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RESEARCH PAPER

Two Statistical Methods for Resolving Healthy Individuals and Those with Congestive Heart Failure Based on Extended Self-similarity and a Recursive Method

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Abstract In this paper we introduce two methods for measuring irregularities in human heartbeat time series (HHTS). First we consider the multi-fractal structure of HHTS to distinguish healthy individuals and from those with congestive heart failure. In this way we modify the Extended Self-Similarity (ESS) method and apply it to HHTS. Our second approach is based on the recursive method, which we use to predict the duration of the next heartbeat by considering a few previous ones. We use standard physiological data and show that these approaches lead to very satisfactory methods to resolve the healthy and CHF individuals. These methods can be used potentially in portable electronic heart alarm systems.

Key words interbeat · congestive heart failure · extended self-similarity · recursive method

1 Introduction

Cardiac rhythms have a highly complex structure. Interbeat interval time series, the output of an integrated control system, normally fluctuate in a complex, apparently noisy manner. Such complexities, associated with the presence of multiple competing interactions, manifest themselves through the non-stationarity and non-linearity of interbeat interval sequences, but reveal scale-invariant structure. The possible existence of scale-invariant properties in seemingly noisy heartbeat fluctuations might be attributed to highly complex,

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non-linear mechanisms of physiological control. The mechanism underlying complex heartbeat variability is influenced by competing neuro-autonomic inputs, sympathetic and parasympathetic stimulation as well as by non-autonomic factors. The study of the statistical properties of these interbeat interval sequences has attracted the attention of researchers in a wide range of fields [1–7]. One general approach to studying the time series is to analyze the ways that such fluctuations obey scaling laws. Marked differences in scaling behavior in health and disease must relate to the hidden control mechanism responsible for the heartbeat dynamics, and will provide practical diagnostic and prognostic information.

In this letter we propose two different approaches for studying statistical properties of the interbeat intervals. The first method is based on extended self-similarity and the second one is related to the well-known recursive model in digital signal processing. In Fig. 1, the interbeat interval fluctuations of healthy subjects and those with congestive heart failure (CHF) are shown. CHF is a serious, chronic condition that causes a deficiency in the heart's ability to pump oxygen-rich blood to the rest of the body and happens when the heart's weak pumping action causes a buildup of fluid called congestion in the lungs and other body tissues.

2 Materials and Methods

2.1 Extended Self-similarity

Here by using the structure function and the extended self-similarity (ESS) characteristics [10, 11], we find differences between healthy subjects and those with congestive heart failure (CHF). The structure function of a time series, $x(t)$, may be defined as:

$$S_q(\tau) = \langle |x(t+\tau) - x(t)|^q \rangle,$$

where $\langle \cdot \rangle$ denotes the average over the time t. In some cases, $S_q(\tau)$ obeys scaling laws ($S_q(\tau) \sim \tau^{\zeta q}$). But indeed most of the data sets for interbeat fluctuation do not have a scaling behavior over a broad range. In these cases ζ_q depends on τ. In Fig. 2, for instance, $\zeta_{0.1}(\tau)$ versus τ is shown.

We find that for the values of τ around $\tau=10$ and above $\zeta_q(\tau)$ is not very sensitive to τ. We choose $\tau=10$ as a beginning of the region where the scaling behavior can be seen. On the other hand, the non-linearity of a time series is related to its multi-fractality. If the exponents ζ_q are linearly dependent on q, the series $x(t)$ is mono-fractal, otherwise $x(t)$ is multi-fractal [8, 9]. In Fig. 3, the scaling exponents ζ_q for $\tau=10$ were plotted against q. It

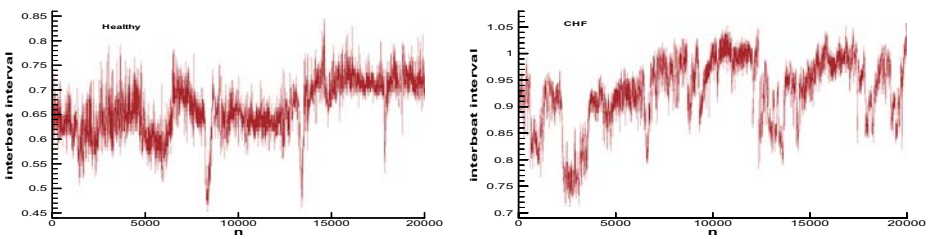

Fig. 1 Interbeat interval fluctuations versus interval number n for typical healthy subject and one with congestive heart failure

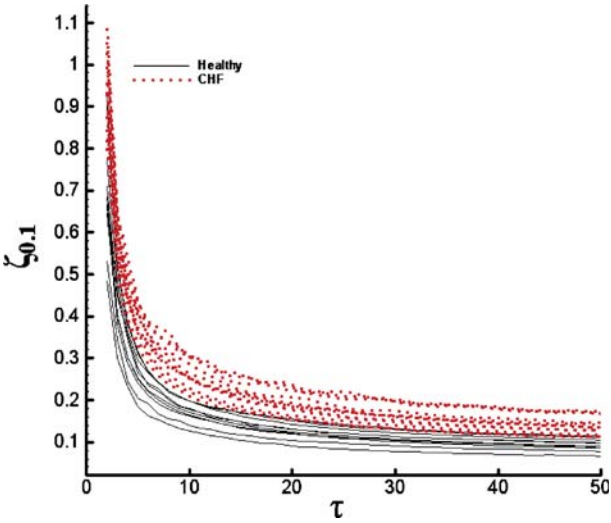

Fig. 2 $\zeta_{0.1}$ plotted against τ for the two classes of subjects

can be seen that ζ_q is almost linear for the subjects with CHF, and has a non-dependence on q for the healthy subjects, confirming mono-fractality and multi-fractality in the two classes of subjects respectively.

A remarkable property of ESS is that it holds rather well even in situations when the ordinary scaling does not exist, or the scaling regime is quite small. In the ESS method, the structure functions $S_q(\tau)$ are plotted against a structure function of specific order. For any Gaussian process an extended scaling regime is found according to $S_q(\tau) \sim S_3(\tau)^{q/3}$[10, 11]. Thus, by plotting $S_q(\tau)$ verses $S_3(\tau)$, the deviation from Gaussian distribution can be found. Furthermore the ESS is a powerful tool to check non-Gaussian properties of the data. It is

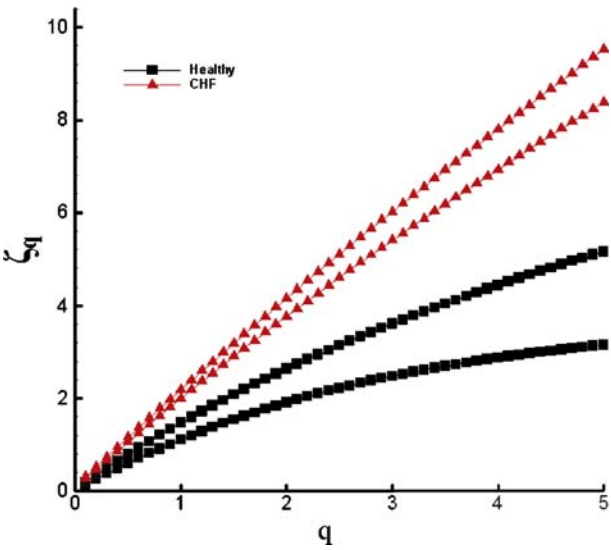

Fig. 3 Plot of ζ_q versus q, which has a nonlinear dependence on q for the healthy subjects but almost linear dependence on q for the patients with CHF

well known that the moments with $q<1$ and $q>1$ are related, respectively, to the frequent and rare events in the time series [10, 11]. Thus, it is important for us to investigate $q<1$, for instance $q=0.1$.

We analyze both daytime (12:00–18:00 P.M.) and nighttime (12:00–6:00 A.M.) heartbeat time series of healthy subjects and the daytime records of patients with CHF. Our data base includes 10 healthy subjects (seven females and three males with ages between 20 and 50 and an average age of 34.3 years), and 12 subjects with CHF (three females and nine males with ages between 22 and 71, and an average age of 60.8 years) [12]. Fig. 1 presents the typical data.

In Fig. 4, we plotted $\zeta_{0.1}$ against ζ_3 where an almost linear behavior can be seen. Each point is obtained for a specific τ, if we determine distance between each point and the origin,

$$D(\tau) = \left[\zeta_{0.1}^2(\tau) + \zeta_3^2(\tau)\right]^{1/2}.$$

$D(\tau)$ can be used to obtain a complete separation of patient and healthy subjects. In Fig. 5, $D(\tau)$ is plotted versus τ. Indeed, subjects with CHF have larger values of D. For example the quantity of $D(\tau=10)$, for the healthy subjects has the average value $\overline{D} = 3.2$, with standard deviation being 0.5, and for patients with CHF, the average and standard deviation are $\overline{D} = 5.3$ and 0.5, respectively. The quantity is statistically significantly different between the two groups of subjects across the data set.

2.2 Recursive Method

Here we investigate whether there are characteristic differences between the results of the recursive method in interbeat intervals of healthy subjects and those with congestive heart failure. In this method we use a moving average filter, which is the most common filter in digital signal processing [13]. In spite of its simplicity, it is optimal for a common task:

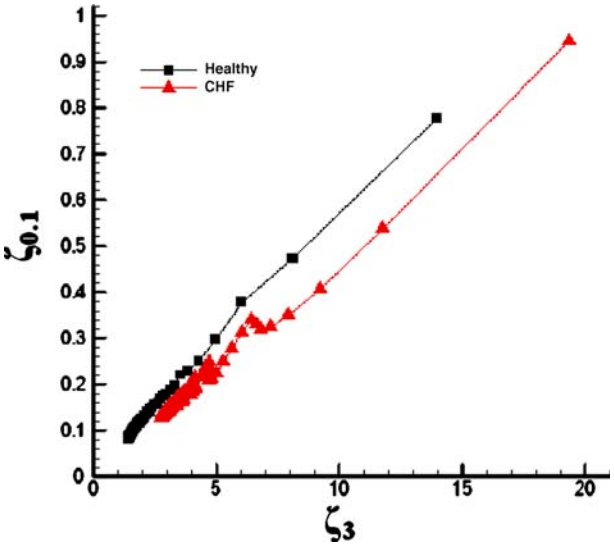

Fig. 4 Plot of $\zeta_{0.1}$ against ζ_3 for a healthy subject and one with CHF

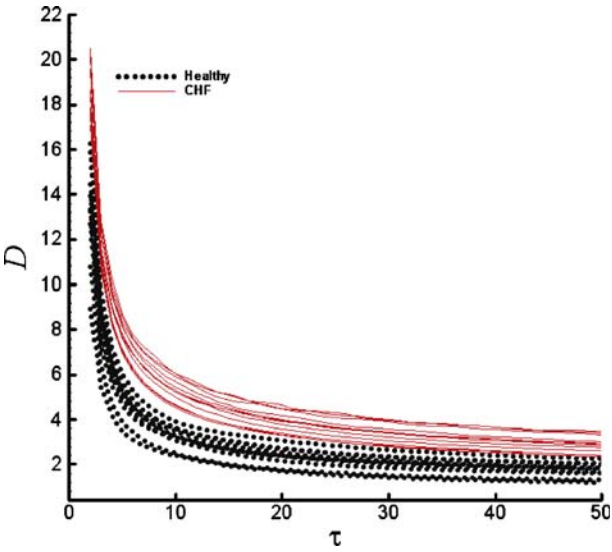

Fig. 5 Plot of D against τ for healthy subjects and those with CHF shows total separation between two classes of subjects

reducing random noise, while retaining a sharp step response. This makes it the premier filter for time domain encoded signals. As the name implies, it operates by averaging a number of points from the input signal to produce each point in the output signal. A slight improvement in computational efficiency can be achieved, if we perform the calculation of the mean in a recursive fashion, which depends on a previously calculated value. Since the noise we are trying to reduce is random, none of input points is special; each is just as noisy as its neighbor. Therefore, it is useless to give preferential treatment to any one of the input points by assigning it a large coefficient. The lowest noise is obtained when all the input samples are treated equally.

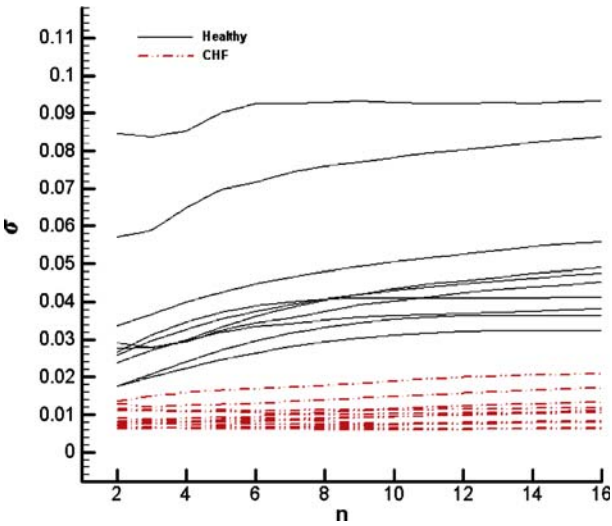

Fig. 6 Plot of σ versus n, indicates nonlinear dependence on n for healthy subjects and linear dependence on n for CHF subjects

In order to process the data, imagine passing $x(t)$, the interbeat interval time series, through a n-point moving average filter to form an output signal $\bar{x}(t)$. And each point in $\bar{x}(t)$ is predicted by:

$$\bar{x}[i+n] = \frac{1}{n}\sum_{j=0}^{n-1} x[i+j] \quad ; \quad i = 0, \cdots, N-n-1$$

where n is the number of points used in moving average and N is the length of time series. Then we calculate the standard deviation for the quantity $\bar{x} - x$ (σ). As an application of the method, we analyzed our data sets for both healthy and patient subjects. In Fig. 6, the standard deviation is shown versus n. The total separation between sick and healthy subjects is obvious. It can be seen the behavior of σ is significantly different for the two classes of subjects. For the healthy subjects, σ is completely nonlinear but, for subjects with CHF, it is almost constant.

As the results for n=10 show, the healthy subjects have, on average, $\overline{\sigma} = 0.048$ with its standard deviation being 0.019, values that are larger by a factor about 5, than those of patients with CHF for whom those values are $\overline{\sigma} = 0.010$ and 0.003, hence providing a clinically significant measure of the presence of cardiac autonomic dysfunction for distinguishing the two data sets.

3 Conclusion

We have analyzed the interbeat fluctuations in heart rates of healthy subjects and patients with CHF by extended self-similarity properties and a recursive model. Both new methods provide useful techniques for distinguishing the heart dynamics of the two classes of subjects. In both methods, no overlap is observed between these two classes. On the other hand, because of their simplicity, being easy to implement and fast to execute, one may use them in small electronic heart monitoring systems.

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