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Effects of detrending for Analysis of Heart Rate Variability using Detrended Fluctuation Algorithmand its Comparison with Pan Tompkin Algorithm using Matlab

Atinderpal Kaur[1], Amanpreet Kaur[2]

Student, Electronics and Communication Engineering Department, Thapar University, Patiala, India[1]

Assistant Professor, Electronics and Communication Engineering Department, Thapar University, Patiala, India[2]

Abstract- This paper presents two different algorithms, one is Detrended Fluctuation Analysis (DFA) algorithm and other is Pan tompkin algorithm. These two algorithms have been implemented in Matlab. Heartbeat signals frequently contain either slow trends or very slow frequency oscillations, detrending was necessary as a pre processing step to prepare for analysis by using non linear method measures, while nonlinear measures were strongly affected by the detrending.DFA is a technique for diagnosis of ECG feature extraction. It is applicable in the context of the non stationary signal, since it involves removing the 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 the experiment duration, which is normally not correct for long-duration signals. It has been speculated that HRV analysis by nonlinear method bring useful prognosis information which will be helpful for assessment of the cardiac condition. So we concluded that 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).

I. INTRODUCTION

Heart rate variability represent variations between consecutive heartbeats.HRV parameters have been used to predict the risk in patients with heart disease, such as life threatening acute coronary events [1, 2]. HRV analysis has become an very important tool in cardiology, its quantifications are noninvasive, have good reproducibility, easy to perform, and provide a prognosticative information of patients with heart disease [3]. Commonly used statistics of HRV, which are average heart rate and standard deviation of all normal-to-normal R-R intervals over a specific time period [1], are not able to describe accurately changes in beats of heart rate dynamics. In time or frequency domain, linear measures have most commonly been used to measure the fluctuation in heart rate, [4]. Therefore, nonlinear methods have been developed to quantify the dynamics of heart rate fluctuations [5,6]. The nonlinear methods inherently consider that the signal is at least weakly stationary. However, a real Heart Rate Variability is slow linear or more complex trends (noise) have to be considered before the analysis. To obtain the results of analysis of HRV, it is necessary to distinguish trends from heart rate fluctuations intrinsic in data. Trends are caused by the external effects. Often, experimental data are affected by non stationarities. Such trends have to be well discriminated from the intrinsic fluctuations of 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.

II. MATERIAL AND METHODS

A. HEART RATE VARIABILITY

Healthy individuals heart rate is neither constant nor periodic. Heart rate variability (HRV) is combination of

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the numerous influences reflecting physiological regulatory mechanism.In the recent past there has been a research efforts include HRV ,based on conviction that disentangling the sources of the variation in cardiac dynamics will provide precise information on cardiovascular autonomic regulation of heart.HRV using Pan Tompkin method and Detrended fluctuation analysis method is shown in Fig. 1

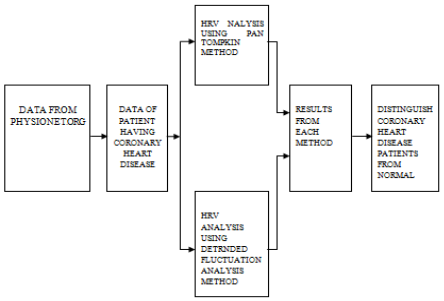

Fig.1 Methodology of work

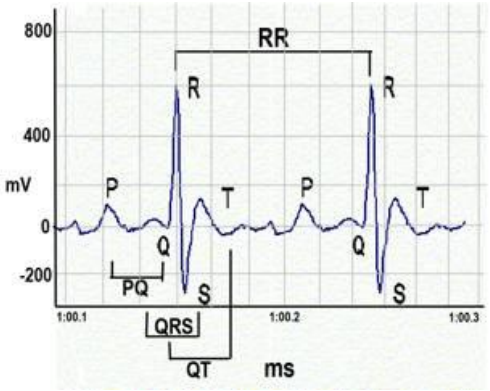

Fig.2 Heart rate variation in signal

B. HRV ANALYSIS USING PAN TOMPKIN METHOD

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

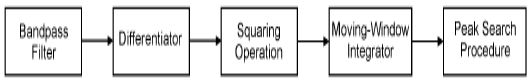

Fig.3 Block diagram of algorithm.

Bandpass filter: The bandpass filter reduces the influence of artifacts in the signal. In this, the highpass filter and low pass filter are applied. The digital lowpass filters with small integer coefficients are designed for fast execution. The cutoff frequency is 11Hz and delay is 25ms.Low-pass filter passes the frequencies that are contain average QRS complex and reduces the 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: The squaring operation leads to positive result and enhances large values more than small values. The squaring operator increases the high-frequency components further.

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

In Fig. 4 illustrate the detected R peaks using (a) dc cancelation and filtering method (b) differentiation, squaring and averaging of signal.

C. R-WAVE DETECTION

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

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

Where, 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 the delay of the bandpass filter had to be taken into consideration. For each event the maximum was found and the location of it set as the R-wave [12]

D. OVERALL PERFORMANCE OF ALGORITHM

To quantify the performance of the Pan tompkin algorithm, performance measures, which categorize the detected and undetected R peaks before and after preprocessing. Using these measures, the performance of the algorithm is quantified by means of the error rate, which is defined as the ratio between the number of errors and the actual number of R peaks.The overall performance achieved by the algorithm is measured in terms of the QRS detection rate, defined as [11]. The define formula is shown as below:

$$\text{Error} = = \frac{FP+FN}{Total} * 100 \quad (2)$$

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

E. HRV USING DETRENDED FLUCTUATION METHOD

In this method the HRV signal is thought as a composition of two classes of fluctuations, one arising from the dynamics of the complex systems which shows long-range correlations and the other type of fluctuation that have a

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characteristic time scale although highly non-stationary. In this algorithm, examining of scaling behavior of heart beat fluctuation is done for correlation measurement. DFA method can be used as diagnosis tool for patient with cardiac disease [13].In DFA, the scaling exponent α indicates the power law correlation in signal fluctuation.

The main objective of DFA is to extract the extrinsic fluctuations in order to allow the analysis of the signal's variability associated exclusively with autonomic control If the value of scaling component α is 1 or around 1, then it represents the healthy condition.

The latter type of fluctuation can be considered as noise, an treated as trend, this is the reason for removed the trends in the algorithm. This trend can be distinguished from the more suitable fluctuations that may reveal intrinsic correlation properties of the dynamics.

In order to calculate the scaling exponents with DFA, a given series 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:

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

where, $RR_{avg} = \frac{1}{N}\sum_{i=1}^{N} RR_i$

where, RR_i is the mean of the time series.RR interval time series and integrated time series is shown in Fig. 5 (a) and (b)

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

2. In each segment, a least squares line is fitted to the data. This line represents the trend in that segment, see Fig 5(c). The straight line is denoted by yn(k) in each segment.

3. Finally, subtracting this trend from y(k), the root-square fluctuation is calculated by:

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

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

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

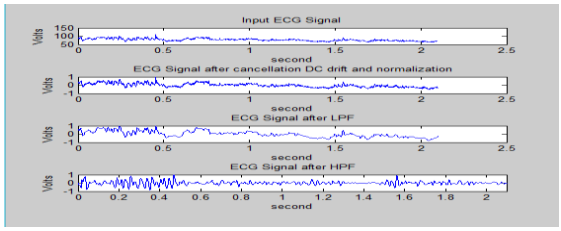
$$f(n) \propto \alpha \quad (5)$$

The scaling exponent α can be estimated by the linear fit on the log-log plot of *f(n)* versus n using least-squares, see Fig. 6.The α value represents the correlation properties of the signal. Fig. 6 shows value of α in log-log plot of f(n) versus n.

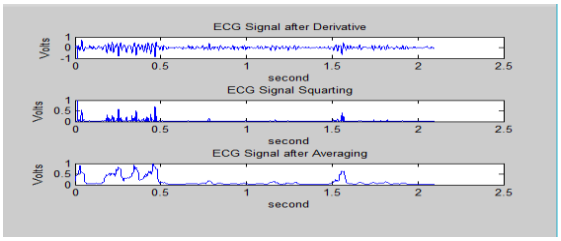
This method represent that a fractal-like signal results in a scaling exponent value of 1.The Brownian noise signals with a spectrum of rapidly decreasing power in the higher frequencies results in 1.5 [6].If $\alpha > 0.5$ the signal is positively persistent (correlation), when $\alpha < 0.5$ the signal is a non-persistent.

The general phenomenon is that larger value of scale exponent α represents smaller fractal dimension.

III. RESULTS

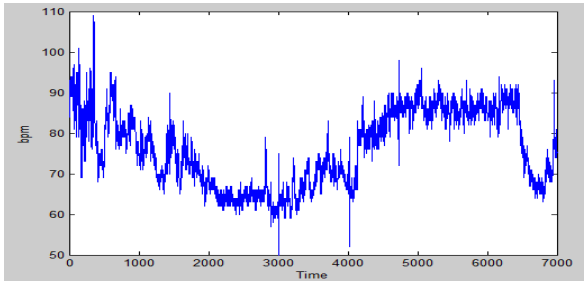


(a)

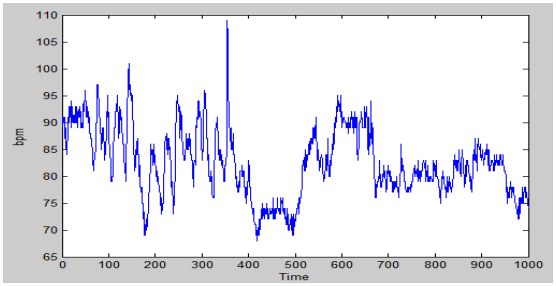


(b)

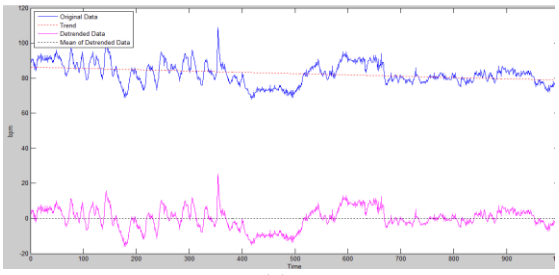
Fig.4 HRV of heart disease patient using Pan tompkin algorithm (a) dc cancellation and filtering methods (b) differentiation,squaring and averaging of signal in matlab.



(a)



(b)



(c)

Fig.5 (a) RR interval Time series of heart disease patient (b) Integrated time series of heart disease patient (c) Detrended integrated signal and mean of Detrended signal of heart disease patient.

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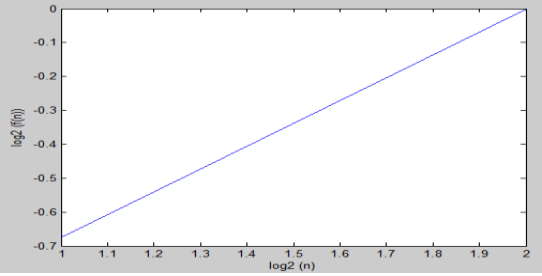

Fig.6 Sample graph of the scaling exponent of heart disease paient representing the slope of the line relating to, and fitted line for Detrended R-R interval series.

Using the Band pass filter in Fig. 4, we were concerned with a few things. We were concerned with the amount of drift that can eliminated, the amplitude of the voltage (not being attenuated), also that physiological features are not eliminated.Fig. 4 represent the steps Pan Tompkin method. 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. We used database from UCI Repository of the 100 RR interval time series(Fig. 5(a)) of approximately 5 minutes each, from heart disease subjects.In Fig. 5(b) 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.Each sub set was fitted with polynomial.Average fluctuations versus box-size were plotted on a log-log graph, see Fig. 6. 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< <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 >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. In Table I, 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.

TABLE I. 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

IV. 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 mental stress levels.

REFERENCES

[1] Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, Circulation 93, 1043 (1996).
[2] S. Thurner, M. C. Feurstein and M. C Teich, Phys. Rev. Lett. 80, 1544 (1998); L. A. Amaral, A. L. Goldberger, P. Ch. Ivanov and H. E. Stanley, Phys. Rev. Lett. 81, 2388 (1998).
[3] H. Huikuri, J. Intern. Med. 237, 349 (1995).
[4] D. Kaplan and A. L. Goldberger, J.Cardiovasc. Electrophysiol. 2, 342 (1991).
[5] Y. Ashkenazy, P. Ch. Ivanov, S. Havlin, C. K. Peng, A. L. Goldberger and H. E. Stanley, Phys. Rev. Lett. 86, 1900 (2001).
[6] M. Akimoto and A. Suzuki, J. Korean Phys. Soc. 38, 460 (2001).
[7] C. Peng, S. Havlin, H. Stanley and A. Goldberger, Chaos 5, 82 (1995).
[8] C. Peng, S. Buldyrev, S. Havlin, M. Simons, H. Stanley and A. Goldberger, Phys. Rev. E 49, 1685 (1994).
[9] J. Pan and W. Tompkins, "A real-time QRS detection algorithm" , IEEE Transactions on Biomedical Engineering, 32: 230-236, 1985
[10] R. M Rangayyan, "Biomedical Signal Analysis", IEEE Press Series on Biomedical Engineering, 2002
[11] S-W. Chen, H-C. Chen, H.-L. Chan, "A real-time QRS detection method based on moving-averaging incorporating with wavelet denoising", Comput. Meth. Prog. Biomed., vol. 82, issue 3, pp. 187-195, June 2006.
[12] Matlab. http://matlabz.blogspot.se/2011/04/contents-cancellation-dc-drift-and.html. Accessed:2014-05-30
[13] C-K. Peng, S. Havlin, H. E. Stanley, A. L. Goldberger, "Quantification of Scaling Exponents and Crossover Phenomena in Nonstationary Heartbeat Time Series", Chaos, vol. 5, pp. 82-87, Jan. 1995.