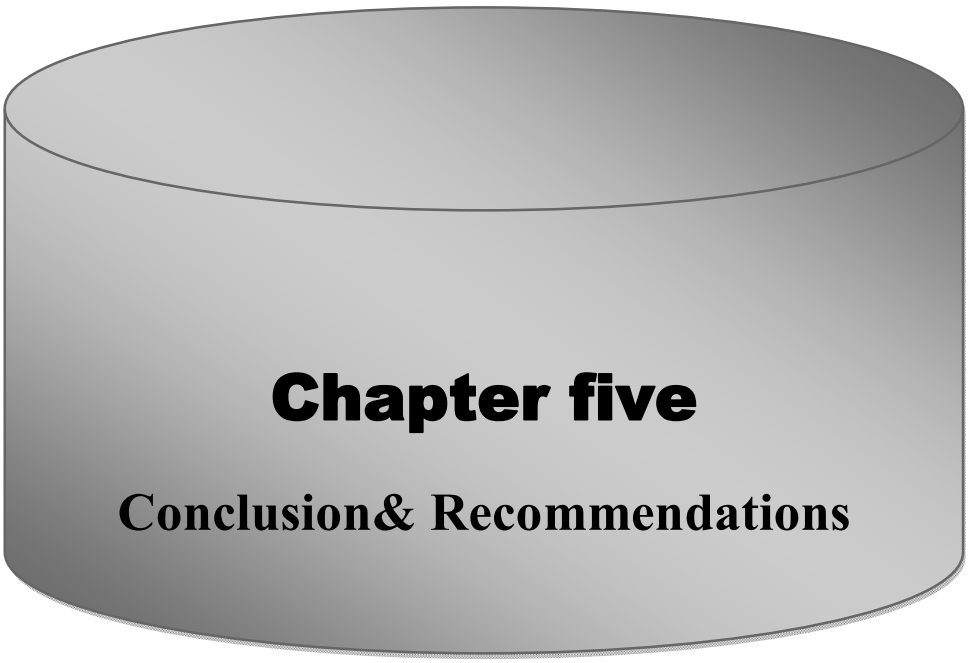
In the paper of the Using Lab View the result of this paper [8] were shown below to compare it with our result.

Table (4.2):The result of HRV analysis using Lab View

RR mean	RR Std	RMS	HRV
0.78 ms	0.045 ms	5.4 ms	77bpm

The results which shown from table 4.1 in section 4.3 above the high sensitive of analysis HRV by using MATLAB code where the record number (5,10,11,12,14,16,17,18,19) represent abnormal cases ,and the other record (1,2,3,4,6,7,8,9,13,15,20) represent normal cases ,this result illustrate that in normal cases the value of the mean of RR and RMS fell between (0.60s - 1.00s) and the HRV value is $60 \leq HRV \geq 100$ which represents the normal value of HRV ,and Std represents a value between (0.25-1) ,but on the other hand the mean of RR and RMS below to (0.60) which represents abnormal cases known (Bradycardia) and the Std ware calculated given value between (0.94-1.34), where another abnormal cases the mean of RR and RMS for it is up to (0.100) which represents abnormal cases of HRV known as (Tachycardia) and the Std from it between (0.25-0.86).

The result is acceptable when compare this result with the result in MIT-BIH data base .


Chapter five
Conclusion& Recommendations

Chapter Five

Conclusions and Recommendations

5.1 Conclusions:

HRV represent one of the most promising markers, which represent a non invasive way of measuring autonomic nervous system. HRV computed by analyzing beat-to-beat interval time series derived from an electrocardiogram (ECG).

In this project the statistical methods (the mean, standard deviation and the roots mean squirt) was proposed, and then calculate the HRV.

20 records from the MIT-BIH arrhythmias database are used to evaluate the HRV.

The proposed project consists of three main phases. First phase the pre processing: remove the power line interference and baseline wander , second phase: the feature extraction, the DWT (Daubechies Wavelets db4) is applied on filtered signal and features extracted.

The result of HRV is classified as:

- The Normal case
- Bradycardia
- Tachycardia

The value of each case is equal the HRV ± sd

5.2 Recommendations:

The analysis of HRV give a result discuss previously was showed statistical analysis of ECG signal which represent RR interval value which determined heart status (Bradycardia, Tachycardia and Normal).

future work, first, increase the set of data which will be analysis and increase the statistical which will be used, because the HRV in the near future represent a useful parameter to diagnosis ECG signal lock like blood pressure.

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Appendix (A)

1-The matlab code to analysis HRV

```
%1st:read ECG signal from MIT database
PATH='C:\Users\Dell\Documents\MATLAB\signals'; % path, where data are
saved
HEADERFILE= '231.hea';      % header-file in text format
ATRFILE= '231.atr';         % attributes-file in binary format
DATAFILE='231.dat';         % data-file
SAMPLES2READ=650000;         % number of samples to be read
                            % in case of more than one signal:
                            % 2*SAMPLES2READ samples are read

%------ LOAD HEADER DATA --------------------------------------------
------
%fprintf(1,'\\n$> WORKING ON %s ...\n', HEADERFILE);
signalh= fullfile(PATH, HEADERFILE);
fid1=fopen(signalh,'r');
z= fopen(fid1);
A= sscanf(z, '%*s %d %d %d',[1,3]); %#ok<NASGU>
nosig= 1;  % number of signals
sfreq=12;   % sample rate of data
clear A;
for k=1:nosig
    z= fopen(fid1);
    A= sscanf(z, '%*s %d %d %d %d %d',[1,5]); %#ok<NASGU>
    dformat(k)= 1;           %#ok<*AGROW> % format; here only 212 is
allowed
    gain(k)= 1;              % number of integers per mV
    bitres(k)= 3;            % bitresolution
    zerovalue(k)= 0;         % integer value of ECG zero point
    firstvalue(k)= 2;        % first integer value of signal (to test
for errors)
end;

%------ LOAD BINARY DATA --------------------------------------------
------
%fprintf(1,'\\n$> WORKING ON %s ...\n', DATAFILE);
%if dformat~= [212,212], error('this script does not apply binary
formats different to 212.'); end; %#ok<BDSCA>
signald= fullfile(PATH, DATAFILE);            % data in format 212
fid2=fopen(signald,'r');
A= fread(fid2, [3, SAMPLES2READ], 'uint8')';
%matrix with 3 rows, each 8 bits long = 2*12bit
fclose(fid2);
M2H= bitshift(A(:,2), -4);
M1H= bitand(A(:,2), 15);
PRL=bitshift(bitand(A(:,2),8),9);     % sign-bit
PRR=bitshift(bitand(A(:,2),128),5);   % sign-bit
E( : , 1)= bitshift(M1H,8)+ A(:,1)-PRL;
MM( : , 2)= bitshift(M2H,8)+ A(:,3)-PRR;
fprintf(1,'\\n$>finished:read ECG signal %s ...\n', DATAFILE);
F=E(1:1000);

%_____________________________________________________________________
_____
%Notch filter Second-order IIR to remove 60Hz
%,120Hz,180Hz using Pole-zero placement
```

```
%method:_____________________________________***
%3 dB bandwidth for each filter: 4 Hz
%r=1-(BWdB/fs)*pi
%u=(f0/fs)*360
%K=(1-(2*r*cos(u))+(r^2))/(2-(2cos(u)))
%Hz=K(Z^2-(2*Z*COS(u+1)))/(Z^2-(2*r*Z*cos(u)+(r^2)))
%f0=60,120,180
%fs=600
b1 = [0.9803 -1.5862 0.9803];
a1 = [1 -1.5842 0.9586];
%Notch filter to remove 60 Hz:_________________**
b2 = [0.9794 -0.6053 0.9794];
a2 = [1 -0.6051 0.9586];
% Notch filter to remove 120 Hz:________________**
b3 = [0.9793 0.6052 0.9793];
a3 = [1 0.6051 0.9586];
% Notch filter to remove 180 Hz:________________**
y1 = filter(b1,a1,F);
%The first filtering
y2 = filter(b2,a2,y1);
%The Second filtering
y3 = filter(b3,a3,y2);
%The Third filtering
%freqz(b1,a1,512,fs);
%freqz(b2,a2,512,fs);
%freqz(b3,a3,512,fs);
%_____________________________________________________________________
_____
%Bandpass filter IIR Chebyshev fourth order using Bilinear
transformation
%method:_____________________________________***
%Passband frequency range: 0.25-40 Hz
%Passband ripple: 0.5 dB
fs =600 ;
%sampoling rate
T =1/600;
% Sampling interval
% BLT design_____________________________**

wd1 =2*pi*0.25;
wd2 =2*pi*40;
wa1 = (2/T)*tan(wd2*T/2);
wa2 =(2/T)*tan(wd2*T/2);
[B,A] =lp2bp(1.4314, [1 1.4652 1.5162],sqrt(wa1*wa2),wa2-wa1);
[~,a] =bilinear(B,A,fs);
b = [0.046361 0 -0.092722 0 0.046361];
%numerator coefficients
a = [1 -3.352292 4.255671 -2.453965 0.550587] ;
%denominator coefficients
y =filter(b,a,y1);
%Bandpass filtering
%freqz(b,a,512,fs);
t =1:1000 ;
subplot(3,1,1);plot(t,F);grid;ylabel('(a)');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('The origenal ECG signal');
subplot(3,1,2);plot(t,y1);grid;ylabel('(b)');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('ECG signal after removing power line interference ');
```

```
subplot(3,1,3);plot(t,y);grid;ylabel('(c)');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('ECG signal after removing baseline wander ');

%_____________________________________________________________________
_____
%tht wavelet transform using daubechies
method_____________________**

%[c,l]= wavedec(y,4,'db4');
%extract the coefficients after the wavelet transform
%ca1=appcoef(c,l,'db4',1);
%ca2=appcoef(c,l,'db4',2);
%ca3=appcoef(c,l,'db4',3);
%ca4=appcoef(c,l,'db4',4);
%figure(2)
%subplot(4,1,1);plot(ca1);
%subplot(4,1,2);plot(ca2);
%subplot(4,1,3);plot(ca3);
%subplot(4,1,4);plot(ca4);
%_____________________________________________________________________
__

%tht wavelet transform using daubechies
method_____________________**
[cA,cD]=dwt(y,'db4');
figure, subplot(3,1,1), plot(cA) ;title('y CA using wavelet
transform')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,1,2),plot(cD) ;title('y CD using wavelet transform')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
% 2 Detect COEF of ECG(y)_____________________________________**

[C,L] = wavedec(y,8,'db4');
[cD1,cD2,cD3,cD4,cD5,cD6,cD7,cD8] = detcoef(C,L,[1,2,3,4,5,6,7,8]);
figure, subplot(3,3,1),plot(cD1);title('y Detail CD1')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,2),plot(cD2);title('y Detail CD2')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,3),plot(cD3);title('y Detail CD3')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,4),plot(cD4);title('y Detail CD4')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,5),plot(cD5);title('y Detail CD5')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,6),plot(cD6);title('y Detail CD6')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,7),plot(cD7);title('y Detail CD7')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,8),plot(cD8);title('y Detail CD8')
```

```
xlabel('sampling frequency');
ylabel('amplitude(mV)');
cA8 = appcoef(C,L,'db4',8);
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,9),plot(cA8);title('y CA8')
xlabel('sampling frequency');
ylabel('amplitude(mV)');

% 3 Reconstruct
COEF_____________________________________________**

A8 = wrcoef ('a', C, L,'db4', 8);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D1 = wrcoef ('d', C, L,'db4', 1);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D2 = wrcoef ('d', C, L,'db4', 2);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D3 = wrcoef ('d', C, L,'db4', 3);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D4 = wrcoef ('d', C, L,'db4', 4);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D5 = wrcoef ('d', C, L,'db4', 5);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D6 = wrcoef ('d', C, L,'db4', 6);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D7 = wrcoef ('d', C, L,'db4', 7);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
D8 = wrcoef ('d', C, L,'db4', 8);
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
figure,Subplot (9, 1, 1);plot(A8) ;title('Approximation A8');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 2);plot(D1) ;title ('Detail D1');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 3); plot(D2) ;title ('Detail D2');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 4); plot(D3) ;title ('Detail D3');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 5); plot(D4) ;title ('Detail D4');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 6); plot(D6) ;title ('Detail D6');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 7); plot(D7) ;title ('Detail D7');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 8); plot(D8) ;title ('Detail D8');
```

```
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
%_____________________________________________________________________
______

%QRS Complex
Detection:_____________________________________________**

s=D3+D4+D5;
figure,Subplot(2, 2, 1);
plot(s);
title ('Detail D3+D4+D5');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
R1=max(s);
threshold1=0.2*max(s);
for i=1:1:length(s)
if s(i)< threshold1
s(i)=0;
end
end
Subplot(2, 2, 2); plot(s);title ('s after thresholding');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
thresholdr =max(0.6*s);
 RPeaks=find(s>=thresholdr);
R2=RPeaks;
R3=R2';

for i=1:1:length(R3)
  Rrange=R3(i)-3:R3(i)+3;
  Rmax=max(s(Rrange));
  R_no=find(s(Rrange)==Rmax);
  Rloc=Rrange(R_no);
  Rvalues(i)= Rmax;
  Rlocation(i)=Rloc;
end
figure ,plot ( Rlocation, Rvalues,'go'),hold on, plot(s)
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('R peaks');

%_____________________________________________________________________
__


%To find the RRinterval we
use:_____________________________________**
for i=1:length(R3)-1 ;
 RRs = Rlocation(i+1)- Rlocation(i);
  RR(i)= RRs ;
end
p=1;
for a=1:length(R3)-1 ;
    if(RR(1,a)~=0)
     r(1,p)=RR(1,a);
     p=p+1;
    else
    end;
end;
```

```
meanRR=mean(r)
Mi=mean(r)
stdRR=std(r)
rms=sqrt(Mi^2)
MDi=median(r)
```

2-The matlab code to analysis HRV

```
%1st:read ECG signal from MIT database
PATH='E:\Rythmia'; % path, where data are saved
HEADERFILE= '18184.hea';      % header-file in text format
ATRFILE= '18184.atr';         % attributes-file in binary format
DATAFILE='18184.dat';         % data-file
SAMPLES2READ=650000;         % number of samples to be read
                            % in case of more than one signal:
                            % 2*SAMPLES2READ samples are read

%------ LOAD HEADER DATA --------------------------------------------
------
%fprintf(1,'\\n$> WORKING ON %s ...\n', HEADERFILE);
signalh= fullfile(PATH, HEADERFILE);
fid1=fopen(signalh,'r');
z= fopen(fid1);
A= sscanf(z, '%*s %d %d %d',[1,3]); %#ok<NASGU>
nosig= 1;  % number of signals
sfreq=12;   % sample rate of data
clear A;
for k=1:nosig
    z= fopen(fid1);
    A= sscanf(z, '%*s %d %d %d %d %d',[1,5]); %#ok<NASGU>
    dformat(k)= 1;           %#ok<*AGROW> % format; here only 212 is
allowed
    gain(k)= 1;              % number of integers per mV
    bitres(k)= 3;            % bitresolution
    zerovalue(k)= 0;         % integer value of ECG zero point
    firstvalue(k)= 2;        % first integer value of signal (to test
for errors)
end;

%------ LOAD BINARY DATA --------------------------------------------
------
%fprintf(1,'\\n$> WORKING ON %s ...\n', DATAFILE);
%if dformat~= [212,212], error('this script does not apply binary
formats different to 212.'); end; %#ok<BDSCA>
signald= fullfile(PATH, DATAFILE);            % data in format 212
fid2=fopen(signald,'r');
A= fread(fid2, [3, SAMPLES2READ], 'uint8')';
%matrix with 3 rows, each 8 bits long = 2*12bit
fclose(fid2);
M2H= bitshift(A(:,2), -4);
M1H= bitand(A(:,2), 15);
PRL=bitshift(bitand(A(:,2),8),9);     % sign-bit
PRR=bitshift(bitand(A(:,2),128),5);   % sign-bit
E( : , 1)= bitshift(M1H,8)+ A(:,1)-PRL;
MM( : , 2)= bitshift(M2H,8)+ A(:,3)-PRR;
fprintf(1,'\\n$>finished:read ECG signal %s ...\n', DATAFILE);
fs =600 ;
T =1/600;
F=E(1:1000);
```

```
ff=length(F);
pp=(ff-1)*T ;
tt=0:T:pp;
figure ,plot(tt,F)

%_____________________________________________________________________
_____
%Notch filter Second-order IIR to remove 60Hz
%,120Hz,180Hz using Pole-zero placement
%method:_____________________________________***
%3 dB bandwidth for each filter: 4 Hz
%r=1-(BWdB/fs)*pi
%u=(f0/fs)*360
%K=(1-(2*r*cos(u))+(r^2))/(2-(2cos(u)))
%Hz=K(Z^2-(2*Z*COS(u+1)))/(Z^2-(2*r*Z*cos(u)+(r^2)))
%f0=60,120,180
%fs=600
b1 = [0.9803 -1.5862 0.9803];
a1 = [1 -1.5842 0.9586];
%Notch filter to remove 60 Hz:_________________**
b2 = [0.9794 -0.6053 0.9794];
a2 = [1 -0.6051 0.9586];
% Notch filter to remove 120 Hz:________________**
b3 = [0.9793 0.6052 0.9793];
a3 = [1 0.6051 0.9586];
% Notch filter to remove 180 Hz:________________**
y1 = filter(b1,a1,F);
%The first filtering
y2 = filter(b2,a2,y1);
%The Second filtering
y3 = filter(b3,a3,y2);
%The Third filtering
%freqz(b1,a1,512,fs);
%freqz(b2,a2,512,fs);
%freqz(b3,a3,512,fs);
%_____________________________________________________________________
_____
%Bandpass filter IIR Chebyshev fourth order using Bilinear
transformation
%method:_____________________________________***
%Passband frequency range: 0.25-40 Hz
%Passband ripple: 0.5 dB
fs =600 ;
%sampoling rate
T =1/600;
% Sampling interval
% BLT design_____________________________**

wd1 =2*pi*0.25;
wd2 =2*pi*40;
wa1 = (2/T)*tan(wd2*T/2);
wa2 =(2/T)*tan(wd2*T/2);
[B,A] =lp2bp(1.4314, [1 1.4652 1.5162],sqrt(wa1*wa2),wa2-wa1);
[~,a] =bilinear(B,A,fs);
b = [0.046361 0 -0.092722 0 0.046361];
%numerator coefficients
a = [1 -3.352292 4.255671 -2.453965 0.550587] ;
%denominator coefficients
y =filter(b,a,y1);
%Bandpass filtering
%freqz(b,a,512,fs);
```

```
t =1:1000 ;
figure ,subplot(3,1,1);plot(t,F);grid;ylabel('(a)');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('The origenal ECG signal');
subplot(3,1,2);plot(t,y1);grid;ylabel('(b)');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('ECG signal after removing power line interference ');
subplot(3,1,3);plot(t,y);grid;ylabel('(c)');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('ECG signal after removing baseline wander ');

%_____________________________________________________________________
_____
%tht wavelet transform using daubechies
method_____________________**

%[c,l]= wavedec(y,4,'db4');
%extract the coefficients after the wavelet transform
%ca1=appcoef(c,l,'db4',1);
%ca2=appcoef(c,l,'db4',2);
%ca3=appcoef(c,l,'db4',3);
%ca4=appcoef(c,l,'db4',4);
%figure(2)
%subplot(4,1,1);plot(ca1);
%subplot(4,1,2);plot(ca2);
%subplot(4,1,3);plot(ca3);
%subplot(4,1,4);plot(ca4);
%_____________________________________________________________________
__

%tht wavelet transform using daubechies
method_____________________**
[cA,cD]=dwt(y,'db4');
figure, subplot(3,1,1), plot(cA) ;title('y CA using wavelet
transform')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,1,2),plot(cD) ;title('y CD using wavelet transform')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
% 2 Detect COEF of ECG(y)_____________________________________________**

[C,L] = wavedec(y,8,'db4');
[cD1,cD2,cD3,cD4,cD5,cD6,cD7,cD8] = detcoef(C,L,[1,2,3,4,5,6,7,8]);
figure, subplot(3,3,1),plot(cD1);title('y Detail CD1')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,2),plot(cD2);title('y Detail CD2')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,3),plot(cD3);title('y Detail CD3')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,4),plot(cD4);title('y Detail CD4')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,5),plot(cD5);title('y Detail CD5')
```

```
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,6),plot(cD6);title('y Detail CD6')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,7),plot(cD7);title('y Detail CD7')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,8),plot(cD8);title('y Detail CD8')
xlabel('sampling frequency');
ylabel('amplitude(mV)');
cA8 = appcoef(C,L,'db4',8);
xlabel('sampling frequency');
ylabel('amplitude(mV)');
subplot(3,3,9),plot(cA8);title('y CA8')
xlabel('sampling frequency');
ylabel('amplitude(mV)');

% 3 Reconstruct
COEF_____**

A8 = wrcoef ('a', C, L,'db4', 8);
xlabel('sampling frequency');
ylabel('amplitude(mV)');
D1 = wrcoef ('d', C, L,'db4', 1);
D2 = wrcoef ('d', C, L,'db4', 2);
D3 = wrcoef ('d', C, L,'db4', 3);
D4 = wrcoef ('d', C, L,'db4', 4);
D5 = wrcoef ('d', C, L,'db4', 5);
D6 = wrcoef ('d', C, L,'db4', 6);
D7 = wrcoef ('d', C, L,'db4', 7);
D8 = wrcoef ('d', C, L,'db4', 8);
figure,Subplot (9, 1, 1);plot(A8) ;title('Approximation A8');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 2);plot(D1) ;title ('Detail D1');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 3); plot(D2) ;title ('Detail D2');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 4); plot(D3) ;title ('Detail D3');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 5); plot(D4) ;title ('Detail D4');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 6); plot(D6) ;title ('Detail D6');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 7); plot(D7) ;title ('Detail D7');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
subplot (9, 1, 8); plot(D8) ;title ('Detail D8');
%xlabel('sampling frequency');
%ylabel('amplitude(mV)');
%_____
______

%QRS Complex
Detection:_____**
```

```
s=D3+D4+D5;
figure,Subplot(2, 2, 1);
plot(s);
title ('Detail D3+D4+D5');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
R1=max(s);
threshold1=0.2*max(s);
for i=1:1:length(s)
if s(i)< threshold1
s(i)=0;
end
end
Subplot(2, 2, 2); plot(s);title ('s after thresholding');
xlabel('sampling frequency');
ylabel('amplitude(mV)');
thresholdr =max(0.6*s);
 RPeaks=find(s>=thresholdr);
R2=RPeaks;
R3=R2';

for i=1:1:length(R3)
  Rrange=R3(i)-3:R3(i)+3;
  Rmax=max(s(Rrange));
  R_no=find(s(Rrange)==Rmax);
  Rloc=Rrange(R_no);
  Rvalues(i)= Rmax;
  Rlocation(i)=Rloc;
end
figure ,plot ( Rlocation, Rvalues,'go'),hold on, plot(s)
xlabel('sampling frequency');
ylabel('amplitude(mV)');
title('R peaks');

%_____________________________________________________________________
__


%To find the RRinterval we
use:_____________________________________**
for i=1:length(R3)-1 ;
 RRs = Rlocation(i+1)- Rlocation(i);
  RR(i)= RRs ;
end
p=1;
for a=1:length(R3)-1 ;
    if(RR(1,a)~=0)
     r(1,p)=RR(1,a);
     p=p+1;
    else
    end;
end;
meanRR=mean(r)
Mi=mean(r)
stdRR=std(r)
rms=sqrt(Mi^2)
MDi=median(r)
```

Appendix (B)

Equation	Equation Numper	Equation Page
$W(a,b)=c(j,k)=\sum_{n=z} f(n)\Psi j,k(n)$	1	15
$\Psi j,k(n)=2^{-j}*\Psi(2^{-j}\ n-k)$	2	28
$r \approx 1-(BW_{3db}/f_s)*\pi$	3	28
$\Theta = (f_0/f_s)*360^o$	4	28
$k=(1-2r\cos\theta+r2)/(2-2\cos\theta)$	5	28
$H(z)=(z2 - 2z\cos\theta+1)/(z2 - 2rz\cos\theta+r2)$	6	28
$\omega_a = \frac{2}{T} \tan \frac{(\omega_d T)}{2}$	7	31
$\omega_d = \frac{2}{T} \tan^{-1} \frac{(\omega a T)}{2}$	8	31
$\omega_{al} = \tan^{-1} \frac{(\omega l T)}{2}$	9	31
$\omega_{ah} = \tan^{-1} \frac{(\omega_h T)}{2}$	10	31
$\omega_0 = \sqrt{\omega_{al}\omega_{ah}}$	11	31
$W=\omega_{ah}-\omega_{al}$	12	31
$H(s)=Hp(s)\ \|_{s=} \frac{(s2+\omega 02)}{sW}$	13	32
$Hp(s)= \frac{1}{(s+1)}$	14	32

$H(z)=H(s)\|_{s=\frac{2}{T}\frac{z-1}{z+1}}$	15	32
$H_0(z)=z^{-N}\,G_0(-Z^{-1})$	16	33