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Non-Linear Methods in HRV Analysis

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Abstract

Heart rate variability (HRV) analysis has become an important tool in cardiology, these noninvasive measurements are relatively easy to perform, have good reproducibility and also provide prognostic information on patients with cardiac diseases. There are various methods in use to analyze the HRV; these methods usually can help in the early detection of some cardiac diseases. HRV analysis (meaning the study of hearts inter-beat time intervals) is useful for understanding the status of the Autonomic Nervous System (ANS). HRV reflects the cardiac system's ability to adapt to the changing external or internal circumstances by detecting and fast responding to the unexpected and unpredictable stimuli. HRV analysis has the ability to assess overall cardiac health and the state of the ANS responsible for regulating cardiac activity. This paper presents a detrended fluctuation analysis of RR time intervals and of their discrete wavelet transforms, comparing longer and shorter time series in order to find long term significant variations in the studied signals. Signals are taken from MIT-BIH Long Term ECG database, the analysis is performed under MATLAB environment.

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Keywords: HRV analysis; non-linear methods; detrended fluctuation; MATLAB.

1. Introduction

Heart rate variability (HRV) analysis attempts to assess cardiac autonomic regulation through quantification of sinus rhythm variability. Sinus rhythm time series is derived from the RR interval (interval between consecutive heartbeats) sequence by extracting only normal sinus to normal sinus (NN) inter-beat intervals.

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The traditional analysis of heart rate variability (HRV) in the time and frequency domains seems to be an independent predictive marker for cardiovascular mortality, including sudden cardiac death. Besides linear methods there are a large number of non-linear approaches in HRV analysis where the extracted parameters quantify complicated processes and their complex relationships. The use of nonlinear methods in combination with parameters of the time and frequency domains in HRV offers possibilities for improved classification of HRV behavior. It is suggested that this could lead to a better risk stratification [3].

1.1. The Autonomic Nervous System

The autonomic nervous system regulates certain body processes, such as blood pressure and the rate of breathing. The HRV is strongly related to the activity of autonomic nervous system as heart rate and rhythm are mostly under the control of the autonomic nervous system. This system works automatically (autonomously), without a person's conscious effort and maintains internal physiologic homeostasis [1]. The autonomic nervous system has two main divisions sympathetic and parasympathetic Sympathetic and parasympathetic nerve cords start from the central nervous system and lead to different target organs all around the human body [2]. After the autonomic nervous system receives information about the body and external environment, it responds by stimulating body processes, usually through the sympathetic division, or inhibiting them, usually through the parasympathetic division. Many organs are controlled primarily by either the sympathetic or the parasympathetic division. Sometimes the two divisions have opposite effects on the same organ. For example, the sympathetic division increases blood pressure, and the parasympathetic division decreases it. Overall, the two divisions work together to ensure that the body responds appropriately to different situations. Generally, the sympathetic division prepares the body for stressful or emergency situations—fight or flight, by accelerating bodily functions Thus, the sympathetic division increases heart rate and the force of heart contractions and widens (dilates) the airways to make breathing easier. The parasympathetic division controls body process during ordinary situations. Generally, the parasympathetic division is primarily involved in relaxation, preparing the body to rest and recover. Thus, parasympathetic system slows the heart rate and decreases blood pressure. The rhythm of the heart is controlled by the cardiac sinoatrial node located in the heart. The sinoatrial node receives nerve impulses from the autonomic nervous system, including both sympathetic and parasympathetic branches [1]. This is why the outcome of the interrelationship between the sympathetic and parasympathetic nervous system can be "read" from HRV. Generally, increased HRV is linked to good health and decreased stress. A high variability is a sign of high vagal tone, and has been related to a better prognosis after acute myocardial infarction and in patients with congestive heart failure, while depressed HRV due to increased sympathetic activity or reduced vagal activity is associated with poor prognosis independent of other recognized risk factors. By measuring HRV, the human body can be monitored much more efficiently and accurately than by just measuring traditional heart rate.

1.2. HRV and Cardiac Arrhythmia

The heart rate variability (HRV) data, extracted from the ECG signal, reflects the balance between sympathetic and parasympathetic components of the autonomic nervous system. Hence, HRV signal is an interesting method for the study of the role of the autonomic nervous system leading to cardiac arrhythmias contains information on the imbalance between these two nervous system components that results in cardiac arrhythmias.

2. Methods for analysis of HRV

2.1. Time Domain Analysis

Time domain analysis methods treat the NN interval sequence as an unordered set of intervals (or pairs of intervals) and employ different techniques to express the variance of such data. From the original RR intervals, a number of parameters are calculated such as SDNN, SENN, SDSD, RMSSD, NN50 (%), and pNN50% can be used as time domain parameters. By using long-term recording (24h) more complex statistical time-domain measures can be calculated [11]. This can be divided into two classes those which are derived from (a) instantaneous heart rate,

and (b) differences between NN intervals. The simplest variable to calculate is the standard deviation of the NN interval (SDNN), i.e. the square root of variance. Since variance is mathematically equal to total power of spectral analysis, SDNN reflects all the cyclic components responsible for variability in the period of recording [37].Total variance of HRV [38] increases with length of analyzed recorded in table 1. All these measurements of short-term variation estimate high frequency variations in heart rate and thus are highly correlated.

2.2. Frequency Domain Analysis

Power spectral density analysis provides information on how the power (variance) of the ordered NN intervals distributes as a function of frequency. The power spectral density description of HRV shows two distinct peaks: one in the so-called low-frequency (LF) band (0.04–0.15 Hz in humans) and another in the high-frequency (HF) band (0.16–0.4 Hz in humans). HF fluctuations have been attributed to vagal modulation, and LF fluctuations appear to be jointly mediated by sympathetic and vagal influences, together with the baroreflex mechanism [1]. It is well-known that time and frequency domain indexes quantifying HRV are reduced in many pathological conditions. Myocardial infarction, diabetes, coronary artery disease, and end-stage heart failure are some of the most obvious examples in which HRV was found to be associated with survival [14].

2.3. Tme-frequency Analysis

Time-frequency analysis identifies the time at which various signal frequencies are present, usually by calculating a spectrum at regular intervals of time [3]. New method is the wavelet transform based analysis; this transform is a convolution of a signal *s(t)* with a set of functions which are generated by translations and dilations of a main analyzing function known as the mother wavelet and the translated or dilated functions are called wavelets. The Discrete Wavelet Transform (DWT) is an implementation of the continuous wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. This transform decomposes the signal into mutually orthogonal set of wavelets. Usually, the DWT employs a dyadic grid and orthonormal wavelet basis functions exhibiting zero redundancy [13]. The discrete wavelet transform returns a data vector of the same length as the input is [9].

$$s[n]=\frac{1}{\sqrt{M}}\sum_{k}W_{\phi}(j_0,k)\phi_{j_0,k}(n)+\frac{1}{\sqrt{M}}\sum_{j=j_0}^{\infty}W_{\psi}(j,k)\psi_{j,k}(n) \tag{1}$$

Where $s[n]$, $\phi_{j_0,k}(n)$, $\psi_{j,k}(n)$ are discrete functions defined in $[0,M-1]$ totally M points. Because the sets $\phi_{j_0,k}(n)$ and $\psi_{j,k}(n)$ are orthogonal to each other. We can simply take the inner product to obtain the wavelet coefficients:

$$W_{\phi}(j_0,k)=\frac{1}{\sqrt{M}}\sum_{n}s[n]\cdot\phi_{j_0,k}(n) \tag{2}$$

$$W_{\psi}(j,k)=\frac{1}{\sqrt{M}}\sum_{j=j_0}^{\infty}s[n]\cdot\psi_{j,k}(n),\ j\geq j_0 \tag{3}$$

$W_{\phi}(j_0,k)$ are called approximation coefficients while $W_{\psi}(j,k)$ are called detailed coefficients. The DWT decomposition of the signal into different frequency bands can be obtained by successive high-pass and low-pass filtering, as seen on figure1.

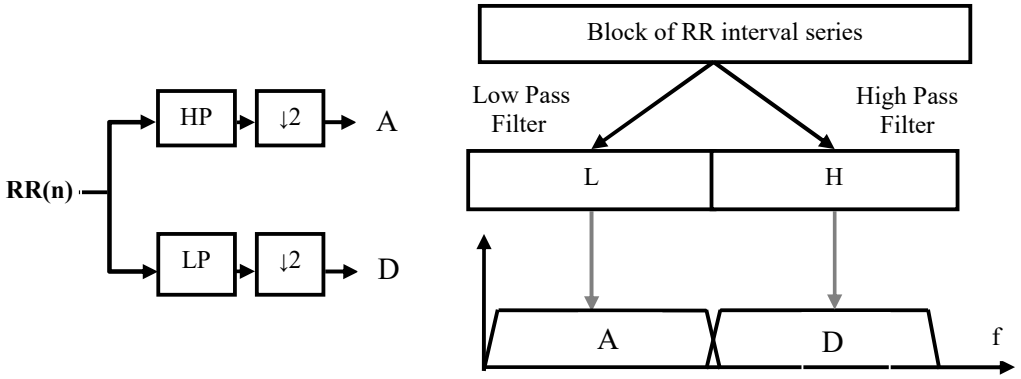

Fig. 1. First order Discrete Wavelet Transform of a discrete signal and the corresponding frequency bands

The wavelet analysis provided information is the time localization of different frequency components which is an important tool for the detection of dynamic changes and patterns of discrete time series signals [3].

2.4. Nonlinear Analysis

Non-linear measuring methods try to quantify the structure and complexity of RR interval time series. The HRV signals are non-stationary and non-linear in nature [5]. Analysis of HRV dynamics by methods based on chaos theory and nonlinear system theory is based on observations suggesting that the mechanisms involved in cardiovascular regulation likely interact with each other in a nonlinear manner [14]. The most important indexes which describes nonlinear HR dynamics are short-term fractal scaling exponent measured by detrended fluctuation analysis (DFA), the approximate entropy, which describes the complexity of R-R interval behavior, the Lyapunov exponent and correlation dimensions [17]. Many of these non-linear indices of the HRV have been introduced and new are developed continuously. Only the few of them have shown established clinical utility.

3. The proposed procedure

The proposed procedure is presented on figure 2. The Detrended Fluctuation Analysis (DFA) analysis is performed on RR time series and their first order discrete wavelet transform coefficients too. Signals 14046, 15814 from MIT-BIH Long Term ECG database are taken, RR intervals are extracted, first order Discrete Wavelet Transform (DWT) is performed, the resulting signals are analyzed as follows, see figure 2.

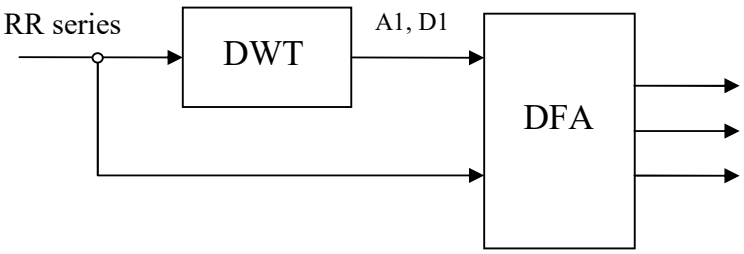

Fig. 2. The proposed procedure

In the DFA analysis the RR interval time series to be analyzed (with N samples) is first integrated. Next, the integrated time series is divided into boxes of equal length, n. In each box of length n, a least squares line $y_n(k)$ is fit to the data representing the trend in that box. The y coordinate of the straight line segments is denoted by $y_n(k)$.

Next, we detrend the integrated time series, $y(k)$, by subtracting the local trend, $y_n(k)$, in each box. The root-mean-square fluctuation of this integrated and detrended time series is calculated by (4)

$$F(n)=\sqrt{\frac{1}{N}\sum_{k=1}^{N}\left[y(k)-y_n(k)\right]^2} \tag{4}$$

This computation is repeated over all time scales (box sizes) to characterize the relationship between $F(n)$, the average fluctuation as a function of box size, and the box size, n (the number of beats in a box which is the size of the window of observation). Typically, $F(n)$ will increase with box size. Typically, $F(n)$ will increase with box size n. A linear relationship on a log-log plot indicates the presence of power law (fractal) scaling. The fluctuations can be characterized by a scaling exponent α, the slope of the line relating *log F(n)* to *log n*.

4.Results

Results of detrended fluctuation analysis of different RR intervals (different lengths from signal 14046) time series are presented. The slope of the line α characterizes the fluctuations. The average component from DWT1 shows the same results as the longer RR interval series, meaning that for the same analysis could be enough analyzing a shorter DWT averaged signal. The obtained results are presented on figure 3. For a totally uncorrelated data (as white noise) the integrated value corresponds to a random walk, therefore α is around 0.5.

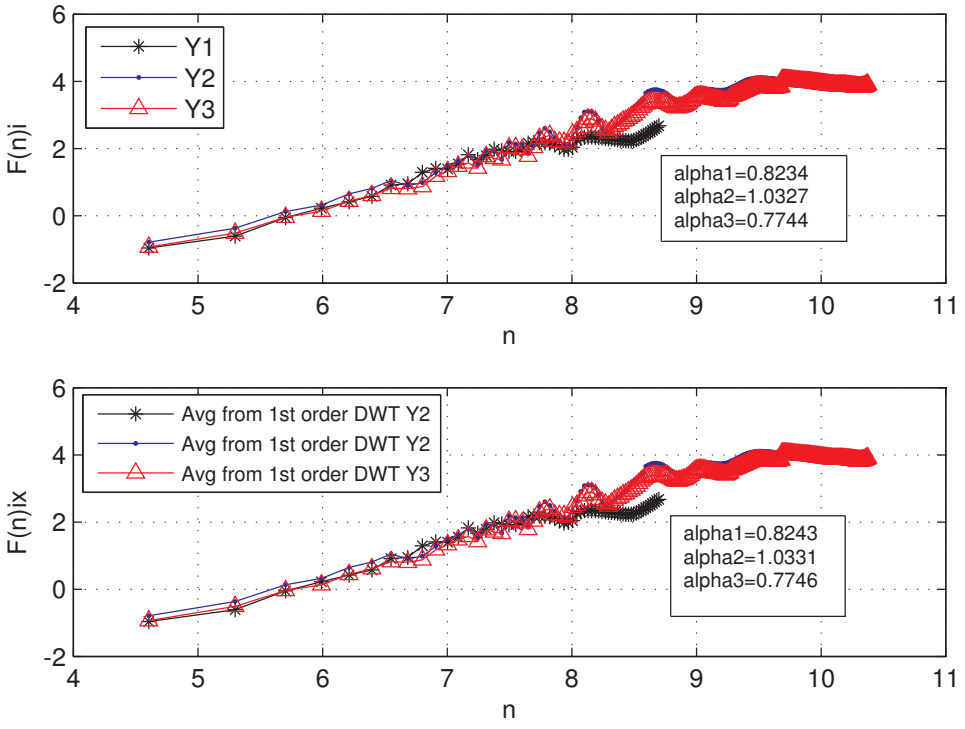

Fig. 3. The comparison between the signals and its DWT transform detrended fluctuation analysis

An α greater than 0.5 but less than 1 indicates persistent long-range power-law correlations. The α exponent can be viewed as an indicator which describes the roughness (or smoothness) of the original time series (for larger values of α, smoother time series and reverse). Figure 4 presents the comparison between the first half, the second half and the total length of 12 hours long 15814 HRV signal from MIT-BIH Long-term ECG database.

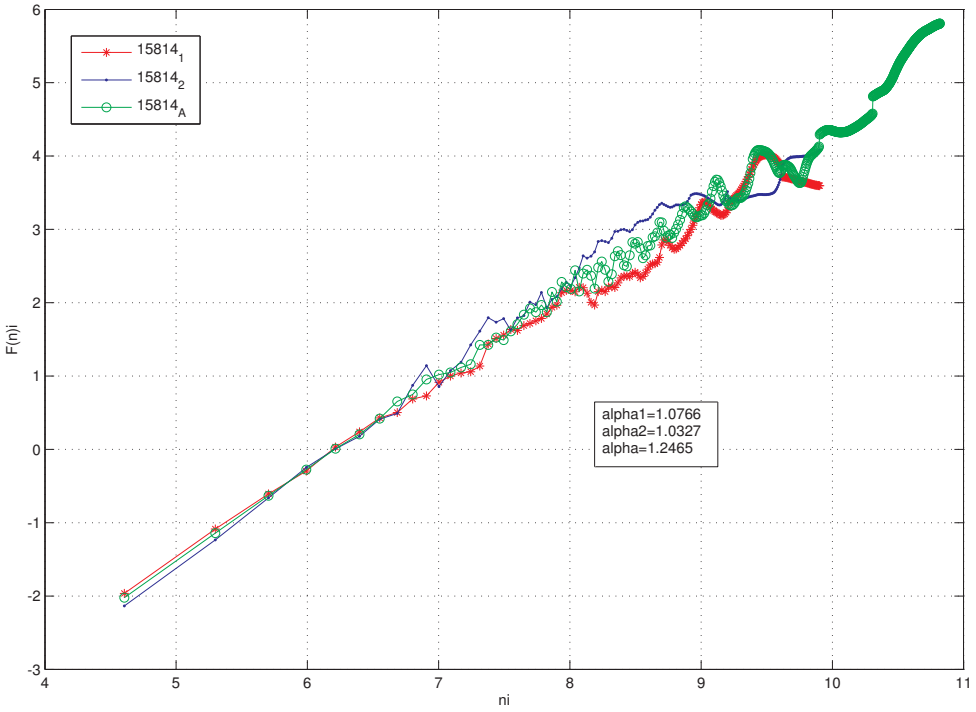

Fig. 4. Detrended fluctuation of signal 15814.

5. Conclusions and further work

The α value represents a correlation properties of the signal, log-log plot of the *f (n)* versus *n* and characterizes the fluctuations of RR interval time series. The α values requires a minimum length of time series for calculations in order to achieve reliable results. Measuring these nonlinear parameter values, a qualitative idea of heart condition can be obtained. When α >0.5 and α<=1.0 indicates a persistent long-range power-law correlations. When 0< α <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 α >1, correlations exist but cease to be of power-law form (pathological RR intervals) α =1.5 indicate Brownian noise (integration of the white noise). Detrended fluctuation analysis is capable of identifying crossover behavior due to differences in scaling over short versus long time scales. This asymptotic scaling index can be a useful parameter for selected diagnostic purposes but the disadvantage is that very long data sets are required. In this case from a DWT average components rebuild signal can bring the same results having smaller length that the original, because contains the main gross features (tendencies) of the signal. Nonlinear analysis is a great area for future research to expand our knowledge concerning the behavior of RR interval fluctuations in normal healthy and disease conditions.

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