ANALYSIS OF HEART RATE VARIABILITY USING DETRENDED FLUCTUATION ALGORITHM AND ITS COMPARISON WITH PAN TOMPKIN ALGORITHM

A thesis submitted in partial fulfilment of the requirements
for the award of degree of

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In

Wireless Communication

Submitted By

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CERTIFICATE

I hereby declare that the work which is being presented in the thesis entitled, **"Analysis Of Heart Rate Variability Using Detrended Fluctuation Algorithm And Its Comparison With Pan Tompkin Algorithm."** in partial fulfilment of the requirement for the award of degree of M.E in Wireless Communication submitted in Electronics and Communication Engineering Department of Thapar University, Patiala is an authentic record of my own work carried out under the supervision of Ms. Amanpreet Kaur, Assistant Professor, ECED, Thapar University, Patiala.

The matter presented in this thesis has not been submitted in any other University/Institute for the award of degree.

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(Atinderpal kaur)

ABSTRACT

Signal Processing is the best real time implementation of a specific problem. . This thesis deals with assessment of the different heart rate analysis methods for distinguishing between the heart disease and normal rhythm. Many linear and nonlinear methods, such as the time domain, frequency domain and the detrended fluctuation analysis, were tested and the reached results are presented. This work utilises the above techniques for diagnosis of an ECG signal by determining its nature as well as exploring the possibility for real-time implementation of the above techniques. This presents two algorithms, one is the Detrended Fluctuation Analysis algorithm and other is Pan tompkin algorithm. These two algorithms have been implemented in Matlab. The Heartbeat signals were frequently contain either slow trends or very slow frequency oscillation, the detrending was necessary as a preprocessing step to prepare for an analysis by using non-linear method measures, while the nonlinear measure were strongly affected by detrending. The DFA is technique for diagnosis of an ECG feature extraction. It is applicable in context of the nonstationary signal. It involves removing fluctuation trends from the signal. Such trends have to be well distinguished from the intrinsic fluctuations of the system in order to find the correct scaling behavior of fluctuations. Experimental data are affected by non-stationarities. HRV analysis is performed using the methods that are based on assumption that the signal is stationary within experiment duration, which is the normally not correct for the long-duration signals. The HRV analysis by nonlinear method brings useful prognosis information which will be helpful for the assessment of the cardiac condition. So we concluded that the DFA is suitable for the long-term analysis of non-stationary time series such as HRV signals.

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LIST OF ABBREVIATIONS

ECG	Electrocardiogram
HRV	Heart Rate Variability
ANS	Autonomic Nervous System
SN	Sinoatrial Node
RCV	Respiratory Cardiovascular
CNS	Central Nervous System
MI	Myocardial Infarction
nVLF	normalized Very Low Frequency
nLF	normalized Low Frequency
nHF	normalized High Frequency
dLFHF	difference of Nlf and nHF spectrum
DFA	Detrended Fluctuation Analysis

CHAPTER-1

INTRODUCTION

1.1 Overview

Over the last 20 years there has been widespread interest in the study of the variations in the beat-to-beat timing of the heart called heart rate variability (HRV). In certain circumstances, the evaluation of the HRV has been shown to give an indication of cardiovascular health. The electrocardiogram (ECG) is a noninvasive test which is used to measure the electrical activity of the heart. ECG can be used to measure the rate and regularity of heartbeats and devices used to control the heart. This procedure is a very useful for the monitoring people with heart disease or to provide diagnosis. Leads are placed on the body in the several pre-determined location, usually the front of the chest, which give information about the heart condition, as shown in Fig. 1. Most ECG are performed for diagnostic purposes on human hearts , usually for diagnosis of heart abnormalities. This techniques for signal processing of the HRV from motivation to application, in an attempt to develop strong and healthy methods for the HRV analysis. A report of the common types of signals that can be derived from the ECG is also presented and together with the motivation behind the analysis of these signals. Detailed report of how the different branch of the human central nervous system (CNS) and respiratory cardiovascular (RCV) system interact to produce the beat-to-beat variability in human heart.

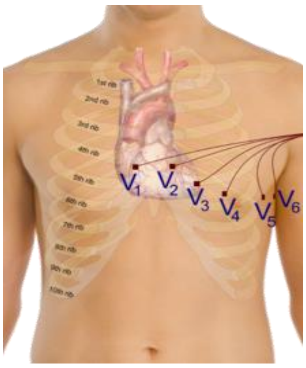

Figure 1: Placement of the leads

1.2 Function

ECG is a way to measure abnormal rhythms of the heart, particularly abnormal rhythm caused by a damage to the conductive tissue that carries electrical signals, or abnormal rhythms caused by electrolyte imbalance. In the myocardial infarction (MI), an ECG can identify if the heart muscle has been damaged in a specific areas, though not the all areas of heart are covered. An ECG cannot reliably measure pumping ability of heart, for which ultrasound-based or nuclear medicine tests are used. It is possible for the human to be in cardiac arrest, but still have a normal ECG signal.

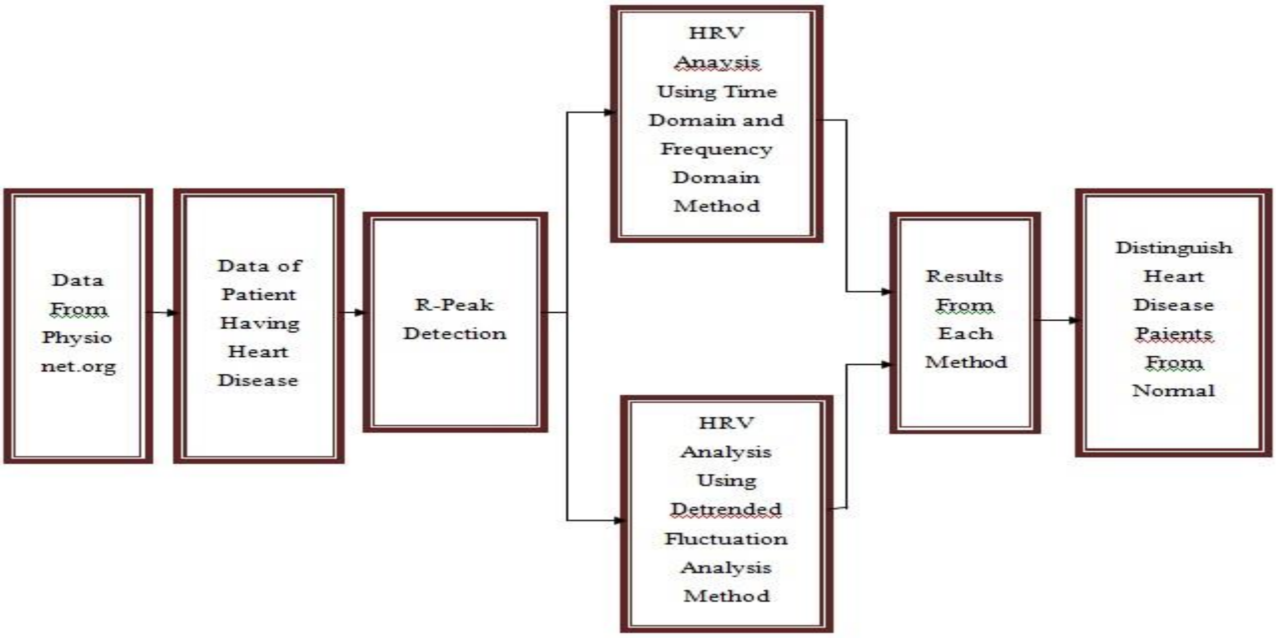

Figure 2: Methodology of work

ECG device detects the tiny electrical changes on skin that are caused when heart muscles depolarizes during the each heartbeat. At rest, the each heart muscle has a negative charge, known as membrane potential, across its cells membrane. Decreasing this negative charge towards a zero, via influx of positive cations, Na+ and Ca++, is known as depolarization, which activates a mechanism in cell that cause it to contract. During the each heartbeat, the healthy heart will have an orderly progression of the wave of depolarization that is a triggered by the cell in the sinoatrial node, spreads out through a atrium, passes through a atrioventricular node and then spread all over the ventricles. This is detected as the tiny rises and falls in the voltage between two electrodes placed either the side of the heart. This indicates the overall rhythm of heart and weaknesses in the different parts of the heart muscles. In Fig. 2 block diagram of methodology of work shows different methods for calculation of Heart Rate Variability of heart disease patients then compare with healthy persons.

1.3 Waves and intervals

An ECG tracing of heartbeat consists of P wave, a QRS complex, a U wave, and a T wave, as shown in Fig 3.The baseline of electrocardiogram is measured as a portion of tracing following T wave and the preceding next P wave and a segment between the P wave and the following QRS complex. For normal healthy heart, the baseline is equivalent to a isoelectric line (0mV) and then represent the periods in heartbeat when there are no currents flowing towards either a positive or a negative ends of an ECG leads. However, in a diseased heart the baseline may be the elevated (e.g. cardiac ischaemia) or depressed (e.g. myocardial infarction) relative to the isoelectric line due to injury currents flowing during TP and PR intervals when ventricles are at rest.

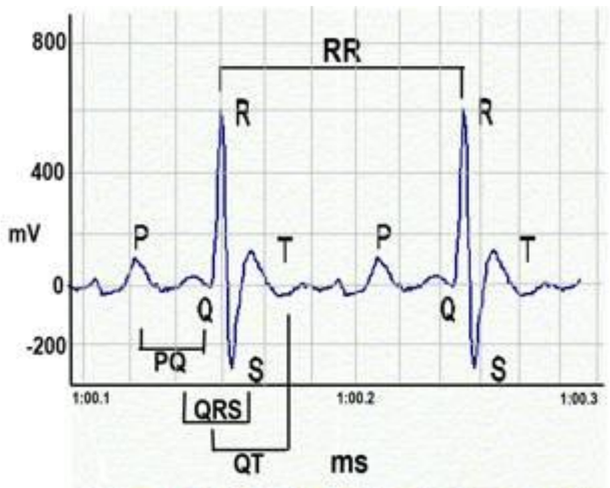

Figure 3: One second of a typical ECG waveform for one heart beat.

The ST segment remains close to isoelectric line as this is the period when the ventricles are fully depolarized so thus no current can flow in an ECG leads. Most of the ECG recordings do not indicate that where the 0mV line is, baseline depression gives the appearance of an elevation of the ST segment and baseline elevation gives the appearance of depression of the ST segment. Table 1 shows the duration of the waves, intervals and segments of typical ECG signal. The first electrical signal on the normal ECG originates from the atria and is called the P wave. Although there is only one P wave in most leads of the ECG. There is then a short delay as atrioventricular (AV) node slow down the electrical depolarization. This delay is a responsible for the PR interval, a short period where no electrical activity on the ECG, represented by the straight horizontal or isoelectric.

Depolarization of the ventricles results in largest part of an ECG signal and this is known as a QRS complex.

- Q wave is a first initial downward or ‘negative’ deflection
- R wave is then a next upward deflection, provided it crosses the isoelectric line and becomes ‘positive’.
- S wave is then a next deflection downwards, provided it crosses the isoelectric line to become negative.

Table 1: Normal Duration of waves, intervals and segments in ECG signal.

Feature	Description	**Duration**
RR interval	The interval between an R wave and the next R wave: Normal resting heart rate is between 60 and 100 bpm.	0.6 to 1.2s
P wave	During normal atrial depolarization, the main electrical vector is directed from SA node towards the AV node, and spreads from the right atrium to the left atrium. This turns into the P wave on the ECG.	80m s
PR interval	The PR interval is measured from the beginning of P wave to the beginning of the QRS complex. The PR interval reflects the time of the electrical impulse which travels from the sinus node through the AV node and entering the ventricles. The PR interval is, therefore, a good estimate of AV node function.	120 to 200ms
PR segment	The PR segment connects P wave and QRS complex. The impulse vector is from the AV node to bundle of His to bundle branches and then to the Purkinje fibers. This electrical activity does not produce contraction directly and is merely traveling down towards the ventricles, and this shows up flat on the ECG. The PR interval is more clinically relevant.	50 to 120ms
QRS complex	The QRS complex reflects the rapid depolarization of the right and the left ventricles. They have a large muscle mass compared to atria, so the QRS complex usually has a much larger amplitude than the P-wave.	80 to 120ms
J-point	The point at which the QRS complex finishes and ST segment begins, it is used to measure the degree of ST elevation or depression present.	N/A
ST segment	The ST segment connects the QRS complex and T wave. The ST segment represents the period when ventricles are depolarized. It is isoelectric.	80 to 120ms
T wave	The T wave represents the repolarization (or recovery) of ventricles. The interval from the beginning of QRS complex to the apex of the T wave is	160ms

	referred to as the absolute refractory period. The last half of the T wave is referred to relative refractory period (or vulnerable period).	
ST interval	The ST interval is measured from J point to end of the T wave.	320ms
QT interval	The QT interval is measured from the beginning of the QRS complex to end of the T wave. A prolonged QT interval is risk factor for ventricular tachyarrhythmias and sudden death. It varies with heart rate and for clinical relevance requires a correction for this, giving QTc.	Up to 420ms in heart rate of 60 bpm
U wave	The U wave is hypothesized to be caused by repolarization of the interventricular septum. They normally have low amplitude, and even more often completely absent. They always follow the T wave and also follow same direction in amplitude. If they are too prominent, suspect hypokalemia, hypercalcemia or hyperthyroidism usually.[29]	

1.4 Abnormalities in the ECG - ectopic beats

Most of the human beings exhibit normal cardiac rhythm composed of similar beats occurring at a regular intervals. These are also called escape rhythms. If R-peak of beat occurs earlier than the expected then it is known as an ectopic beat.

1.5 Identifying the problem

Heart is formed of the muscle tissue that contracts and relax in the coordinated manner when an electrical stimulus is applied. Heart’s function is to pump blood around the body, through the arterial system ,which enables the transport of the vital nutrients and oxygen. Like all the other muscles, the heart receives oxygen and nutrients from arteries. Blockage of these vessels often leads to a heart attack. . Heart failure, angina, and sudden death can occur from the blockages which takes place in the coronary arteries. In fact, heart disease has been seen as the leading cause of a death in developed countries. However, the heart suffers much damage and muscle-tissue loss, leading to an increased likelihood of re-infarction. Since the cardiovascular system is controlled by the central nervous system (CNS), a deterioration in this control mechanism also cause to cardiac-related problems.

1.6 Objectives

The aim of this project is to investigate different algorithms for R- peak detection and implement and validate suitable algorithms for FHR measurements. The project is done in four steps which are the following:

- Research R-peak detection algorithm
- Implement Methods for HRV in MATLAB
- Decide the criteria to validate the algorithms
- Validate the algorithms by using heart disease database from physionet.org

CHAPTER- 2

HEART RATE VARIABILITY AND QRS DETECTION

2.1 Heart rate variability

HRV describes variation between consecutive heartbeats. HRV can be used as a quantitative marker of the autonomic nervous system. HRV parameters have been used to predict the mortality risk in the patients with heart disease, such as the life threatening arrhythmias, acute coronary events etc. HRV analysis is an important tool in cardiology because its measurements are noninvasive, easy to perform and provide prognostic information on patients with heart disease. In the time or frequency domain, linear measures have most commonly been used to measure fluctuation in the heart. Moreover, commonly used statistics of HRV, which are average heart rate and the standard deviation of normal-to-normal R-R intervals over a specific time period , are not able to describe the accurate changes in the beats of heart rate dynamics. The nonlinear methods have been developed to quantify the dynamics of the heart rate fluctuations. However, real HRV is usually non-stationary, so that non-stationarities such as a slow linear and more complex trends have to be considered before the analysis. To obtain the reliable results of analysis of the HRV, it is essential to distinguish trends from the heart rate fluctuations intrinsic in data. The trends are caused by the external effects and they are supposed to have a smooth and slowly oscillating behavior. Such trends have to be well discriminated from intrinsic fluctuations of the systems in order to find the correct dynamics of fluctuations, but if trends are present in the data, they may give erroneous results.

2.2 Pan-Tompkins algorithm-QRS Detection

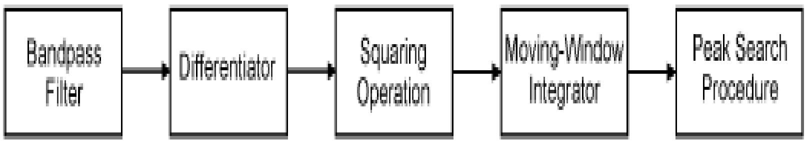

Figure 4: Block Diagram of Pan Tompkin Algorithm.

The HRV analysis is based on the fluctuations in RR interval. The first step in processing the ECG is to determine the R-peaks of QRS-complexes. Pan and Tompkins real-time QRS detection algorithm based on analysis of the slope, width and amplitude of QRS complexes.This algorithm includes series of the filters and methods that perform low-pass, high-pass, derivative, squaring, integration, thresholding, as seen in Fig 4. A recursive low-pass filter provides an attenuation greater than 35 dB at 50 Hz to suppress the power-line interference. The high-pass filter has a cutoff frequency of 5 Hz and it introduces delay of 80 ms. Then the derivative procedure suppresses low frequency components of the P and the T wave and provides the large gain to high frequency components arising from the high slopes of the QRS complex. In next step, the squaring operation makes the results positive and then emphasizes large differences resulting from a QRS complexes. Then Finally, the output of the preceding operations is smoothed through a moving window integration to prevent merging of the QRS and T waves, but large enough to the yield only one peak for the single QRS complex.

A time series of idealised QRS complexes is corrupted by following noise:

1. The power line interference 50/60 Hz is the source of a interference and it corrupt the biomedical signal's recordings such as an ECG, that are extremely important for the diagnosis of the patients. It is hard to find out the problem because the frequency range of an ECG signal is nearly same as the frequency of power line interference. An ECG signal contains the information within the frequency range of around 50 Hz that is why it is known as QRS complex. The QRS complex is a waveform which is most important in the ECG's waveforms and it comes into the view in usual and unusual signals in an ECG.
2. Data collecting device noise-Artifacts generated by the signal processing hardware, such as Signal saturation. The estimate of the QRS complex spectra and suggested that the pass band which maximizes the QRS energy is approximately 5-15 Hz. The Pan and Tompkin method used cascaded the low-pass and high-pass filters to achieve the 3db pass band from about 5-11 Hz and accuracy of QRS detection is affected by the selected frequency band.

In this algorithm all the stages follow filtering procedures:

1. 5-15Hz Band Pass Filtering — The low pass filter to remove the high-frequency noise such as 50Hz mains interference is followed by the high-pass filtering to remove low frequency components due to the breathing (at around 1Hz or below).
2. Slope Information Extraction — The Differentiating signal emphasizes the changes from the baseline.
3. Squaring — This emphasizes the higher frequencies where the R-peak is to be found and ensures that the data is positive for final stage of the filtering.

4. Time Averaging — Integrating the squared signal gives a measure of how the energy is distributed in an ECG.

2.3 Quantifying HRV

The Strong correlation between the Heart Rate (HR) and HRV should not be interpreted as the fact that the HRV is complex way to measure HR. Over the last 20 years, much effort has been put into the quantifying these variations with a view of the making clinically useful assessments of the patient welfare. Furthermore, since the variability in HR occurs on beat-to-beat basis, the time series is inherently spaced along the horizontal axis.

They can be broken down into three basic categories:

(1) That measure the statistical properties of the data.

(2) That evaluate statistics in the time domain and thirdly, frequency domain metrics.

HRV represent one of the most promising markers. A reduction of the HRV has been reported in many cardiological and non-cardiological diseases. Moreover, the HRV also has prognostic value and is therefore very important in the risk stratification.

CHAPTER- 3

LINEAR METHOD AND NON LINEAR METHOD

3.1 Linear Method of HRV

Healthy individuals is neither constant nor periodic. Instead the variability is determined by the complex dynamics of a sympathetic and a parasympathetic branches of the autonomic nervous system (ANS) which interact at impulse generating the tissue located in the right atrium of heart i.e. sinoatrial node (SN). Generally, the sympathetic stimulation increases heart rate, while a parasympathetic stimulation decreases it. HRV is a composite of the numerous influences reflecting the physiological regulatory mechanisms. The RR interval time series extracted from an ECG signal monitored during heart disease. The linear time and frequency domain techniques for HRV were described below.

3.1.1 Time domain analysis

In a time domain analysis of HRV, intervals between the successive normal R waves in an ECG are measured over the period of recording. The variety of the statistical metrics can be calculated from the intervals directly and others can derived from differences between the intervals.

Table 2 shows time domain variables that can be calculated include the mean RR interval and the mean heart rate. These parameters are very sensible to slow trends in HR data. It should also be noted that the total variance of the HRV increases with the length of the analyzed recording. In practice, it is inappropriate to compare RR measures obtained from recordings of the different durations, as shown in Fig. 5. However, the durations of recordings used to determine the RR values should be standardized

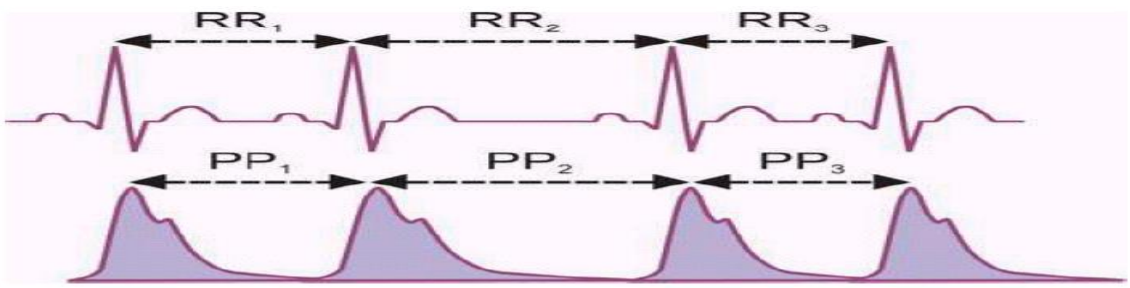

Figure 5: RR intervals of Heartbeat.

Table 2: HRV in Time Domain Analysis.

Measure	Unit	Formula
mean RR interval (mRR)	Ms	$\frac{\sum_{i=1}^{N} RR_i}{N}$
Mean Heart Rate (mHR)	Beats per minute	$\frac{\sum_{i=1}^{N}(60000/RR_i)}{N}$

3.1.2 Frequency domain analysis

The spectral analysis of the HR recording reveals information about slower oscillations. Lowest frequency band in the power spectrum which quantifies the fluctuations in RR intervals. The various spectral methods for analysis of tachogram have been applied. The Power spectral density (PSD) analysis provides the information. Table 3 shows HRV in frequency domain analysis.

Table 3: HRV in Frequency Domain Analysis.

Measure	Unit	Formula
normalized very low frequency spectrum (nVLF)	%	(VLF / VLF+LF+HF) □□100
normalized low frequency spectrum (nLF)	%	(LF / VLF+LF+HF) □□100
normalized high frequency spectrum (nHF)	%	(HF / VLF+LF+HF) □□100
difference of Nlf and nHF spectrum (dLFHF)	%	| nLF−□nHF |

The high frequency band (0.15 to 0.4 hz) reflects respiratory modulation via different impulses on the cardiac nerves. The low frequency band (0.04 to 0.15 Hz) is modulated by the baroreflexes with combination of a sympathetic and a parasympathetic different nerve traffic to the SN. Finally, mechanism responsible for the very low frequency (VLF) spectral band (0 to 0.04Hz).

3.2 Non Linear method of HRV

The Time domain and frequency domain of the HRV quantify the variability of the HR fluctuations in the characteristics time scales. The Non linear measures on contrary

attempt to complexity of RR interval time series. The large number of the non linear indices of the HRV has been studied and new are developed continuously. The characteristic 1/f or pink noise observed in the complex biological systems, which do not represent any characteristic scale . This relationship can also be plotted as log of the power versus log of the frequency , which transforms the exponential curve to line whose slope can be estimated. The cardiac system is the dynamic, nonlinear, and the non stationary, with performance continually fluctuating on the beat-to-beat basis. A nonlinear system is mathematically defined as second- or higher-order power system, meaning that an independent variable in the mathematical equation contains an exponent.
Whereas in the linear system the variables produce an output response, in the nonlinear system variables contribute to the output response. Various detrending techniques have been proposed to remove the baseline shift but usually the scale must be chosen over which the detrending is performed and HRV is over-estimated at this scale.
Detrended Fluctuation Analysis (DFA) is a non linear technique in which integrated RR interval time series, is divided into boxes of the equal length n. In the each box of length n, a least squares line is fit to data. Local trend is then removed from the box (detrending). A root-mean-square fluctuation of this integrated series and detrended time series is denoted by f(n).The linear relationship of log-log plot indicates presence of the power law (fractal) scaling and under such conditions the fluctuations can be characterized by a scaling exponent, the slope of this plot. In order to perform the spectral analysis, detrending schemes have been used as preprocessing step to prepare the HRV for the analysis. DFA is a well-established method for determining the scaling behavior of noisy data in the presence of the trends, without knowing their origin and shape. In this case, a possible approach is to recognize and the filter out the trends before we attempt to quantify dynamics of the HRV. Characteristic measures of the linear and nonlinear analysis, and compare the effect of the detrending between raw HRV and detrended HRV and discuss the role of detrending procedure in various linear and nonlinear measures. rate.Conventionally, power spectra can be estimated only from the regularly sampled signals, although some techniques have proposed the direct estimation of power spectra of the unevenly sampled data.

3.2.1 Detrending of HRV

The Trend in the time series is a slow, gradual change in some property of the series over whole interval under the investigation. In the traditional time series analysis, a time series was decomposed into the trend, periodic components, and the irregular fluctuations, and the various parts were studied separately. Detrending is mathematical operation of removing the trend from the time series. Because the HRV signals frequently contain either the slow trends or very slow frequency oscillations, so detrending was necessary as a preprocessing step to prepare the HRV for the analysis. Many alternative methods are available for detrending. The linear trend in mean can be removed by subtracting the least-square straight line. The more complicated trends might require different procedures. The detrending procedures based on smoothness approach . We denote R-R interval time series as:

S = (R2 - R1;R3 - R2; : : : ;$\mathrm{R_n} - \mathrm{R_{n-1}}$); eqn(1)

where n is the number of the R peaks detected.

The eqn (1) shows R-R interval series could be considered to have two components:

S = $S_{stat} + S_{trend}$ eqn (2)

Where eqn (2) shows S_{stat} is nearly R-R series of interest and S_{trend} is a low frequency periodic trend component.

3.2.2 Effects of Trends on Scaling

Calculating the fluctuations at a certain time-scale is strongly influenced by whether the signal has a steady trend on the longer time-scale. This trend is unlikely to be part of the process on the time-scale and may be removed by subtracting linear trend in window, and then calculating standard deviation. Detrending the signal profile, efficiently reveals the true scaling of signal with superimposed the trend both for uncorrelated and the correlated signals.

3.2.3 Detrended Fluctuation Analysis

The detrended fluctuation analysis (DFA), the algorithm has found widespread application and it is one of most commonly used methods to quantify the scale-free nature of the physiological time series. The latter type of fluctuation, as shown in Fig. 6, can be considered as a noise, and treated as the trend, this is the reason for removed the trends in algorithm. This trend can be distinguished from suitable fluctuations that may reveal intrinsic correlation properties of dynamics.

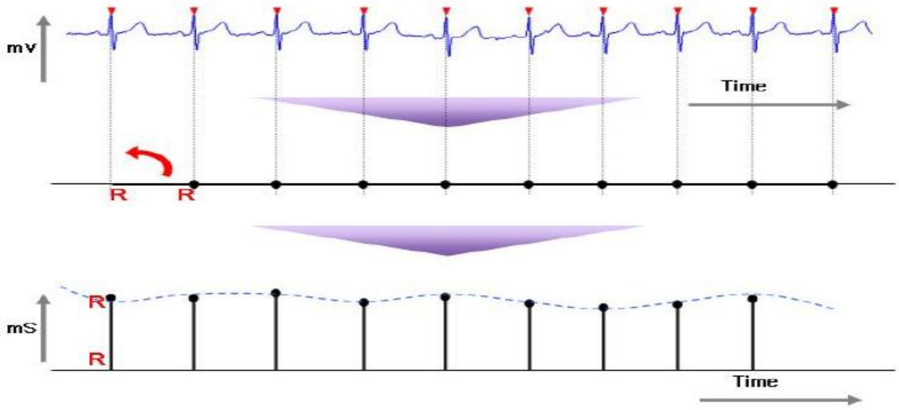

Figure 6: RR intervals and their Fluctuations.

In order to calculate scaling exponents with DFA, a given series RR_i of length N is firstly integrated. The integrated values of the time series is given in eqn (3), RR interval time series y(k) is integrated:

$$y(k) = \sum_{i=1}^{k} (RR_i - RR_{avg}) \qquad \text{eqn (3)}$$

where, mean of the time series, $RR_{avg} = \frac{1}{N}\sum_{i=1}^{N} RR_i$

where, RR_i is a successive interval time series.

Next, the integrated time series is divided into segments of the equal length n.

In the each segment, a least squares line is fitted to the data. This line represent trend in that segment. The straight line is denoted by y_n(k) in each segment. Finally, subtracting this trend from y(k), root-square fluctuation is calculated by eqn (4):

$$f(n) = \sqrt{\frac{1}{M}\sum_{k=1}^{M} (y(k) - y_n(k))^2} \qquad \text{eqn (4)}$$

where, f(n) is a fluctuation function of segment size n.

The computation is repeated over all scales, i.e. segments size to provide the relationship between f(n) and segment size n.

$$f(n) \propto \alpha \qquad \text{eqn(5)}$$

Under the such conditions, the fluctuations can be characterized by the scaling exponent α by using Eq. (4), α represents the slope of line relating log_{10}f(n) to log_{10} n, as shown in eqn (5).

$$\alpha = \frac{\log_{10} F(n)}{\log_{10} n} \qquad \text{eqn (6)}$$

The DFA exponent α, is slope of trend line in the range of time-scales of interest and can be estimated using linear regression. We have chosen a logarithmically spaced window sizes, because it gives equal weight to all time-scale when fit a line in a log-log coordinates using the linear regression using eqn (6). The lower end of fitting range is at least four samples, because the linear detrending will perform poorly with less points. For the high end of fitting range, DFA estimates for the window sizes >10% of the signal length are more noisy due to a low number of window available for averaging. The DFA exponent is interpreted as an estimation of the Hurst parameter, as explained with the random walker example, i.e., the time series is an uncorrelated if $\alpha = 0.5$. If $0.5 < \alpha < 1$ then positive correlations present in the time series as you are getting the larger fluctuations on the longer time-scales than the expected by chance. If $\alpha < 0.5$ then time series is anti-correlated, that the fluctuations are smaller in larger time windows than the expected by chance. DFA was first introduced the several papers have tested the performance of the DFA in relation to the trends, pre-processing such as artifact rejection. Other trend-removal techniques such as a higher-order polynomial or adaptive detrending.

CHAPTER- 4

LITERATURE SURVEY

T.Y. Young *et al.* [1] proposed with sophisticated statistical analysis of the medical signalslike the electrocardiogram (ECG). This is the problem of efficient representation of signals, i.e., to approximate signal with the smallest number of basis signals. This paper begins with a discussion of signal representation in general, which is very much helpful in understanding the ideas of the signal representation. These components are so-called orthonormal exponential signals. An iterative process is developed which enables us to find set of the matched exponents. With six pairs of such exponentials, average error of the ECG representation is in vicinity of five per cent. Using this representation, further statistical analysis can be carried out with ease.

C Lamberti *et al.* [2] presented a technique for the electrocardiogram (ECG) synthesis is described. A synthesizer is based on identifying the several characteristic points by their first derivative. It describes ECG signal morphology by the piecewise cubic approximation. The technique has been implemented on personal computer.

S Muthulakshmi *et al.* [3] presented ECG classification problems that have been solved by the means of methodology. This method reduces computational complexity which mainly occurs during feature selection. The computational requirements of the exhaustive search method increase exponentially with number of features in original set. The proposed system use the particle swarm optimization. PSO is attractive for the feature selection, in that particle swarms will discover the best feature combination. Thus SVM is used for the classification, which is based on the local approximation strategy. It is well suited for the larger datasets.

Yun-Chi Yeh *et al.* [4] proposed Fuzzy Logic Method (FLM) to analyze ECG signals for determining heartbeat case. This proposed method can accurately distinguish both the normal heartbeats (NORM) and the abnormal heartbeats. Th abnormal heartbeats include left bundle branch block (LBBB), right bundle branch block (RBBB), atrial premature contractions (APC). ECG signal analysis comprises three main stages: (i) the qualitative features stage for the qualitative feature selection of the ECG signal; (ii) fuzzy rules base establishment; and (iii) classification stage for determining the patient heartbeat cases. It generates one output “heartbeat case”. Through fuzzy inference engine, we can make decision to determine heartbeat case of patient’s heart disease. An ECG records available in MIT-BIH arrhythmia database are utilized to illustrate effectiveness method. In the experiments, sensitivities were 95.06%, 91.03%, 90.50%, 92.63% and 93.77% for NORM, LBBB, RBBB, VPC and APC, respectively.

Can Ye *et al.* [5] proposed a new approach for the heartbeat classification based on combination of morphological. Wavelet transform and independent component analysis (ICA) are applied separately to each heartbeat to extract the morphological features. These two different types of features are support vector machine classifier is utilized for classification of the heartbeats into one of 16 classes. This procedure is independently applied to data from two ECG leads. The proposed method is validated on baseline MIT-BIH arrhythmia database and it yields an overall accuracy in "class-oriented" evaluation and an accuracy of 86.4% in "subject-oriented" evaluation, comparable to state-of-the-art results.

V.X. Afonso *et al.* [6] designed multirate digital signal processing algorithm to detect the heartbeats in electrocardiogram (ECG). A algorithm incorporates filter bank (FB) which decomposes the ECG into subbands with the uniform frequency bandwidths. Features computed from set of sub bands and a heuristic detection strategy are used to fuse decisions from multiple one-channel beat detection algorithms. Furthermore this is real-time algorithm since its beat detection latency is minimal. The FB-based structure is potentially useful for performing the multiple ECG processing tasks using one set of preprocessing filters.

W.J. Tompkins *et al.* [7] proposed an algorithm which can potentially perform the multiple ECG processing tasks using filter bank (FB). Since the subbands have narrower bandwidth than input ECG, they can be down sampled to get a lower rate subband signal. The Time and frequency dependent processing can be performed at lower rate. A beat detection algorithm is presented which has minimal detection latency. The ECG can be enhanced by processing the sub bands to remove the noise. The Features computed from sub bands can be used to distinguish between some ventricular and sinus beats. FB offers a strategy to perform multiple tasks on ECG using one set of filters operating at computationally efficient rate.

J. Bushra *et al.* [8] Electrocardiogram (ECG) signals are used to analyze cardiovascular activity in human body and primary role in the diagnosis of several the heart diseases. QRS complex is the most distinguishable component in the ECG because of the spiked nature. Automatic detection and delineation of the QRS complex in the ECG is of importance for the computer aided diagnosis of the cardiac disorder. The accurate detection of this component is crucial to performance of the subsequent machine learning algorithms. The aim of present work is to detect QRS wave from the electrocardiogram (ECG) signals. Modulus maxima approach proposed by Mallat has been used to compute Lipschitz exponent of the components. We have applied K means clustering technique to classify the QRS complex. So in order to evaluate algorithm, the analysis has been done on the MIT-BIH Arrhythmia database.

P. de Chazal *et al.* [9] presented classification performance of an automatic classifier of electrocardiogram (ECG) for the detection of normal, premature ventricular contraction and the fusion beat types. Features based on ECG waveform shape and heart beat intervals were used as the inputs to classifiers. The data was obtained from MIT-BIH arrhythmia database. Cross-validation was used to measure classifier performance. The classification accuracy of 89% was achieved which is significant improvement on the previously published results.

M. Kundu *et al.* [10] presented the rule-based expert system which uses generalized modus ponens (GMP) from the fuzzy logic for the classification of the abnormalities related to the rhythm disorder in the human heart, through interpretation. Application of GMP makes the diagnosis of wide range of variations in input ECG patterns possible even if they differ from patterns. The work shows how fuzzy logic with suitably drawn possibility distributions of the variables of the cardiological domain plays the significant role in the making expert system sensitive to finer variations, which are very common in the bioelectric signals, without enhancing the size of rulebase.

S.S. Mehta *et al.* [11] presented a fuzzy theory based pattern recognition technique for the correct identification of P and T waves. The candidate P or T waves are selected from the background of the noisy peaks. The fuzzy membership of each peak is calculated using their average peak-to-peak amplitude, total energy and incremental energy. The method has a success rate of about 94%

J Leski *et al.* [12] described an application of energy measure of fuzziness to the high-resolution alignment of QRS complexes of an ECG signals is presented. In the first part of the paper the formulation of the problem and an idea of energy measure of fuzziness is recalled. First a fuzzy signal is created on the basis of the original signal. Next for such a signal an energy measure of fuzziness is computed and filtered by means of a lowpass filter. The performances of the method are compared by means of trade-off studies with the methods known from literature.

G Bortolan *et al.* [13] described a technique for the automatic acquisition of expert knowledge in order to set up knowledge base for diagnostic classification of an ECG signals. The method is indirect, because knowledge of the expert, in contrast with a general approach which learns through the direct communication of rules and facts. It is, on the other hand, different from conventional statistical techniques because (1) reference classification is given by the experts and not by independent exams like autopsy, echocardiography, cardiac surgery, and so on, and (2) this classification can be uncertain, i.e. various classes are associated with each ECG with certainty factors. The data are derived from the CSE pilot diagnostic library.

A. Cabasson *et al.* [14] presented a novel analysis tool for time delay estimation in the electrocardiographic signal processing. Our approach consists of modeling the T wave, canceling its influence, and the finally estimating the PR intervals during exercise and the recovery with proposed generalized Woody method. Among the different models tested, we found that a piecewise linear function significantly reduces T wave-induced bias in estimation process. Combining modeling with proposed time delay estimation method leads to accurate PR interval estimation. The slopes of PR interval series in the early recovery phase are dependent on the subjects' training an hysteresis phenomenon exists in the relation PR/RR intervals when data from recovery are compared.

Chendi Wang *et al.* [15] proposed a method to evaluate human's emotion and the stress based on heart rate variability (HRV). Firstly, scheme has been designed to induce 4 kinds of emotions and the corresponding electrocardiogram changes have been measured in a laboratory setting; Secondly, an improved fast denoising the method based on wavelet transform threshold denoising was proposed to process the noisy ECG signal, then realize automatic extraction of HRV sequences; Finally, the wide range of physiological features from various analysis domains, frequency, nonlinear analysis is proposed in order to find best emotion-relevant features and some important conclusions have been obtained. Key words-Emotion monitoring, HRV, the autonomic nervous system.

S. Korsakas *et al.* [16] presented a new electrocardiosignals (ECGs) and motion signals telemonitoring. The developed system is intended to facilitate the couch in optimizing and individualizing the training of elite athletes. The hardware system consists of rower and coach components. Rower components include 5 sensors for monitoring of mechanical and physiological parameters. The coach software works in two modes:

online version during training and off-line the detailed data analysis after training. The accuracy of systolic blood pressure prediction could exceed range of 90.

M. Laurino *et al.* [17] described Several methods for automatic heartbeat classification have been developed. Herein, we describe a procedure for the extraction, selection and classification of features summarizing morphological ECG changes. The selection of a subset of features enabled us to summarize an ECG changes with only three non redundant features. In order to cope with thepossible non linear separation problem, we evaluated two strategies: a subject factor normalization on feature space and the usage of kernel functions for classifiers. The results of comparison recommended the usage of subject normalization, irrespectively from classificator: with and without normalization we had the best performance of classification for the linear-SVM and ANN.

G Deak *et al.* [18] proposed a fuzzy based method to evaluate the level of physical preparedness of both nonathletes and athletes based on a number of physiological parameters. Having an objective tool to assess whether theirathletes are responding correctly to the training, The proposed assessment fuzzy method was implemented in Java 2 Standard Edition. Data were collected from three subjects during a six months training program. The obtained results are in accordance with the values given by the scientific literature.

A. E. Aubert *et al.* [19] review examines the influence on heart rate variability (HRV) indices in athletes from training status, different types of the exercise training. The predictability of HRV in the over-training, athletic condition and athletic performance is included. The cardiovascular system is mostly controlled by the autonomic regulation through the activity of the sympathetic and parasympathetic pathways of autonomic nervous system. It can easily be determined from an ECG recordings, resulting in the time series (RR-intervals) that are usually analysed in time and frequency domains. During the dynamic exercise, it is generally assumed that heart rate increases due to both a parasympathetic withdrawal and an augmented sympathetic activity.

C. S. Yoo *et al.* [20] investigated how preprocessing used to remove a trend from heart rate variability can have some effects on the linear and nonlinear analysis. For heartbeat time series obtained from 30 female patients undergoing surgery, the linear and the nonlinear measures were calculated in raw and detrended heart rate variability, respectively. The Linear measures did not show significant differences between raw and the detrended heartbeat signals, while nonlinear measure were strongly affected by

detrending. We conclude that the nonlinear analysis could be performed without detrending, but removal of the trends from time series is still often
required in linear analysis.

Geert Morren *et al.* [21] reveals Detrended fluctuation analysis (DFA), a fractal analysis method which is widely used in heart rate variability (HRV) studies, is used to analyze the scaling behaviour of RR interval series. The average scaling behaviour, calculated using 30000 RR intervals (3 - 4 hours. It is shown that the scaling behaviour is not constant over such long segments and how heart rate patterns, associated with specific physiological mechanisms, contribute to the observed variation of the scaling exponents. The effect of the two most important patterns, spikes (either due to faulty peak detection or true decelerations in heart rate) and periodic fluctuations, on the scaling behaviour is investigated.

Rong-Guan Yeh [22] proposed Heart rate variability (HRV) analysis is used to explore the rapid physiologic fluctuations that reflect changes of sympathetic and vagal activity. Detrended fluctuation analysis (DFA) is a nonlinear analysis method and has been demonstrated to be useful to distinguish the heartbeat time series signal between healthy subjects and those with severe congestive heart failure (CHF) diseases. In this paper, we consider how a short-term time series can still present useful analysis results. The measurement groups included 37 healthy (17 young and 20 old), 43 CHF and 9 atrial fibrillation (AF) adults. Ten minutes, data may be the minimum to reliably predict healthy adults by the DFA method. Just as with the α value, we could predict the $\alpha1$ and $\alpha2$ values of time series points for four groups. The reliable prediction points for the $\alpha1$ value of young, old, CHF and AF groups needed at least 10-minute, 20-minute, 30-minute and 2-hour time series in our study, respectively. Moreover, α and $\alpha2$ had lower coefficient of the variation value and better indices than $\alpha1$ for the physiological condition from point of view of convergence.

Umme Mumtahina *et al.* [23] presented a variation in time between two successive heart beats occurring due to internal and the external stimulation causes Heart Rate Variability (HRV). The HRV is a tool for indirect investigation of both cardiac and the autonomic system function in both healthy and diseased condition. In this study, HRV from two types of data sets (normal sinus rhythm and sinus arrhythmia) are analyzed which are stored in MIT-BIH database, an extended collection of recorded physiological signals. Two nonlinear methods, approximate entropy (ApEn) and the detrended fluctuation analysis (DFA), have been applied to analyze HRV of both Arrhythmia patients and people having normal sinus rhythm. Thus, value of the nonlinear parameters found in this work can be used as standard when treating suspected patients for diagnosis of Arrhythmia.

J. W. Kantelhardt *et al.* [24] investigated sleep has been regarded as a testing situation for the autonomic nervous system, its activity is modulated by sleep stages. The sleep-related breathing disorders also influence autonomic nervous system and can cause heart rate changes known as cyclical variation. Since spectral analysis is suited for the identification of cyclical variations and detrended fluctuation analysis can analyze the scaling behavior and to detect long-range correlations, we compared the results of the both complementary techniques in 14 healthy subjects, 33 patients with moderate, and 31 patients with severe sleep apnea. Discriminance analysis was used on a person and sleep stage basis to determine the best method for the separation of sleep stages and sleep apnea severity. We conclude that changes in HRV are better quantified by scaling analysis than by spectral analysis.

JC Perfetto *et al.* [25] reveals the detrended fluctuation analysis (DFA) method is used to quantify fractal-like scaling properties of variability of cardiac parameters, i.e. R-R interval data. The DFA has proved to be a useful index in predicting survival in heart failure. The several authors have proposed to break numerical series in the two zones with linear slopes. DFA method to process records of passive head up tilt (H.U.T.) test done to patients who have suffered one or more faint episodes. Slopes of numerical series obtained from real signals neither change at a specific point, nor have only one breakpoint, especially. On the contrary some of them present abrupt changes in slope. A method that tracks the DFA function, detect breakpoints, and to obtain a continuous set of the lines between them, and their corresponding slopes, is proposed.

Yamini Goyal [26] proposed Heart rate variability (HRV) provides a noninvasive means of quantifying cardiac autonomic activity. It has been shown to be a powerful predictor of arrhythmia related complications in patients surviving the acute phase of myocardial infarction. Additionally, it aims to compare results based on wavelet analysis and the Pan Tompkins algorithm. Both time domain analysis and frequency domain analysis of HRV are presented. The HRV dynamics is evaluated using non-parametric method. Results of stimulations in MATLAB are presented.

Sellappan Palaniappan *et al.* [27] presented the healthcare industry collects huge amounts of healthcare data . Discovery of hidden patterns and relationships often goes unexploited. This research has developed a prototype Intelligent Heart Disease Prediction

System (IHDPS) using data mining techniques Neural Network. Results show that each technique has its unique strength in realizing the objectives of the defined mining goals. Using medical profiles such as age, sex, blood pressure and blood sugar it can predict the likelihood of patients getting a heart disease.

Devy Widjaja *et al.* [28] presented Heart rate variability (HRV) analysis is well-known to give the information about the autonomic heart rate modulation mechanism. Therefore, preprocessing of the RR interval time series is necessary. Validation of this algorithm was performed on one hour ECG signals of 20 pregnant women. The R peaks before and after preprocessing were manually revised for spurious and missed R peak detections. Our automated preprocessing technique therefore restricts manual data check to the absolute minimum and to allows a reliable HRV analysis.

Hariton Costin *et al.* [29] investigated mental stress is one of the major risk factors for many diseases such as hypertension, heart attack, stroke, even sudden death. In our study, we have investigated objective characteristics, like the various short term heart rate variability (HRV) measures and morphologic variability (MV) of an ECG signals for detecting mental stress. Experiments involved 16 recordings of ECG signals during mental stress state and normal state, data base on physionet.org portal. Results revealed that the HRV measures named mHR, mRR, normalized VLF/LF/HF, the difference between normalized LF and normalized HF, and SVI are effective metrics for mental stress detection. The better results were obtained by using the MV analysis and decision-support module based on both methods, HRV and MV.

Philip de Chazal *et al.* [30] described a method for the automatic processing of the electrocardiogram (ECG) for the classification of heartbeats is presented. Data was obtained from the 44 nonpacemaker recordings of the MIT-BIH arrhythmia database. The first dataset was used to select a classifier configuration from candidate configurations.The twelve configurations processing feature sets derived from two ECG leads were compared. Feature sets were based on ECG morphology, heartbeat intervals. All configurations adopted a statistical classifier model utilizing supervised learning. This assessment resulted in a sensitivity of 75.9%, a positive predictivity of 38.5%, and a false positive rate of 4.7% for the SVEB class. For the VEB class, the sensitivity was 77.7% and the false positive rate was 1.2%. These results are an improvement on previously reported results for automated heartbeat classification systems.

Faezeh Marzbamad *et al.* [31] represented Heart Rate Variability (HRV) has been extensively investigated for the characterizing the autonomic nervous system (ANS) in controlling heart rate. Since the ectopic beats, artefacts and noise of the ECG can affect the estimation of the HRV features, pre-processing of the RR tachogram can improve the accuracy of the HRV analysis and discriminatory power. Results show that smaller p-values and therefore higher discriminatory capability are found when the preprocessing is used, while none of the features can show significant difference. Secondly, the preprocessing methods do not have the same effect for all HRV features.

Arvind Ramanathan *et al.* [32] described ambulatory 24-hour heart rate variabiliiy (HRV) data were used to thirty congestive heart.failure (CHF) patients. Eight of these patients subsequently died. The simple nonstationarity index WSI) was used to sort the data from least to most stationary. Beginning with stationary segments, periodogram spectra were cumulaffvely estimated. Spectra were computed using only those segments which yielded narrower confidence intervals, and also using all the data segments. Spectral measures extracted included low to high frequency power ratio. A comparison between patients alive improved the statistical of spectral measures, Thus preprocessing of HRV data prior to the spectral analysis might ,provide better means of risk among cardiac patients with subtle dflerences in the spectral characteristics.

Devy Widjaja *et al.* [33] proposed Heart rate variability (HRV) analysis is well-known to give information about the autonomic heart rate modulation mechanism. Therefore, preprocessing of the RR interval time series is necessary. Validation of this algorithm was performed on one hour ECG signals of 20 pregnant women. Before preprocessing, more than 1% of the detected R peaks were incorrect while preprocessing corrected more than 94% of these errors leading to an overall error rate of 0.06%.

P. K. Gakare *et al.* [34] presented ambulatory cardiac monitoring has become an important scenario nowadays as a standard preventive cardiological procedure. In the proposed system it is achieved with the Android smart phone. In order to avoid erroneous conclusions, it is of utmost importance that only sinus rhythms are present in the cardiogram. This paper presents an advanced automated algorithm to preprocess RR intervals obtained from a normal ECG. The proposed algorithm therefore restricts the manual data check to the absolute minimum and allows a reliable HRV analysis.

P. K. Stein *et al.* [35] described Abnormal HRV could confound risk stratification. Hourly short and longer-term fractal scaling exponent and interbeat correlations were calculated. Scores were summed by subject and normalized to create nn abnormalig score (ABN,O- 100. Increased ABN was associated with mortality, p=O.O0.5. After adjustment for age (p=O.OOI) and gender (p=O.OOS). When ABN was dichotomized at 57%. HR and SDNN were not diflerent, but higher ABN (N=67) had significantly increased short and intermediate-term XRV. Conclusion: Even with a relatively crude guant$cation method, abnormal rhythms were associated with increased HRV.

CHAPTER- 5
RESULTS

In time domain, the indexes mRR and mHR were not able to statistically differentiate between the two risk groups, however their mean values tended to be higher in low stress group than in high stress group.

- Time and frequency domain analysis

Table 4: Heart Rate Vribility using Time Domain and Frequency Domain Analysis.

Record	State	HRV-mRR(sec)	HRV-mHR(sec)	HRV-nVLF(%)	HRV-nLF(%)	HRV-Nhf (%)	HRV-dLFHF(%)	HRV-SVI
S 1	Low	1.079	57.302	19.933	27.532	52.538	0.275	0.525
	High	1.054	58.624	15.293	27.885	56.821	0.284	0.493
S 2	Low	1.404	63.891	12.932	31.715	55.351	0.354	0.575
	High	1.324	66.010	21.664	27.783	50.543	0.213	0.551
S 3	Low	1.261	68.354	18.192	29.835	51.974	0.203	0.576
	High	1.224	69.343	31.621	31.963	36.405	0.014	0.876
S 4	Low	1.372	64.836	39.672	33.448	26.881	0.103	1.247
	High	1.273	68.021	40.292	39.182	20.519	0.137	1.911
S 5	Low	1.431	62.402	42.816	27.982	29.195	0.011	0.952
	High	1.165	76.153	33.901	46.814	19.272	0.914	2.425
S 6	Low	1.142	52.716	26.994	43.406	29.60	0.064	1.467

						4		
	High	0.941	64.267	61.214	25.347	13.446	0.034	1.883
S 7	Low	1.274	67.455	48.644	29.133	22.211	0.032	1.315
	High	1.236	68.808	41.701	27.304	30.991	0.014	0.882
S 8	Low	1.484	60.536	28.377	22.082	49.538	0.143	0.442
	High	1.431	62.012	51.474	26.752	21.764	0.015	1.228
S 9	Low	1.411	62.973	46.842	15.723	37.433	0.182	0.425
	High	1.343	65.026	48.538	24.451	27.014	0.017	0.907
S 10	Low	1.302	66.484	24.165	35.187	40.645	0.032	0.868
	High	1.167	72.401	42.290	24.519	33.191	0.054	0.736
S 11	Low	1.531	59.645	21.823	28.858	49.313	0.240	0.588
	High	1.391	63.492	42.367	22.284	35.357	0.083	0.631
S 12	Low	1.593	58.139	14.245	32.292	53.461	0.312	0.607
	High	1.434	62.077	23.794	32.590	43.602	0.093	0.744
S 13	Low	1.131	53.259	14.097	69.781	16.124	0.152	4.320
	High	0.843	72.090	32.318	29.754	37.930	0.015	0.789
S 14	Low	1.137	53.258	14.092	69.785	16.123	0.153	4.328

	High	0.846	72.090	32.316	29.754	37.930	0.016	0.787
S 15	Low	1.491	60.563	37.472	14.168	48.361	0.197	0.298
	High	1.428	62.419	46.007	30.689	23.318	0.028	1.312
S 16	Low	1.057	57.323	24.283	53.178	22.540	0.064	2.353
	High	0.884	70.567	28.954	30.392	40.654	0.058	0.747
S 17	Low	1.251	68.344	18.182	29.845	51.964	0.213	0.566
	High	1.234	69.333	31.611	31.953	36.415	0.019	0.866
S 18	Low	1.382	64.846	39.632	33.458	26.891	0.113	1.257
	High	1.283	68.321	40.298	39.192	20.529	0.147	1.921
S 19	Low	1.251	68.454	18.182	29.825	51.964	0.213	0.566
	High	1.274	69.363	31.631	31.943	36.415	0.024	0.866
S 20	Low	1.342	64.826	39.652	33.488	26.871	0.113	1.267
	High	1.253	68.041	40.242	39.152	20.579	0.147	1.931
S 21	Low	1.471	62.432	42.826	27.962	29.145	0.031	0.945
	High	1.183	76.185	33.983	46.864	19.242	0.934	2.431

Table 4 contains the mean RR interval and mean HR of time domain measures and contains the nLF, nVLF, nHF, DLFHF, SVI of frequency domain measures, as well as the significance level of the statistical classification of subjects in their respective risk groups: low stress (low risk group) and high stress (high risk group). In frequency domain, nVLF, nLF and nHF showed significant differences when risk groups were statistically compared. The values of nVLF, nLF and nHF were lower in high risk group than in low risk group, suggesting a reduction in the sympathetic branch activity of the autonomic nervous system in arrhythmia group. spectral analysis of the RR series would be reasonably expected to manifest predominantly LF component, but our results have revealed a decreased nLF component in high risk group compared with low risk group. However, the interpretation of a reduced nLF in high stress patients is still an open question including a depressed sinus node responsiveness, central abnormality in autonomic modulation, limitation in responsiveness to high levels of cardiac sympathetic activation. Concerning to the interpretation of nVLF power spectral component, different physiological mechanisms have been proposed: physical activity, slow respiratory patterns, and parasympathetic mechanism. In this sense, the obtained nVLF behaviour could have been influenced by a reduced physical activity in the patients who were more ill.

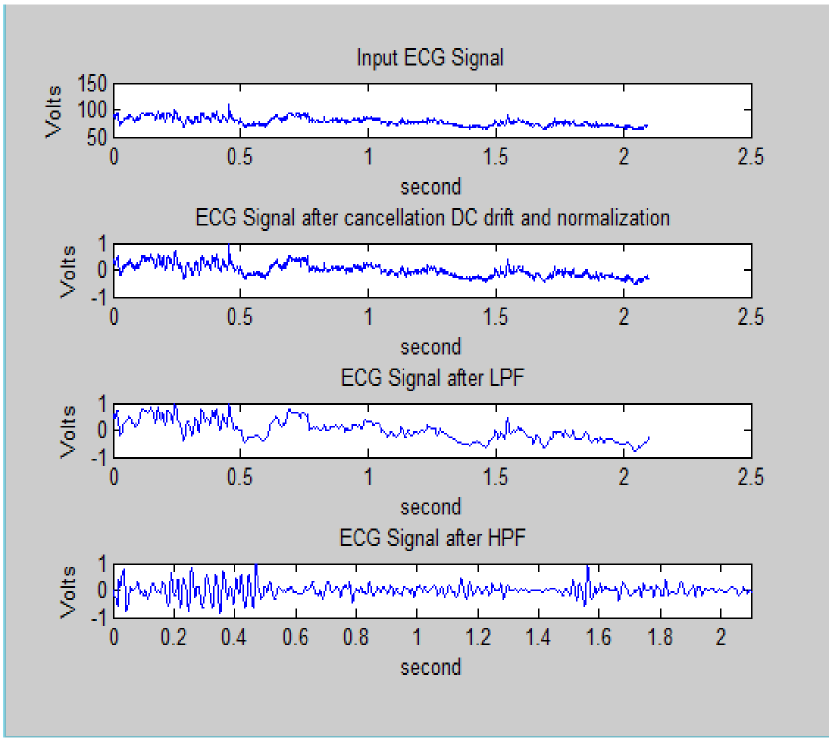

Figure 7: ECG signal of heart disease patient using dc cancellation and filtering in MATLAB.

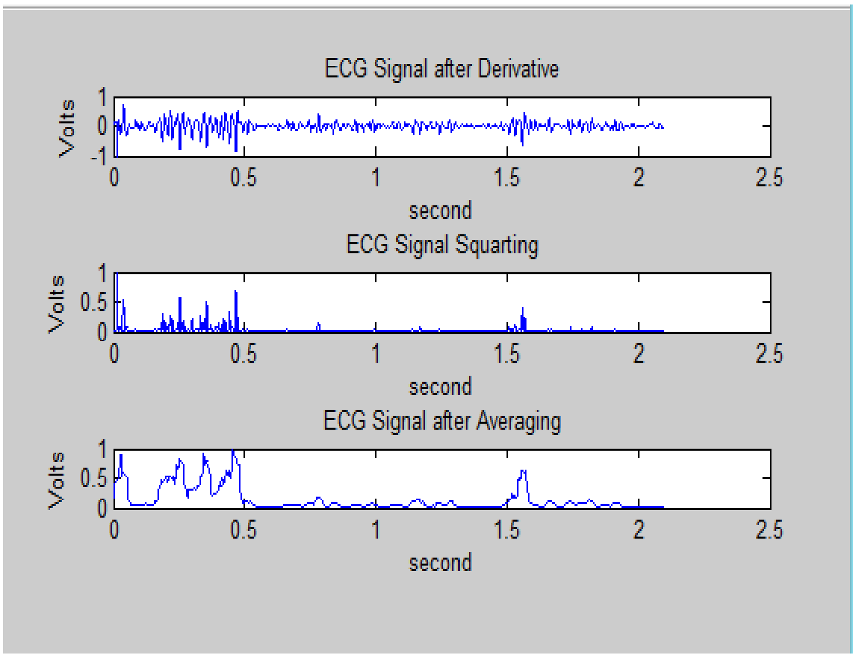

Figure 8: HRV of heart disease patient using differentiation, squaring and averaging of signal in matlab.

Fig. 7 shows a raw ECG signal of patient from live ECG application. Using the Band pass filter , we were concerned with a few things, that were amount of drift that can be eliminated. Fig. 7 represent the steps of Pan Tompkin method.This signal when passed through Low Pass Filter which is nothing but moving average filter with window size of 10 samples resulted output is as shown in figure 7. Mathematically, the moving average is a type of a convolution and so it can be viewed as low-pass filter. They smooth the curve and they cut the highest frequencies. Fig. 7 shows output of High-pass filter. It does not introduce delay in samples and it preserves most of the energy at high frequencies corresponding to QRS complex.

After filtering the raw ECG signal, it is applied to Differentiator, Squarer and Integrator for QRS complex detection, as shown in Fig 8. After the filtering, the signal is differentiated to provide QRS complex slope information. Then signal is squared point by point.

$y(nT)= [x(nT)]^2$ eqn (7)

Eqn (7) represents all data points positive and does nonlinear amplification of the output of derivative emphasizing the higher frequencies. The purpose of moving-window integration is to obtain the waveform feature information in the addition to the slope of the R wave.

$y(nT) = (1/N) [x(nT- (N - 1) T) +x(nT- (N - 2) T) + - * * + x(nT)]$ eqn (8)

Eqn (8) represents that N is the number of samples in width of the integration window. Fig. 8 shows that the relationship between the moving-window integration waveform and QRS complex. The number of the samples N in the moving window is important. Generally, width of the window should be approximately the same as the possible QRS complex. If the window is too wide, the integration waveform will merge the QRS and the T complexes together. If it is too narrow, some QRS complexes will produce the several peaks in integration waveform. These can cause difficulty in the subsequent QRS detection processes.Application of the Pan-Tompkins algorithm resulted in an error rate of 1.0936%. This indicates that the Pan-Tompkins algorithm detected almost 99% of the R peaks correctly.So, in this algorithm fluctuation of signal is not determine completely.

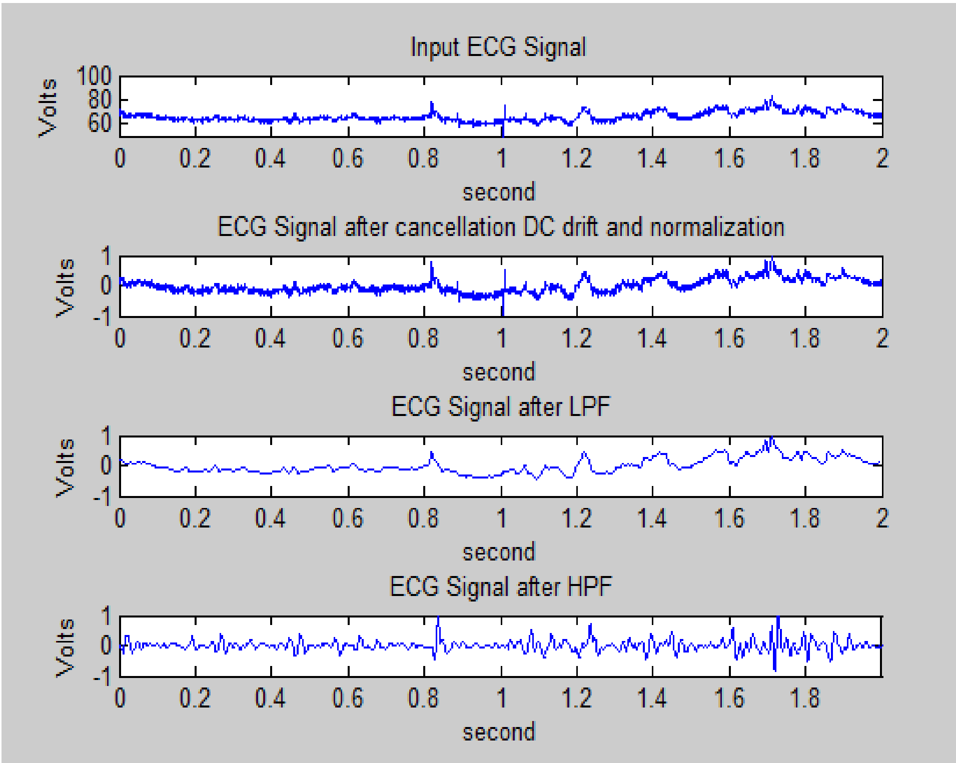

Figure 9: ECG signal of patient 2 using dc cancellation and filtering in matlab.

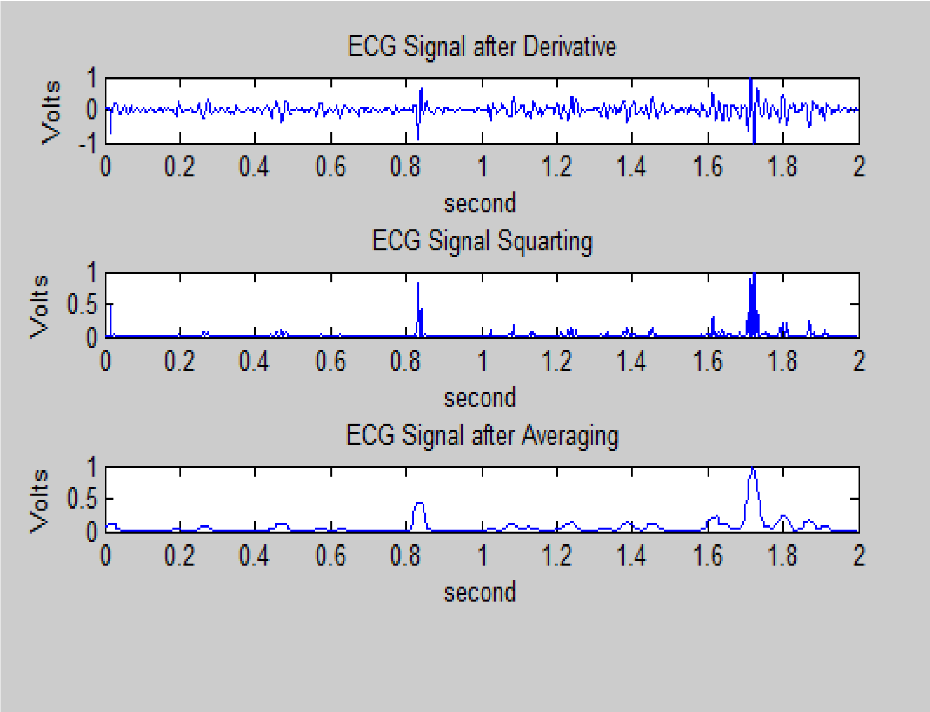

Figure 10: HRV of heart disease patient 2 using differentiation, squaring and averaging of signal in matlab.

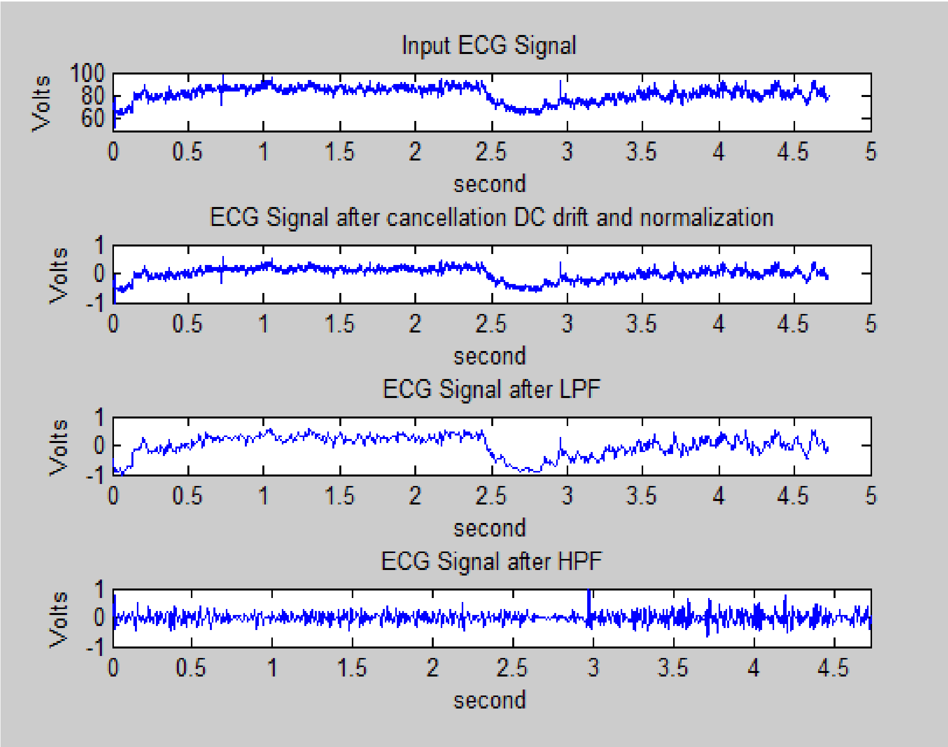

Figure 11: ECG signal of patient 3 using dc cancellation and filtering in matlab.

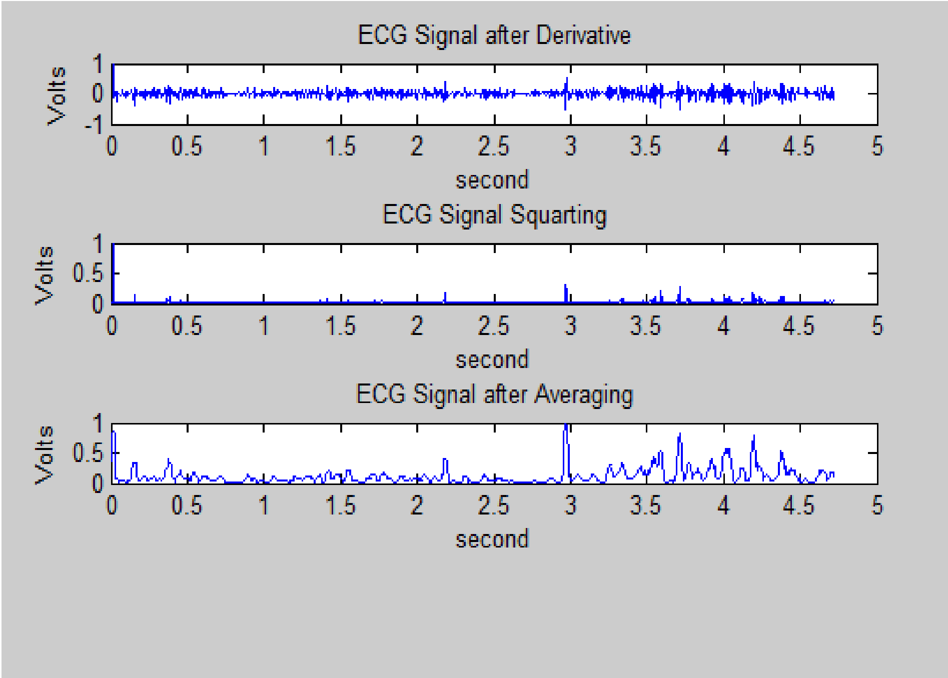

Figure 12: HRV of heart disease patient 3 using differentiation, squaring and averaging of signal in matlab.

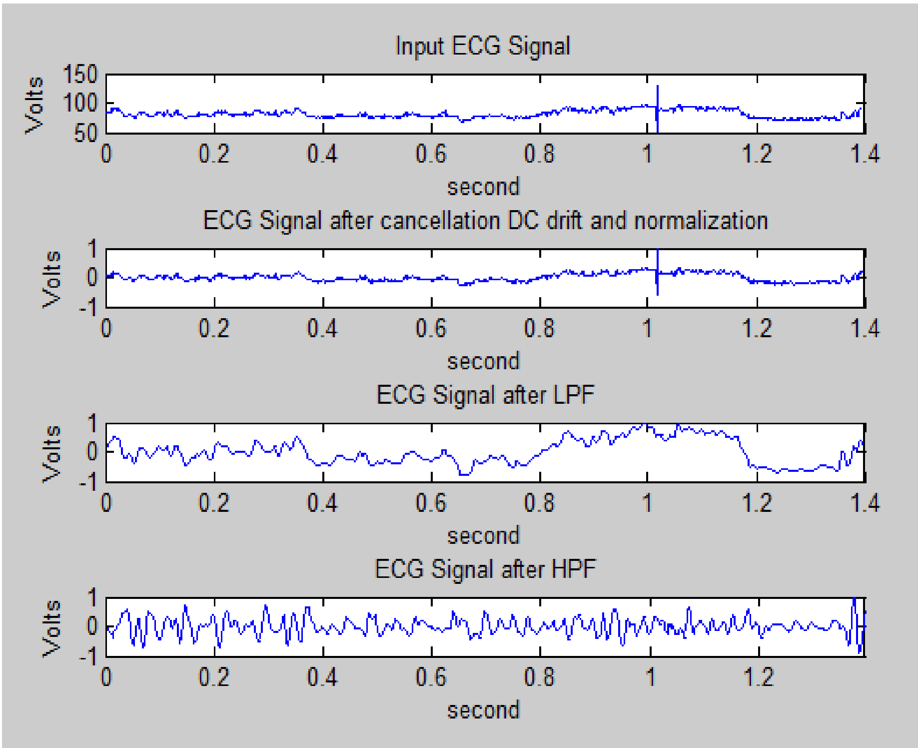

Figure 13: ECG signal of patient 4 using dc cancellation and filtering in matlab.

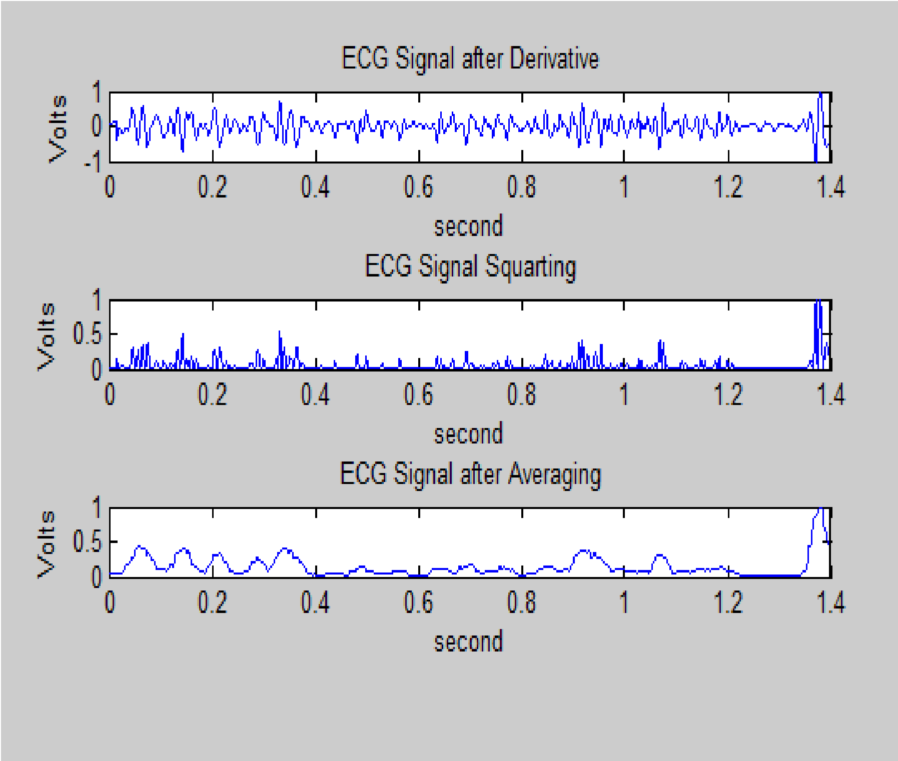

Figure 14: HRV of heart disease patient 4 using differentiation, squaring and averaging of signal in matlab.

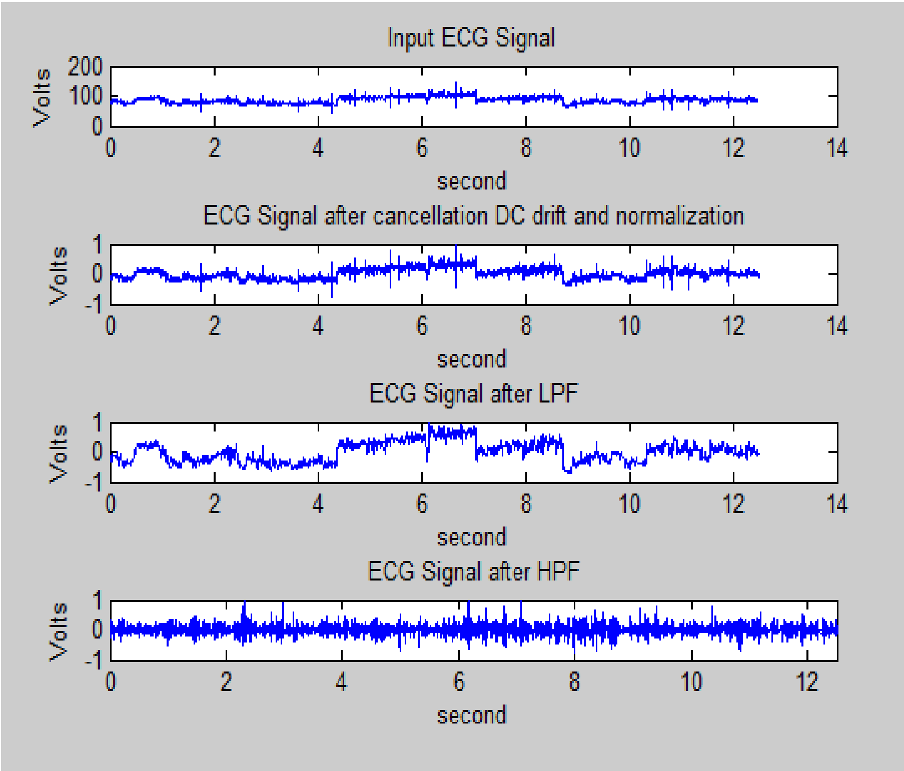

Figure 15: ECG signal of patient 5 using dc cancellation and filtering in matlab.

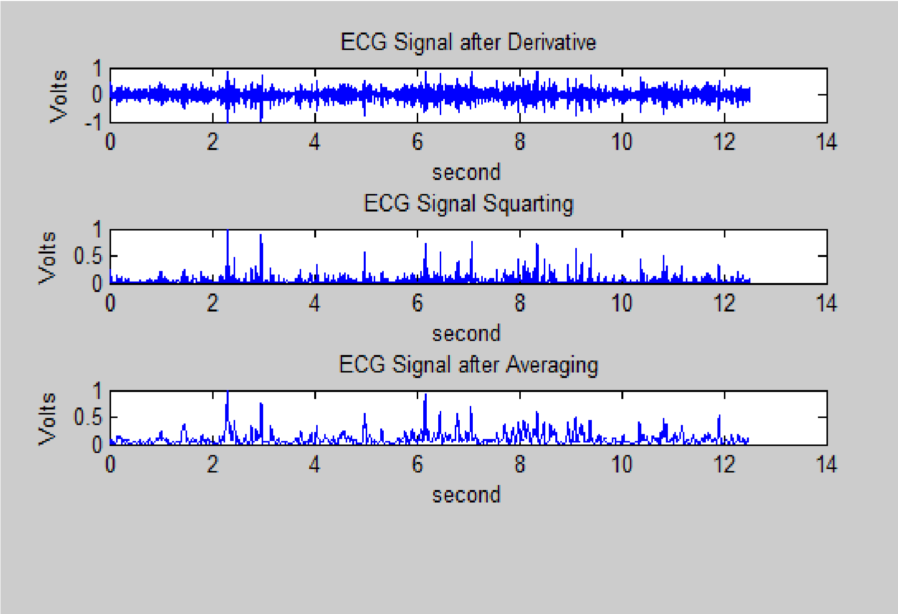

Figure 16: HRV of heart disease patient 5 using differentiation, squaring and averaging of signal in matlab.

- Detrended fluctuation analysis

The values of DFA scaling exponents measured over RR series, are shown in Table 5. A better significance level can be observed using RR series than using RR series. Magnitude of RR series has not presented scaling exponents able to differentiate both risk groups. RR series exhibited scaling exponents slightly better than those calculated over the original RR series.

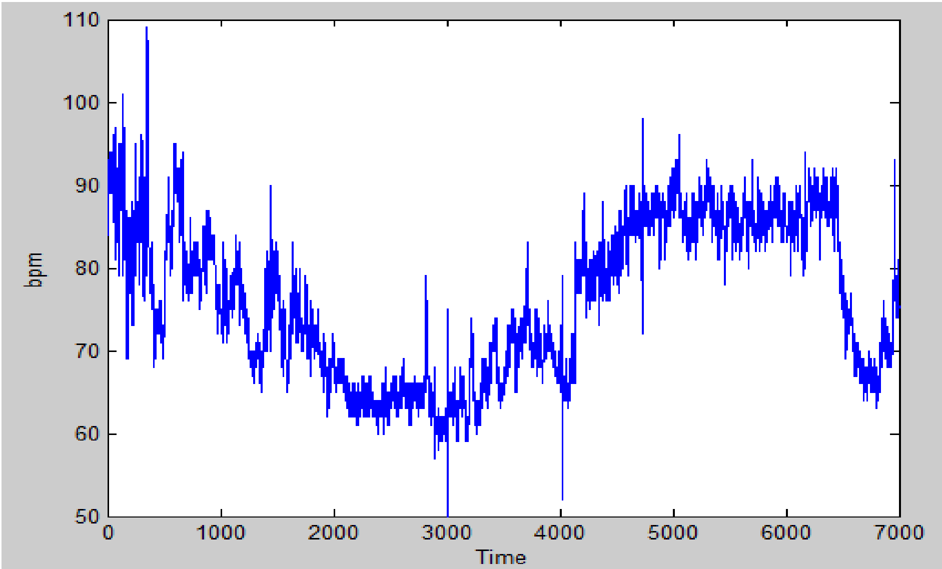

Figure 17: RR interval Time series of heart disease patient using DFA in matlab.

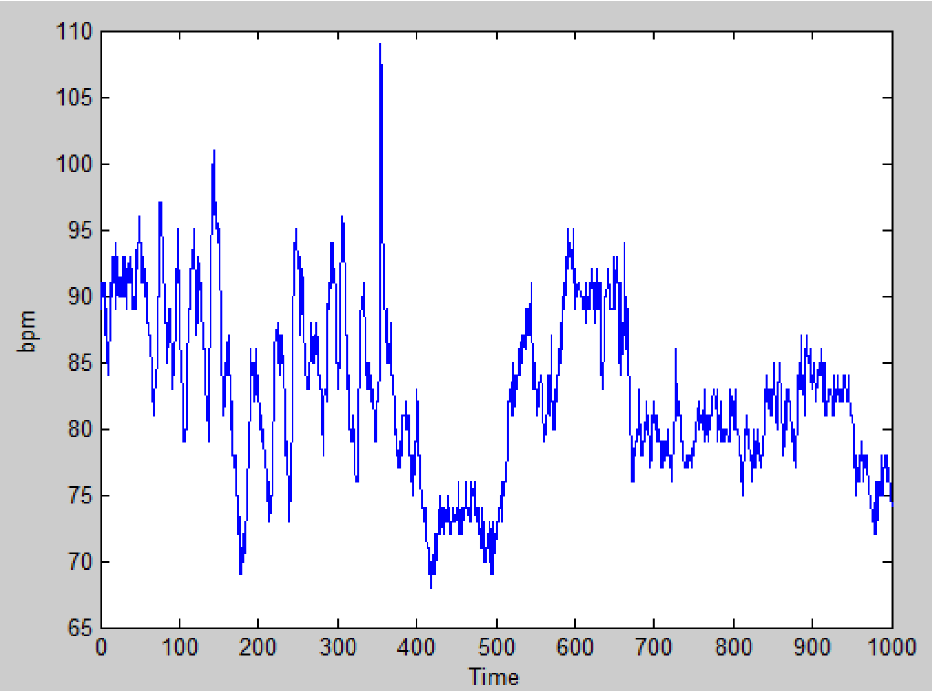

Figure 18: Integrated time series of heart disease patient

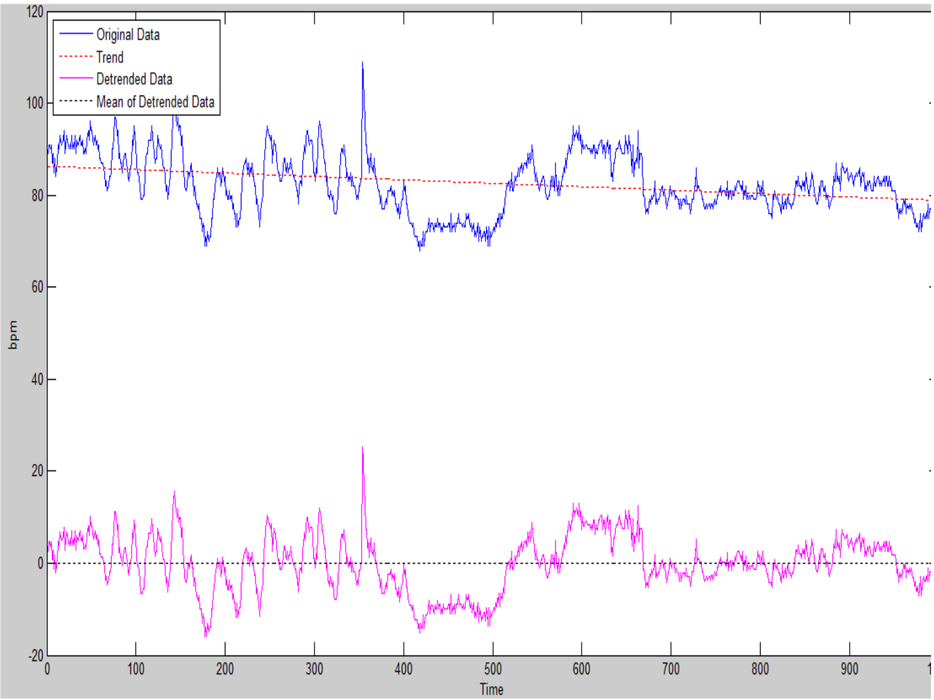

Figure 19: Detrended integrated signal and mean of Detrended signal of heart disease patient.

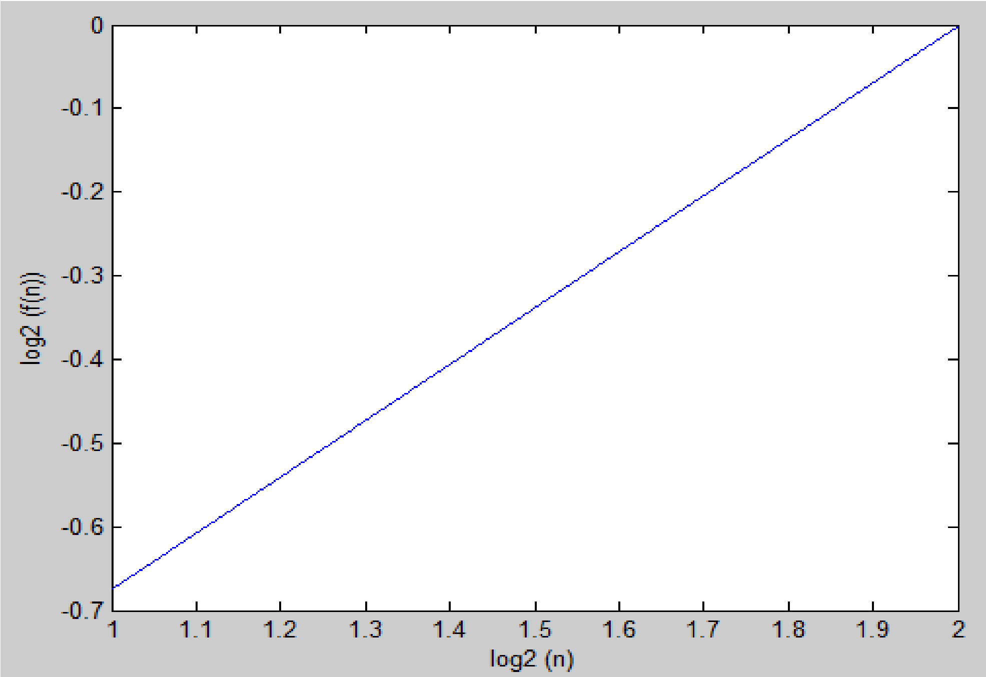

Figure 20: : Sample graph of the scaling exponent of heart disease paient representing the slope of the line relating to, and fitted line for Detrended R-R interval series.

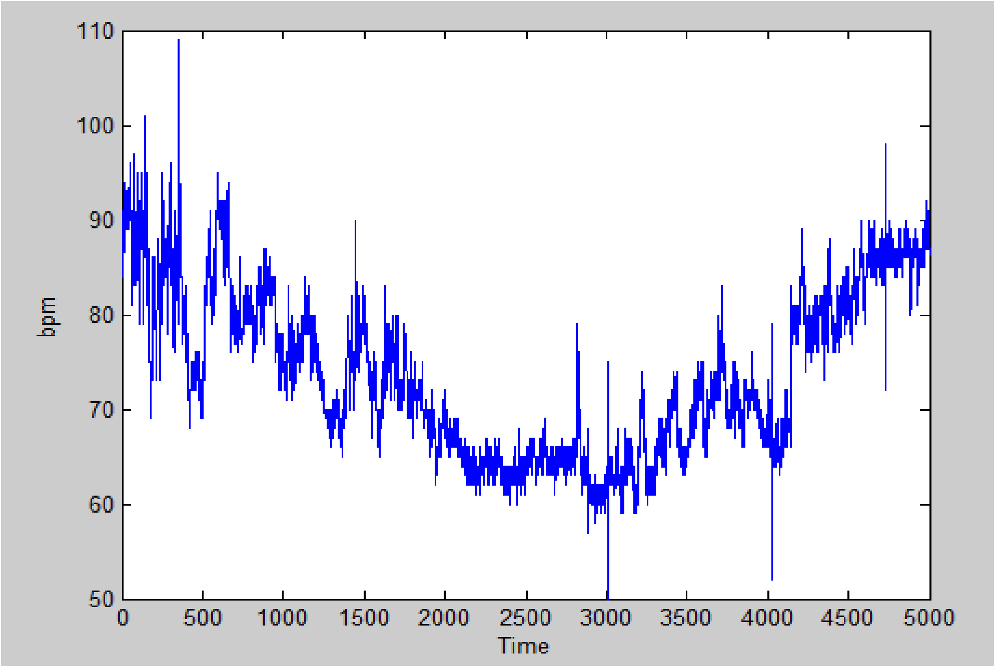

Figure 21: RR interval Time series of heart disease patient 2 using DFA in matlab.

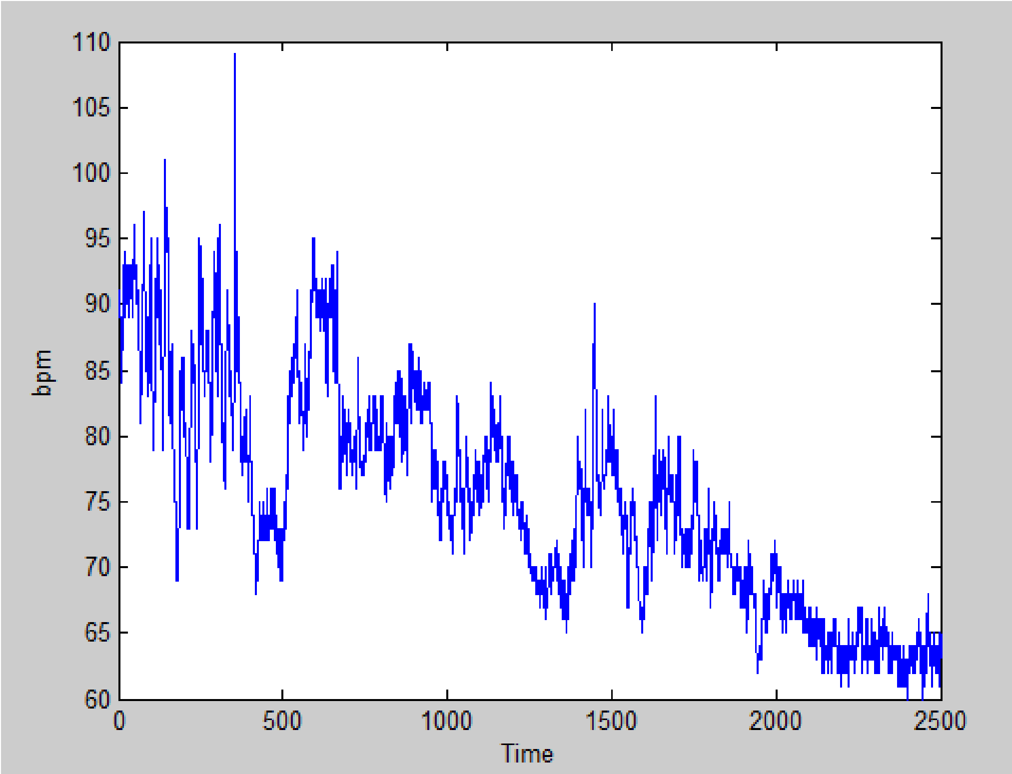

Figure 22: Integrated time series of heart disease patient 2

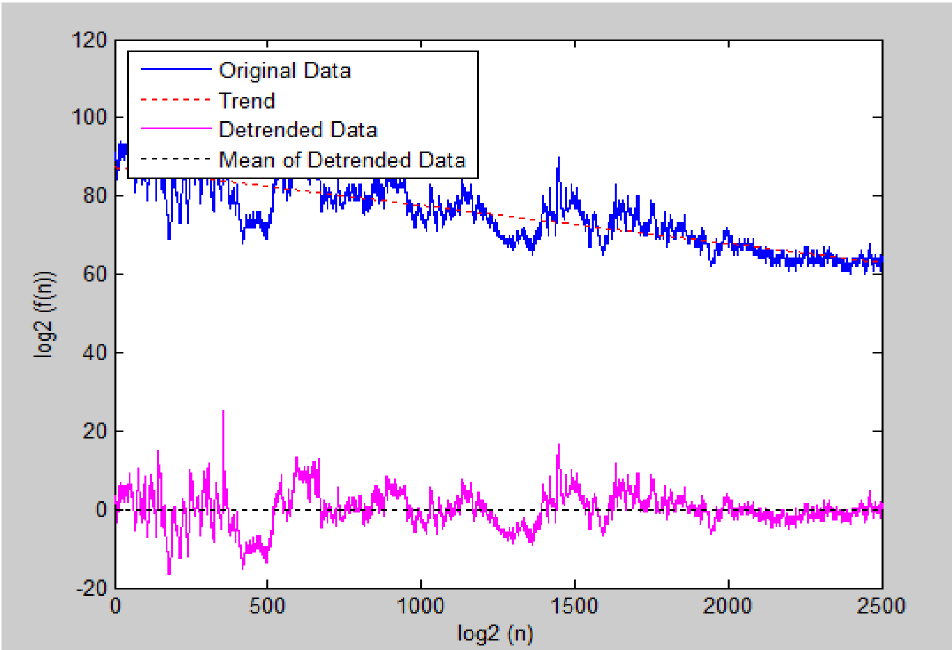

Figure 23: Detrended integrated signal and mean of Detrended signal of heart disease patient 2.

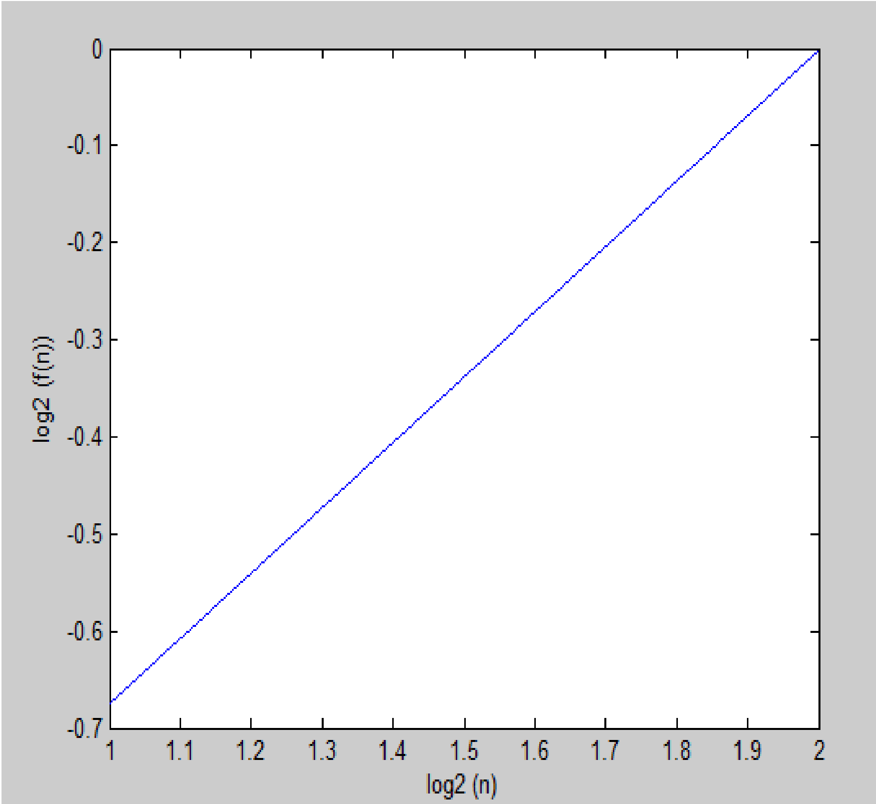

Figure 24: Sample graph of the scaling exponent of heart disease of paient 2 representing the slope of the line relating to, and fitted line for Detrended R-R interval series.

We used database from physionet.org of the 100 RR interval time series of approximately 5 minutes each, from heart disease subjects, as shown in Fig. 9. In Fig.10 represents, RR interval time series was integrated to generate the profile of time series. Then trends were removed by detrending the RR interval time series by divided into sub segments, as shown in Fig. 11. Each sub set was fitted with polynomial.Average fluctuation was plotted on a log-log graph, see Fig. 12. The self-similarity parameter was derived from the slope of line. When α >0.5 and α<=1.0 indicate a persistent long-range power-law correlation.

When 0< α <0.5, power-law anti-correlation are present such that the large values are more likely to be followed by a small values and vice versa. When α >1, correlation exist but the cease to be of power-law form.α =1.5 indicates brownian noise, integration of white noise. Exponent can also be viewed as an indicator of roughness of the original time series.

Table 5: Values of alpha for Healthy people and Heart Disease Patients.

Data seet For Healthy People	Scaling exponent α	Data set for people having heart disease	Scaling exponent α
15652	1.8890	107	1.4567
15551	0.4553	105	1.4849
16434	1.5544	104	0.7821
16602	1.3839	114	1.2239
16344	0.9387	119	0.2217
17730	0.2454	200	1.6223
17177	1.8765	209	1.9722
17400	1.4900	211	1.2628
17522	0.4456	213	0.7329

In Table 5, we can see that the scaling exponent α for healthy people around one and for people having coronary heart disease is away from one. Power law correlation in signal fluctuation and opposite heart condition of the two types of subjects under study, healthy and diseased, is reflected clearly from the scaling exponent α value. So, by Detrended Fluctuation technique, we can easily differentiate between healthy and patients.

Pan-Tompkins method is easy to implement, but the fluctuation in the signal, yielding the positive and negative slopes as the useful feature, can result in false peaks searching interval. In conclusion, we found the DFA α values of different groups required minimum time series for calculations in order to achieve reliable results. As cardiovascular regulation mechanism is a nonlinear process, nonlinear methods, like Detrended Fluctuation Analysis may provide powerful prognostic information than Pan tompkin HR variability indexes.

Thus, value of the nonlinear parameters found in this work can be used as standard in diagnosis of heart disease in probable patients. Also, by measuring these nonlinear parameter values, a qualitative idea of heart condition can be obtained. In future, this work can be extended to distinguish heart rate data for people in various opposite heart conditions, for example, in different mental stress levels.

CHAPTER- 6
CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

The main goal of this thesis was to investigate the nonlinear system dynamics in the autonomic regulation of heart rate. Heart rate variability was used here as a tool to study the autonomic nervous system with a focus on the nonlinear techniques. We investigated whether they provide additional information about the nonlinearity in the cardiovascular system which can not be reflected by standard HRV analysis. Therefore, several completely different data sets were used on which those techniques were applied. The nonlinear HRV parameters will not replace linear analysis, but have to be considered as a complement, yielding extra information about a specific aspect of scaling behavior or complexity of the underlying cardiovascular system. Nonlinear system dynamics provide additional and independent information about physiological as well as pathophysiological cardiovascular regulation. Therefore, it also might provide a valuable addition to current patient monitoring systems.

6.2 Future Scope

There exists a growing body of evidence that the useful information concerning variability of the heart rate can be gained from the using of the nonlinear and nonstationary mathematical techniques. A method for locating significant changes in the RR tachogram based upon statistical tests of shifts in mean values over varying windows may provide segmenting for spectral analysis, without the need for other information. However, this does not address the problem of comparing the HRV estimates between patients experiencing similar activity states. Furthermore, prior information about the noise and signal structure of data being analysed can be included in the estimation. It may also be possible to quantify the nonlinear components of an RR tachogram.

REFERENCES

[1] T. Y. Young, W.H. Huggins, “On the Representation of Electrocardiograms,” *IEEE Transaction Bio-medical Electronics*, vol. 10, no. 3, 1963.

[2] C. Lamberti, G. Fanti, "ECG waveform synthesizer," *International Conference of the IEEE Engineering in Engineering in Medicine and Biology Society*, vol. 2, 1989.

[3] S. Muthulakshmi, and K. Latha, "Classification of ECG waveform using feature selection Algorithm," *International Conference on Advanced Communication Control and Computing Technologies*, 2012.

[4] Yun-Chi Yeh, Wen-June Wang, and Che Wun Chiou , "Heartbeat Case Determination Using Fuzzy Logic Method on ECG Signals," *International Journal of Fuzzy Systems* vol. 11, no. 4, 2009.

[5] Can ye, B. V. K. V. Kumar, M. T. Coimbra, "Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals," *IEEE Transactions on Biomedical Engineering*, vol. 59, no. 10, 2012.

[6] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, and S. Luo, "ECG beat detection using filter banks," *IEEE transaction on biomedical engineering*, vol. 46, no.2, 1999.

[7] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, and S. Luo, "Multirate processing of the ECG using filter banks," *Computers in Cardiology*, 1996.

[8] J. Bushra, L. Olivier, F. Eric, and B. Ouadi, "Detection of QRS complex in ECG signal based on classification approach," *IEEE International Conference on Image Processing*, 2010.

[9] P. de Chazal, and R. B. Reilly, "Automatic classification of ECG beats using waveform shape and heart beat interval features," *International Conference on Acoustics, Speech, and Signal Processing*, vol. 2, 2003.

[10] M. Kundu, M. Nasipuri, and D. K. Basu, "A knowledge-based approach to ECG interpretation using fuzzy logic," *IEEE Transactions on Systems Man and Cybernetics* vol. 28, no. 2, 1998.

[11] S. S. Mehta, S.C. Saxena, and H. Verma, "Recognition of P and T waves in electrocardiograms using fuzzy theory," *Conference of the Biomedical Engineering Society of India*, 1995.

[12] J. Leski, and N. Henzel, "A fuzzy method for high resolution localization of ECG waves," *Fuzzy Systems Conference Proceedings*, vol. 1, 1999.

[13] G. Bortolan, R. Degani, and W. Pedrycz, "A fuzzy pattern matching technique for diagnostic ECG classification," *Computers in Cardiology,* 1988.

[14] A. Cabasson, O. Meste, G. Blain, and S. Bermon, "Quantifying the PR Interval Pattern During Dynamic Exercise and Recovery Evolvable," *IEEE Transactions on Biomedical Engineering*, vol. 56 , no. 11, 2009.

[15] C. Wang, F. Wang, "An Emotional Analysis Method Based on Heart Rate Variability," *International Conference on Biomedical and Health Informatics*, 2012.

[16] S. Korsakas, A. Vainoras, V. Miskinis, R. Ruseckas, V. Jurkonis, R. Jurkoniene, K. Berskiene, L. Siupsinskas, and V. Marozas, "Electrocardiosignals and Motion Signals Telemonitoring and Analysis System for Sportsmen," *Computers in Cardiology*, 2005.

[17] M. Laurino, A. Piarulli, R. Bedini, A. Gemignani, A. Pingitore, A. L'Abbate, A. Landi, P. Piaggi, and D. Menicucci, "Comparative study of morphological ECG features classificators: An application on athletes undergone to acute physical stress," *International Conference on Intelligent Systems Design and Applications*, pp. 242 – 246, 2011.

[18] G. Deak, R. Miron, A. Astilean, and C. Domuta, "Fuzzy based method for assessing the training level of nonathletes and athletes," *International Conference on Automation Quality and Testing Robotics*, vol. 2 , pp. 1 – 5, 2010.

[19] A. E. Aubert, B. Steps, and F. Beckers, "Heart rate variability in athlete," vol. 8, no. 4 pp. 311–315, 2003.

[20] C. S. Yoo, and S. H. Yi,"Effects of Detrending for Analysis of Heart Rate Variability and Applications to the Estimation of Depth of Anesthesia," *Journal of the Korean Physical Society*, vol. 44, no. 3, pp. 561-568, 2004.

[21] G. Morren, P. Lemmerling, H. Daniels, G. Naulaers, S. V. Huffel, "Sensitivity of detrended fluctuation analysis applied to heart rate variability of preterm newborns," *Proceedings of Engineering in Medicine and Biology*, pp. 319-322, 2005.

[22] Rong-Guan Yeh, Gau-Yang Chen, Jiann-Shing Shieh1, and Cheng-Deng Kuo,"Parameter Investigation of Detrended Fluctuation Analysis for Short-term Human Heart Rate Variability," *Journal of Medical and Biological Engineering*, vol. 30, no. 5, pp. 277-282, 2010.

[23] A. A. S. Khan, U. Mumtahina, and Nusrat Yeasmin, " Heart Rate Variability Analysis Using Approximate Entropy and Detrended Fluctuation for Monitoring

Heart Condition," *International Conference on Informatics, Electronics & Vision,* pp. 1-5, 2013.

[24] T. Penzel, Member, J. W. Kantelhardt, L. Grote, Jörg-Hermann Peter, and A. Bunde Comparison of Detrended Fluctuation Analysis and Spectral Analysis for Heart Rate Variability in Sleep and Sleep Apnea," *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, vol. 50, no. 10, 2003.

[25] J. C. Perfetto, A. Ruiz, and C. D'Attellis,"Detrended Fluctuation Analysis (DFA) and R-R Interval Variability: A New Linear Segmentation Algorithm," *Computers in Cardiology*, vol. 33, pp. 629−632, 2006.

[26] Y. Goyal, and A. Jain, "Study of HRV dynamics and comparison using wavelet analysis and Pan Tompkins algorithm," *International Conference on BioMedical Computing*, 2012.

[27] S. Palaniappan, and R. Awang, "Intelligent Heart Disease Prediction System Using Data Mining Techniques," *Proceeding of Computer Systems and Applications*, 2008.

[28] D. Widjaja, S. Vandeput, J. Taelman, M. AKA Braeken, R. A Otte , Bea RH Van den Bergh, and S. V. Huffel , "Accurate R Peak Detection and Advanced Preprocessing of Normal ECG for Heart Rate Variability Analysis," *Computing in Cardiology*, vol. 37, pp. 533−536, 2010.

[29] Mental Stress Detection using Heart Rate Variability and Morphologic Variability of ECG Signals.

[30] Philip de Chazal, Maria O'Dwyer, and Richard B. Reilly, " Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features," *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, vol. 51, no. 7, 2004.

[31] F. Marzbanrad, H. Jelinek, E. Ng, and M. Tamayo, "The Effect of Automated Preprocessing of RR Interval Tachogram on Discrimination Capability of Heart Rate Variability Parameters," *Computing in Cardiology Conference*, pp. 483-486, 2013.

[32] A. Ramanathan, M. G. Kienzle, and G. A. Myers, "Preprocessing Heart Rate Variability Data Improves Risk Stratification in Congestive Heart Failure," Proceedings of *Computers in Cardiology*, 1996.

[33] D. Widjaja, S. Vandeput, J. Taelman, M. AKA Braeken, R. A Otte , B. RH Van den Bergh, S. V. Huffel, " Accurate R Peak Detection and Advanced

Preprocessing of Normal ECG for Heart Rate Variability Analysis," *Computing in Cardiology* , vol. 37, pp. 533−536, 2010.

[34] P. K. Gakare, A. M. Patel, J. R. Vaghela, and R. N. Awale, "Real Time Feature Extraction of ECG Signal on Android Platform," *International Conference on Communication, Information & Computing Technology*, 2012.

[35] P. K. Stein, N. Hui, P. P. Domitrovich, J. Gottdiener, and P. RautaharJu, "Distinguishing Normal and Abnormal Heart Rate Variability Using Graphical and Non-Linear Analyses," *Computers in Cardiology*, vol. 31, pp. 205-208, 2004.

LIST OF PUBLICATIONS

Published

- Atinderpal Kaur and Amanpreet Kaur, "Effects of detrending for analysis of heart rate variability using detrended fluctuation algorithm and its comparison with Pan

Tompkin algorithm using Matlab," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 3, no. 6, June 2014.

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Communicated

- Atinderpal Kaur and Amanpreet Kaur, "Analysis of Heart Rate Variability using Linear Method and Non-linear method," *International Journal of Advanced Research in Engineering and Applied Science*, 2014.