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ANALYSIS OF HEART RATE VARIABILITY USING LINEAR METHOD AND NON LINEAR METHOD

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Abstract: *This paper presents two algorithms, one is Detrended Fluctuation Analysis (DFA) algorithm and other is Pan tompkin algorithm. These two algorithm have been implemented in Matlab. Heartbeat signals were frequently contain either slow trends or very slow frequency oscillation, detrending was necessary as preprocessing step to prepare for a analysis by using non linear method measures,while nonlinear measure were strongly affected by detrending. DFA is technique for diagnosis of ECG feature extraction.It is applicable in context of the nonstationary signal, since it involves removing fluctuation trends from the signal.Experimental data are affected by non-stationarities. Such trends have to be well distinguished from the intrinsic fluctuations of the system in order to find the correct scaling behavior of fluctuations. HRV analysis is performed using a methods that are based on the assumption that the signal is stationary within experiment duration, which is normally not correct for the long-duration signals. HRV analysis by nonlinear method bring 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.*

Keywords: *Heart Rate Variabilty (HRV), Detrended Fluctuation Analysis (DFA), Matlab, Electrocardiogram (ECG), Power Spectral Density (PSD).*

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1. INTRODUCTION

Heart rate variability represents the variations between consecutive heartbeats. Heart Rate Variability parameters have been used to predict the risk in the patients with heart disease, such as the life threatening acute coronary events [1, 2]. HRV analysis has become an very important tool in the cardiology,its quantifications are noninvasive, have good reproducibility, very easy to perform, and provide aprognosticative information of patient with heart disease [3]. Commonly used statistics of HRV, which are average heart rate and standard deviation of all the normal-to-normal R-R intervals over a specific time periods [1], are not able to describe the accurately changes in beats of heart rate dynamics. In time and frequency domain, linear measures have most commonly been used to measure the fluctuation in the heart rate, [4]. Therefore, nonlinear methods have been developed to quantify dynamics of heart rate fluctuations [5,6]. The nonlinear method inherently consider that signal is at least weakly stationary. However, a real HRV is slow linear and more complex trends (noise) have to be considered before analysis. To obtain the results of the analysis of the HRV, it is necessary to distinguish trends from heart rate fluctuations intrinsic in the data. Trends are caused by the external effects.Often, data are affected by nonstationarities. Such trends have to be well discriminated from the intrinsic fluctuation of the system in order to find the correct dynamics of fluctuations, but if trend are present in the data, they may give specious results.In order to perform spectral analysis, detrending schemes have been used as a preprocessing step to prepare analysis of HRV by using methods that assume stationarity. DFA is a well-established method for conclusive the scaling behavior of the noisy data in the existence of trends, without intended their origin and shape. In recent years, DFA was developed to accurately quantify long-range power law correlations in a non-stationary time series [5,7,8]. A recent works examined different types of non-stationarities associated with different trends.HRV provides various features for distinguishing heart rate under healthy and life threatening condition.

There are three main approaches in HRV analysis:

1) time domain analysis of HRV for standard deviation of normal to normal intervals (SDNN)
2) frequency domain analysis for Power Spectral Density (PSD)
3) nonlinear method

The ECG waveform is shown in the Fig. 2.The ECG waveform can be broken down into three important parts each denoting a peak on the either side represented by P, Q, R, S, T.In case of a disease afflicting the heart, the waves get distorted according to the area which is not functioning normally. Thus by inspection of the ECG waveform the nature of disease can be found out easily.

2. MATERIAL AND METHODS

A. Heart Rate Variability

Healthy individuals heart rate is neither constant nor periodic. Heart rate variability (HRV) is the combination of numerous influences reflecting the physiological regulatory mechanism. In recent past there has been research efforts include HRV, based on the conviction that disentangling sources of the variation in the cardiac dynamics will provide precise information related to cardiovascular autonomic regulation of heart.HRV using Pan Tompkin method and Detrended fluctuation analysis method is shown in Fig. 1

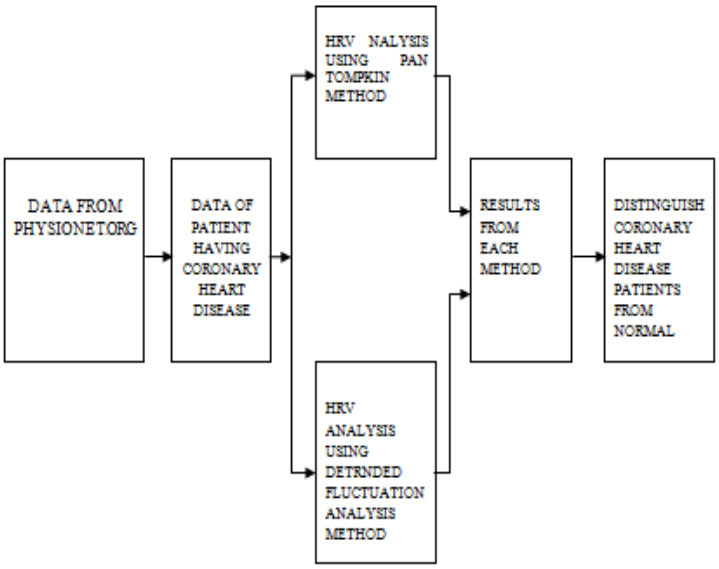

Figure 1. Methodology of work

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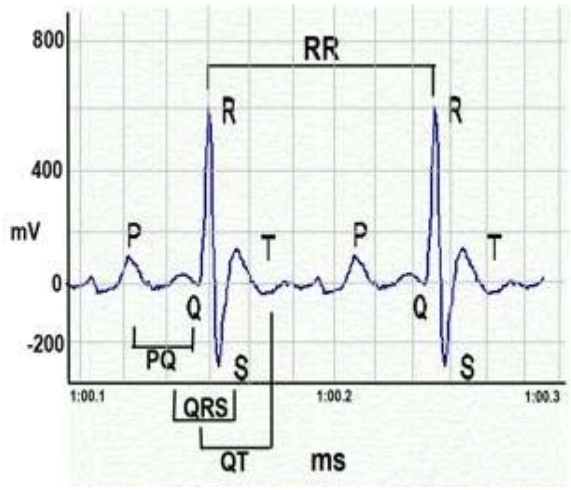

Figure 2. Heart rate variation in signal

B. HRV Analysis using Pan tompkin method

Pan-Tompkins method: Pan and Tompkins introduced a real-time algorithm for the detection of the R peak in the ECG signal [9],[10]. This algorithms involve series of the filters, derivative, squaring, integration for the preprocess and adaptive thresholds for the peak searching. Fig. 3 illustrates steps of the algorithm in a schematic form. The ECG signal of human exists in frequency between 0.5Hz~30Hz which is generated in periodical electronic signal to create the periodical exercises of heart. The frequencies that are concentrated by the QRS complex are existing in 5Hz~15Hz.

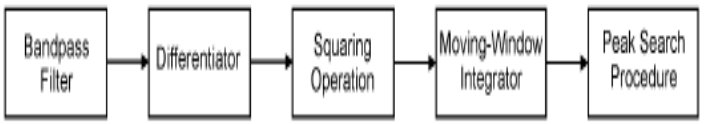

Figure 3. Block diagram of algorithm.

Band pass filter: The band pass filter reduces the influence of the artifacts in signal. In this, the high pass filter and the low pass filter are applied. The digital low pass filters with small integer coefficients are designed for the fast execution. The cutoff frequency is 11Hz and the delay is 25ms.Low-pass filter passes frequencies that contain average QRS complex and reduces noises if they are strayed from such frequencies. High-pass filter is a result of subtract from existed signals after dividing the result of low-pass filter by D.C gain. The cutoff frequency is 5Hz, delay is 80ms.

Differentiator: It takes the properties of QRS complex by applying differentiator after pass the signals through band-pass filter.

The squaring techniques: Squaring operation leads to positive result and it enhances large values more than small values. The squaring operator increase the high-frequency components further.

Threshold adjustment and Decision making: After passing window integration proper thresholds are adjusted to detect R-peaks [8]. In order to detect the R-peaks correctly i.e. no R peaks are missed out and no any false peak is detected, decision making block is implemented which will decide that the detected peak is valid QRS complex or not.

C. R-wave detection

For the R-wave detection a threshold was calculated from he equation:

Threshold=p.max(y(n)).mean(y(n)) eqn(1)

Where, the p is a weighing factor.

Where, y(n) is the output of the moving window integration. Events were located where the output of the moving window was higher than the threshold. The lower and upper limit of each event were located and to find the R -wave, delay of the band pass filter had to be taken. For each event the maximum were found and the location of it set as the R-wave [12].

D. Overall Performance of algorithm

Performance of the Pan tompkin algorithm measures, which categorize the detected and the undetected R peaks before and after the preprocessing. Using these measures, performance of algorithm is quantified by mean of error rate, i.e defined as the ratio between the number of the errors and the actual number of R peaks. The overall performance achieved by algorithm measured in the terms of the QRS detection rate, defined as [11].

By the Pan-Tompkins algorithm, false detections occur mostly due to the noise. Often, noise causes spurious R peak detections, i.e harmless, since no information is lost. On the other hand, undetected R peaks always result in loss of information.

3. LINEAR METHOD OF HRV

Variability is determined by complex dynamics of the sympathetic and the parasympathetic branches of the autonomic nervous system which interact impulse generating tissue located in right atrium of the heart i.e. sinoatrial node. The RR interval time series extracted from an ECG signal monitored during the heart disease. The tachogram has length that contain heart beats. Before calculate HRV parameters, preprocessing was necessary as explained in the paragraph. Some irregular or the faulty RR intervals were corrected this way. The linear time and frequency domain techniques for the HRV were described below.

I. Time domain analysis

Time domain analysis for HRV contains intervals between the successive normal R waves in a ECG are measured over periods of the recording. A variety of statistical metrics calculated from the intervals directly and others can derive from differences between the interval.

Table 1 shows time domain variables that can be calculated include mean RR interval and mean heart rate. Both of the parameters are very sensible to slow trends in heart rate data. These are used to quantify long term fluctuations. It should also be noted that the total variance of the HRV increases with the length of the analyzed recording. On arbitrarily selected ECG, RR interval not a well defined statistical quantity because of dependence on length of the recording period. Consequently, in practice, it is inappropriate to compare RR measures obtained from recordings of the different durations. However, durations of recordings used to determine RR values (and similarly other HRV measure) should be standardized. Another commonly used statistical variables calculated from the segments of the total monitoring periods. All these measurements of short-term variations estimate high frequency variations in the heart rate and thus highly correlated.

Table 1: HRV in Time Domain Analysis.

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

II. Frequency domain analysis

Various spectral analysis for analysis of the tachogram have been applied. Power spectral density analysis provides the basic information of the how power, and therefore variance, distributes as function of frequency. Independent of method used, only an estimate true PSD signals can be obtained by proper mathematical algorithm. Table 2 shows a Heart Rate Variability in frequency domain analysis.

TABLE 2: HRV IN FREQUENCY DOMAIN ANALYSIS.

Measure	Unit	Formula
normalized very low fre 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 (HF) band (0.15 to 0.4 hz) reflects the respiratory modulation via different impulses on cardiac nerves.In addition, the HF variability is also fully abolished during the breath holding task. The low frequency (LF) band (0.04 to 0.15 Hz) is modulated by baroreflexes with the combination of the sympathetic and the parasympathetic different nerve traffic to SN. Finally, the mechanism responsible for very low frequency (VLF) spectral band (0 to 0.04Hz) id the matter of dispute. VLF power is abolished by the atropine, suggesting that it uses parasympathetic efferent limp.

4. NON LINEAR METHOD OF HRV

Time domain and frequency of the HRV quantify variability of the heart rate fluctuations in the characteristics time scale. Non linear measure on contrary attempt to quantify structure and complexity of RR interval time series. A large number of non linear indices of the HRV has been studied and new are developed continuously. Only the few of them, have shown precise clinical utility One of them is a power law slope which is obtained by the spectral power measured. Spectral power will show progressive exponential increases in the

amplitude with decreasing frequency. This is a characteristics 1/f or pink noise observed in the complex biological system, which do not represents any characteristic scales (scale- in variant or fractal).This relationship can plotted as log of power versus log of frequency , which transforms exponential curve to the line whose slope can estimated. Decreased power law slope is marker for the increased risk of the mortality after myocardial infarction.The cardiac system is the dynamic, nonlinear, and non stationary, with performance continually fluctuating on a beat-to-beat basis as the extrinsic and intrinsic stimuli simultaneously influence state of system. Due to the assumption and conditioning requirement, linear analyses may not account for all the aspects of cardiac performance, particularly subtle interactions between control mechanisms that regulate the cardiac functions. Analysis technique arising from nonlinear systems dynamic theory were therefore developed to the ascertain the multidimensional processes that control the cardiac system.

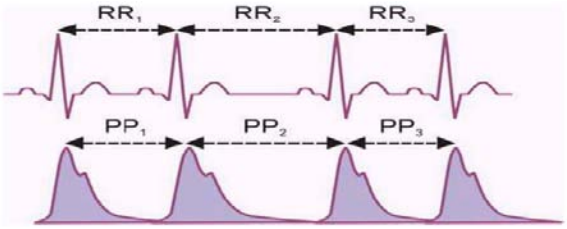

Figure 4. RR intervals of Heartbeat.

i. Detrended fluctuation analysis

HRV signal is a thought as composition of classes of the fluctuations, one arising from the dynamic of a complex system which shows long-range correlations and the other types of fluctuations that have characteristic time scale although highly non-stationary. In this type of the algorithm, examining of the scaling behavior of the heart beat fluctuation is done for the correlation measurement. The DFA method can be used for diagnosis tool for patient with cardiac disease [13]. In DFA, scaling exponent α indicates the power law correlations in signal fluctuation. The main objective of DFA is to extract extrinsic fluctuation in order to allow the analysis of the signal variability associated exclusively with the autonomic control. If values of scaling component α is 1 or around 1, then it represent the healthy condition. The latter type of the fluctuations can be considered as a noise, an treated as trend, this is reason for removed the trends in the algorithm. This trend can be distinguished from more suitable fluctuations that may reveal intrinsic correlation property of a dynamics.

To calculate the scaling exponents with the DFA, given series of RR_i of length N is firstly integrated. The integrated values of time series is given by:

1. First, RR interval time series y(k) is integrated:

$y(k)=\sum_{i=1}^{k}(RR_i - RR_{avg})$ eqn (2)

where, RR_i is the mean of the time series.RR interval time series and integrated time series, as shown in eqn (2).

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

3. In each segments, least squares line fitted to the data. This line represents trends in that segment.

4. Subtracting trend from y(k), root-square fluctuation is calculated by:

$f(n)=\sqrt{\frac{1}{M}\sum_{k=1}^{M}(y(k) - y_n(k))^2}$ eqn (3)

where, f(n) is the fluctuation function of segment size n, as seen in eqn (3).

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

$f(n) \propto \alpha$ eqn(4)

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

$\alpha = \frac{\log_{10} F(n)}{\log_{10} n}$ eqn (5)

The DFA exponent α, is slope of the trend line in the range of a time-scale of interest and can be estimated using a linear regression. Here, we have chosen a logarithmically spaced window sizes, because it give equal weight to all the time-scale, when we fit a line in a log-log coordinates using linear regression using eqn (5). The lower end of fitting range is at least the four sample, because linear detrending will performs poorly with less points. For a high end of the fitting range, the DFA estimates the window sizes >10% of signal length are very noisy due to a low number of the window available for the averaging (i.e., less than 10 window). Finally, 50% overlap between the window is commonly used to increase the number of window, which can be provide a more accurate estimate of fluctuation functions especially for the long-time-scale window. The DFA exponent is interpreted as estimation of

a Hurst parameter, as explained with random walker example, i.e. time series is uncorrelated if α =0.5.

If 0.5< α <1 then there are positive correlation are present in time series as getting the larger fluctuations on the longer time-scale than the expected by chance. If α<0.5 then time series is the anti-correlated, which means that the fluctuations are smaller in the larger time windows than expected by chance. Since DFA were first introduced several papers have tested the performances of DFA in relation to trends , non stationarities, pre-processing such as artifact rejections. Other trends-removal techniques have been proposed, such as a higher-order polynomial or adaptive detrending. However, these have not a yet been tested in DFA analysis of neuronal oscillations.

The scaling exponent α can estimated by the linear fit on a log-log plot of *f(n)* versus n using a least-square. The α value represents a correlation properties of the signal, log-log plot of the f(n) versus n. This method represents that a fractal-like signal results in scaling exponent value of 1.The Brownian noise signal with spectrum of a rapidly decreasing power in the higher frequencies result in 1.5 [6]. If α > 0.5 signal is positively persistent (correlation), when α < 0.5 signal is a non-persistent. The general phenomenon is that the larger value of a scale exponent α represents smaller fractal dimension.

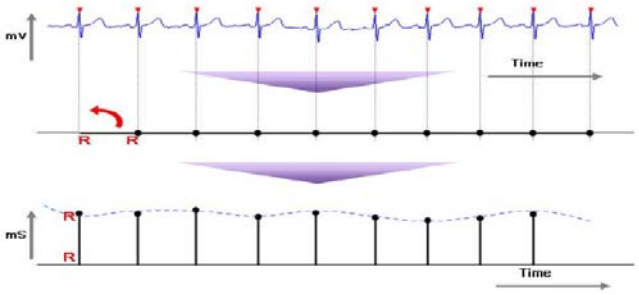

Figure 5. RR intervals and their Fluctuations.

When performing scale-free analysis of time series, it is necessary to have model of whether underlying process is a stationary. This is because many of the method used on the time series to estimate of H makes assumptions about whether a process is a stationary or not. Example, self-affinity as described above the only applies to a non-stationary processes, because by the definition variance of a stationary processes does not alter with amount of time looked. The scale-free processes which are a stationary are usually modeled as the fractional Gaussian noise (fGn), and a non-stationary processes are modeled as the fractional Brownian motion (fBm). Nevertheless, there is strong relationship between two

types of the processes in that, the increments of fBm process are modeled as fGn process with a same Hurst parameter, for more detail on these model. Fluctuations scales according to time is as follow:

• $0<\alpha<0.5$ then process has a memory, and it exhibits anti-correlations. (can be modeled by a fGn with $H = \alpha$)

• $0.5<\alpha<1$ then process has a memory, and it exhibits positive correlations. (can be modeled by a fGn with

$H = \alpha$)

• $\alpha=0.5$ then process is indistinguishable from a random process with no memory. (can be modeled by a fGn with

$H=\alpha$)

• $1<\alpha<2$ then process is a non-stationary. (can be modeled as a fBm with $H = \alpha - 1$).

For a short-range correlations, the scaling exponent will deviate from a 0.5 only for short window sizes. The standard deviation of the integrated signal in the long window will be dominated by fluctuation that have no dependence on the each other. Thus, it is important to report range where scaling is observed. We return to practical issues of the identifying the scaling range in a section on "Insights from the application of the DFA to neuronal oscillations."

ii. Detrending of HRV

Trend in the time series is a slow and gradual change in the some property of series over whole interval under investigation. In the traditional time series analysis, a time series were decomposed into the trend, seasonal and periodic components, and irregular fluctuations, and various parts were studied separately. Detrending is a statistical or mathematical operation of the removing the trends from the time series. Because the HRV signal frequently contain either slow trends or very slow frequency oscillations, detrending was necessary as preprocessing step to prepare HRV for the analysis by using the methods that assume stationarity. Many alternative method are available for detrending. Simple linear trends in mean can be removed by subtracting least-square straight line. More complicated trends require different procedure. Detrending procedures based on smoothness priors approach. The smoothness prior detrending algorithms was recently proposed as an

advanced detrending scheme. It will be briefly summarized here. We denote R-R interval time series as:

$$S = (R2 - R1; R3 - R2; : : : ; \mathbb{R}_n - \mathbb{R}_{n-1}) \quad \text{eqn (6)}$$

where n is the number of the R peaks detected.

The eqn (6) shows R-R interval series could be considered to have two components:

$$S = S_{stat} + S_{trend} \quad \text{eqn (7)}$$

Where eqn (7) shows S_{stat} is the nearly stationary R-R series of interest and S_{trend} is a low frequency periodic trends component. To understand how the DFA algorithm quantify some of properties of a scale-free fluctuations, introduce the concepts of a self-affinity and a stationarity and shows how they apply to scale-free signal.

iii. Effects of Trends on Scaling

We have seen that a calculating the fluctuation of the signal profiles in windows of the different sizes can be used to the quantify the scale free nature of the time series. However calculating a fluctuations at certain time-scales is strongly influenced by whether signal has a steady trend on the longer time-scales. This trends are unlikely to be a part of a process on a time-scale of that the window and may be removed by subtracting linear trends in the window, and then calculating a standard deviation. In this way we know that the processes on a scales larger than the given windows size will only marginally influence a fluctuation function. The standard deviation of integrated signal with a trends necessarily will be larger for window size and, importantly, also grows faster with the increasing window sizes compared to signal without trend . Detrending a signal profile, however, efficiently reveals that the true scaling of a signal with superimposed trend both for uncorrelated and correlated signals. This is the basis for a robust performance of a DFA algorithm which we describe in the next section.

5. RESULTS

- Time and frequency domain analysis

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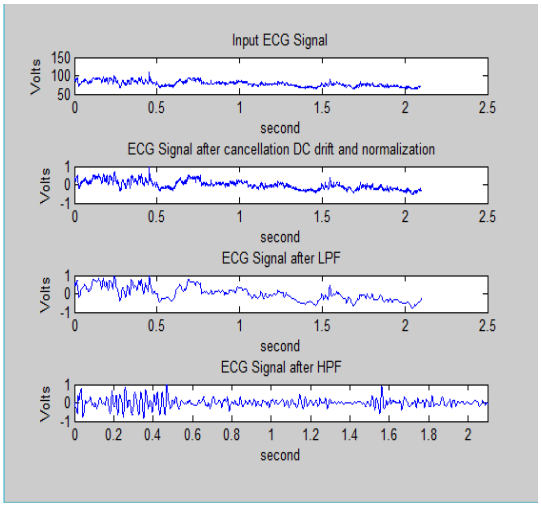

Figure 6. ECG signal of heart disease patient using dc cancellation and filtering in matlab.

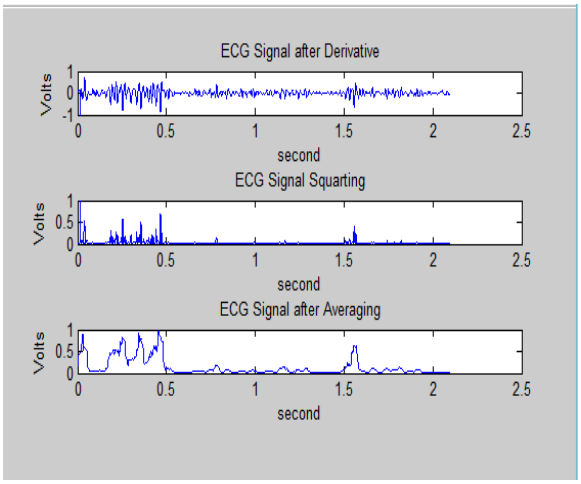

Figure 7. HRV of heart disease patient using differentiation, squaring and averaging of signal in matlab.

Fig. 7 shows a raw ECG signal of patient from a live ECG application. Using Band pass filter , we were concerned with a few things. We were concerned with a amount of drift that can be eliminated, the amplitudes of the voltage (not being attenuated), also that the physiological features are not eliminated.Fig. 6 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 10samples (i.e. for 500 Hz sampling frequency, window size is 20msec) resulted output is as shown in Fig. 7. Mathematically, a 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 frequencie. Fig. 6 shows output of High-pass filter. It does not

introduces delay in the samples and preserves most of a energy at a high frequencies corresponding to a QRS complex.

After filtering a raw ECG signal, it is applied to a Differentiator, Squarer and Integrator for QRS complex detection, as shown in Fig 7. The steps and importance of each step is same as algorithm proposed by Pan- Tompkins. R peak location within each QRS complex. After filtering, the signal is a differentiated to provide the QRS complex slope information. After differentiation, the signal is a squared point by point.

- Detrended fluctuation analysis

The database from a physionet.org of the 200 RR interval time series of the approximately 4 minutes each, from the heart disease subjects, as shown in Fig.. 8 represents, RR interval time series was integrated to generate a profile of time series as shown in Fig 9. Then trends were removed by the detrending the RR interval time series by divided into a sub segments, as shown in Fig.10. Each sub set was fitted with polynomial.Average fluctuation was plotted on log-log graph, see Fig. 11.

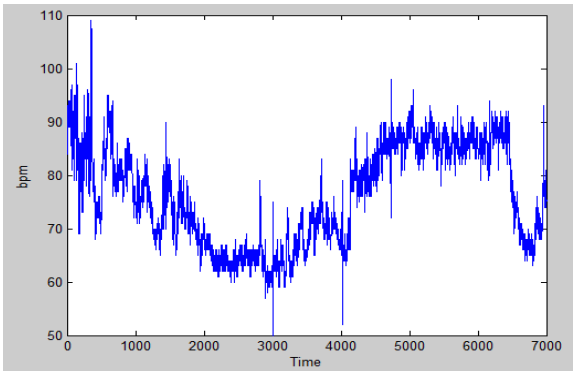

Figure 8. RR interval Time series of heart disease patient using DFA in matlab

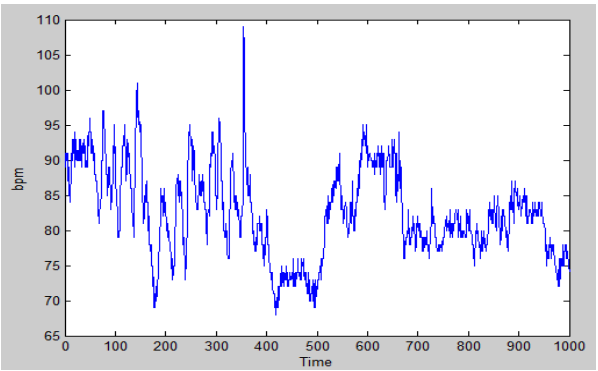

Figure 9. Integrated time series of heart disease patient

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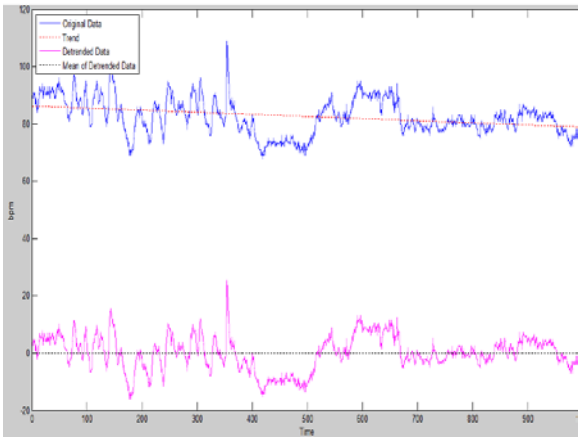

Figure 10. Detrended integrated signal and mean of Detrended signal of heart disease patient.

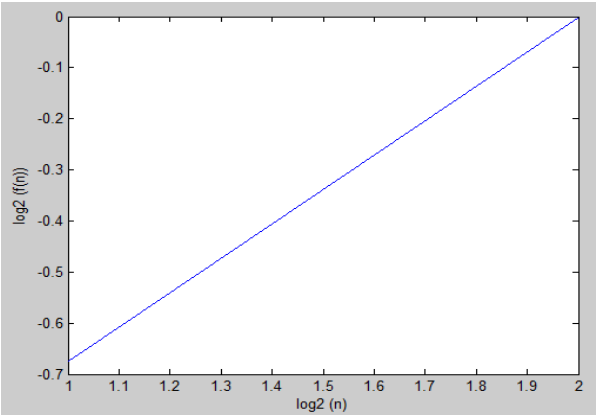

Figure 11. Sample graph of the scaling exponent of heart disease paient representing the slope of the line relating to, and fitted line for Detrended R-R interval series.

Trends were removed by detrending the RR interval time series by a divided into a sub segments. Each sub set were fitted with polynomial. Average fluctuations versus box-size plotted on the log-log graph. The self-similarity parameters was derived from slope of a line. When α >0.5 and α<=1.0 indicates a persistent long-range power-law correlations. When 0< <0.5, power-law anti-correlations are present such that the large values are a more likely to be followed by a small value and vice versa. When >1, correlations exist but the cease to be of power-law form.α =1.5 indicate brownian noise, integration of the white noise. Exponent can also be viewed as an indicator of a roughness of the original time series.

Table 3. Values of alpha for Healthy people and Heart Disease Patients.

Data set for healthy people	Scaling exponent α	Data set for people having heart disease	Scaling exponent α
16552	1.2454	104	1.4540
16570	0.9199	105	2.0323
16630	0.9667	107	2.0620
17455	1.2440	112	1.5350
17554	0.9141	117	1.1331
18696	1.1461	203	1.5400
18717	1.2234	204	1.4401
19900	1.1963	211	2.0554
19919	0.9823	212	1.3900

In Table 3, we see that the scaling exponent α for healthy people around one and for people having coronary heart disease is away from one. Power law correlations in signal fluctuation and opposite heart condition of the two types of subjects under study, healthy and diseased, is reflected clearly from a scaling exponent α value. So, by Detrended Fluctuation technique, we easily differentiate between healthy and patients.

6. CONCLUSIONS

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 heart disease levels.

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