Enhancing Scaling Exponents in Heart Rate by means of Fractional Integration

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Abstract

The characterization of heart rate variability (HRV) series has become important for clinical diagnosis. These series are non-stationary and exhibit long and short-range correlations. The non-parametric methodology detrended fluctuation analysis (DFA) has become widely used for the detection of these correlations. The standard procedure is to apply DFA to the RR series, estimating the desired scaling exponents.

In this work we pursue an alternative approach which consists in applying DFA to the fractionally differenced RR series, $\Delta^d RR$, where $0 < d < 1$ is the long-range correlation parameter. Both methodologies are applied to 24 hour HRV series from the Noltisalis data base. We conclude that changes in HRV are better quantified by DFA scaling exponents calculated over fractionally differenced RR series than by the standard procedure. The results indicate that the scaling exponent corresponding to high frequencies obtained from $\Delta^d RR$ increases the discriminatory power among the groups: from 60% to 87% during the day period and 57% to 77% during the night period.

1. Introduction

Parameters derived from heart rate variability (HRV) data have been associated with the clinical diagnosis and prognosis of certain cardiac diseases [1]. The non-parametric methodology detrended fluctuation analysis (DFA) has become a widely-used technique for the detection of short and long-range correlations in the mean in non-stationary data [2]. In particular, DFA has been shown to be useful in the characterization of HRV, enabling detection of changes in HRV data more efficiently than the traditional approaches. In fact, using HRV data from healthy subjects, patients with moderate and patients with severe sleep apnea, Penzel *et al.* [3] conclude that changes in HRV are better quantified by DFA than by standard spectral analysis. Moreover, the DFA method provides a means for distinguishing between healthy and diseased states [2, 4, 5], sleep and a wake states [5] and monitoring the effect of ageing [6, 7].

Although the standard procedure is to apply DFA to the RR series estimating the desired scaling exponents, recently, Valencia *et al.* [8] applied DFA over RR increment series, ΔRR, to stratify patients with ischemic dilated cardiomyopathy in cardiac risk groups. However, it is acknowledged that RR series present long memory or persistence characteristics common in data arising from natural phenomena: Goldberg *et al.* [9] found long term variations in HRV records similar to those observed in long memory stochastic processes such as factional Gaussian noise or factional Brownian motion. Thus, Leite *et al.* [10] used fractionally integrated autoregressive moving average (ARFIMA) models, an extension of the well-known ARMA models, to describe long and short memory properties of HRV data. This parametric approach has the advantage of allowing the removal of the long-memory component by applying the adequate fractional differencing filter, Δ^d, where d is the long memory parameter and determines the long-term correlations. Along this line, an alternative methodology is introduced in order to improve the statistical differentiation between healthy and sick subjects, by applying DFA over factionally differenced Δ^dRR series.

In this work, HRV is analysed applying DFA to: (a) RR series; (b) RR increment series (or first differenced series), ΔRR; (c) RR fractionally differenced series, Δ^dRR. These methodologies are applied to 24 hour HRV series from the Noltisalis database: healthy subjects, patients suffering from congestive heart failure and heart transplanted patients. Statistical analysis is used to determine the best method for discriminating the groups.

2. Methods

2.1. Data

This study uses HRV data from the Noltisalis database [11] which was collected by the cooperative effort of uni-

versity departments and rehabilitation clinics in Italy. The dataset consists of 24 hour HRV recordings of 30 subjects: 10 healthy subjects (N, 22.5 ± 1.6 hours; 102115.2 ± 11365.4 beats; 42.2 ± 6.4 years), 10 patients suffering from congestive heart failure (C, 22.4 ± 0.9 hours; 107170.5 ± 16689.3 beats; 53.6 ± 11.2 years) and 10 heart transplanted patients (T, 22.4 ± 0.7 hours; 116043.3 ± 11913.2 beats; 44.9 ± 14.8 years). The starting time of the Holter diary is available, enabling to distinguish between day and night periods. Therefore, the 24 hour HRV series are analyzed in two periods: 6 hours during day and 6 hours during night.

2.2. Fractional integration

A parametric approach to describe long term correlations, in particular in HRV data, is to use ARFIMA$(0, d, 0)$ models defined by the following equation:

$$\Delta^d x(t) = \epsilon(t),$$

where Δ^d is the fractional difference operator defined by

$$\Delta^d = (1 - B)^d = \sum_{k=0}^{\infty} \left(\begin{array}{c} d \\ k \end{array} \right) (-1)^k B^k,$$

d is a real number, B is the backward-shift operator, $Bx(t) = x(t-1)$ and $\epsilon(t)$ is a white noise process with variance σ^2. The parameter d determines the long-term behaviour in the mean. For $d = 0$, the ARFIMA$(0, 0, 0)$ process is white noise; for $0 < d < 0.5$, the ARFIMA$(0, d, 0)$ process is a stationary process with long memory, meaning that the autocorrelation decays at a slow hyperbolic rate when compared with the exponential rate of decay of the stationary and invertible ARMA process; for $0.5 \leq d < 1$ the process is non-stationary and mean reverting [12].

Given a time series $x(1), \ldots, x(n)$, d is estimated using the semi-parametric local Whittle estimator. Then, the fractionally differenced series $\Delta^d x(t)$ is obtained by a procedure in the frequency domain, proposed by Geweke and Porter-Hudak [12].

2.3. Scaling exponents

DFA [2] has become an important non parametric tool to assess the correlation properties in non-stationary time series, $x(1), \ldots, x(n)$. The scaling exponent α at time scale k is obtained by fitting a linear model to the log-log relationship

$$F(k) \sim k^{\alpha}, \quad \text{where}$$

$$F(k) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [y(i) - y_k(i)]^2}, \quad y(i) = \sum_{t=1}^{i} [x(t) - \bar{x}]$$

and $y_k(i)$ is the local linear trend is each segment of length k. For uncorrelated data, the scaling exponent is $\alpha = 0.5$. Values of $\alpha > 0.5$ for large scales k (namely, $100 \leq k \leq 100000$ [2]) indicate long range correlations in the data. In the range $0 < \alpha < 1$, the scaling exponent α is related to the long memory parameter d by $\alpha = d + 0.5$.

In this work, two scaling exponents are calculated as proposed in Baumert *et al.* [13]: α_{HF} for $4 \leq k \leq 11$ and α_{LF} for $12 \leq k \leq 32$, corresponding approximately to the well known high and low frequency bands in the power spectral of HRV.

The description of 24 hour HRV recordings which are long (approximately 100 000 beats) and exhibit several non stationary characteristics with circadian variation, is achieved by segmenting the long record into short records of constant length L. In this work $L = 1024$, which allows to estimate the long memory parameter d [10]. The short RR series are subsequently analysed by applying DFA to: (a) RR series; (b) RR increment series, ΔRR; (c) RR fractionally differenced series, Δ^dRR.

2.4. Statistical analysis

A statistical analysis based on a non parametric ANOVA test is applied on each of the scaling exponents α_{HF} and α_{LF} calculated for day and night periods. Statistical differences among the three groups of patients are studied, applying the Kruskal-Wallis rank sum test and multiple comparison procedures (10% level of significance). Additionally, discriminant analysis is applied to determine the ability of the two scaling exponents α_{HF} and α_{LF} to distinguish among the three groups of patients.

3. Results and discussion

The scaling exponents are calculated for the three groups of patients from the Noltisalis database, N, C and T for the segmented 24 hour records. The results are first illustrated for an healthy subject-N4, Figure 1 and an heart transplanted patient-T2, Figure 2. The scaling exponent α_{HF} changes over time showing circadian variation, with lowest values during the night period for subject-N4 and higher values during the same period for patient-T2. For subject-N4, the scaling exponent α_{LF} does not exhibit circadian variation.

Table 1 summarizes the results for all the subjects (mean $\pm$ standard deviation). The scaling exponent α_{HF} decreases for patients suffering from congestive heart failure and heart transplanted patients, both during night and day periods, with the lowest values for the transplanted group. This result had been obtained previously [5] .The scaling exponent α_{LF} takes lower values for heart transplanted patients, compared with healthy subjects and patients suffering from congestive heart failure.

The results of statistical differences among the three groups, applying the Kruskal-Wallis rank sum test and

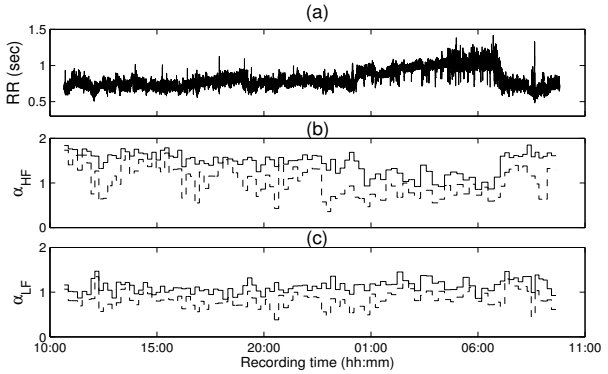

Figure 1. (a) Tachogram of healthy subject-N4, 24 h recordings provided by Noltisalis data base. Evolution over 24 h of α_{HF} in (b) and α_{LF} in (c), obtained using RR series (-) and Δ^dRR series (- -).

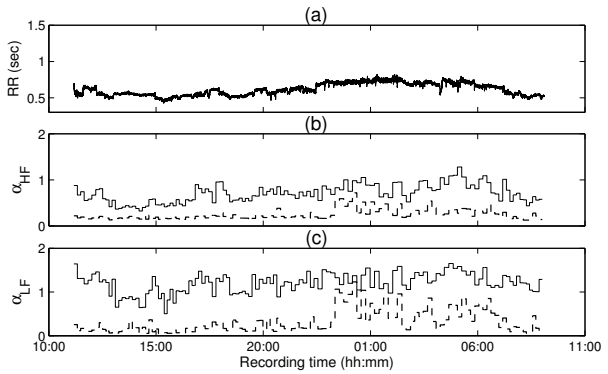

Figure 2. (a) Tachogram of heart transplanted patient-T2, 24 h recordings provided by Noltisalis data base. Evolution over 24 h of α_{HF} in (b) and α_{LF} in (c), obtained using RR series (-) and Δ^dRR series (- -).

multiple comparison procedures, are summarized in Table 2. These results indicate that, during the day period, the scaling exponent α_{HF} of original RR series and ΔRR series differs between the groups N and T, while that of Δ^dRR series differs among the three groups. The scaling exponent α_{LF} of original RR differs between the groups N and C and C and T, while the scaling exponents computed over ΔRR and Δ^dRR differ between N and T and C and T. On the other hand, during the night period, the scaling exponent α_{HF} of original RR and ΔRR differs between the groups N and T, while that of Δ^dRR differs also for the groups C and T. The scaling exponent α_{LF} of ΔRR and Δ^dRR differs between the groups C and T. In summary, computing the scaling exponent α_{HF} over the fractionally differenced series, Δ^dRR, in daytime enables to statistically distinguish the three groups of patients.

Table 1. Scaling exponents calculated over: original RR, ΔRR and Δ^dRR for the 3 groups of patients from the Noltisalis database: healthy (N), subjects affected by congestive heart failure (C) and transplanted (T) during 6 hours of day and 6 hours of night periods. In the Δ^dRR, also reported the long memory parameter d. For each case the average estimates $\pm$ standard deviations are presented.

Day period				
Series	Exponent	N	C	T
RR	α_{HF}	1.53 ± 0.26	1.19 ± 0.32	0.66 ± 0.29
	α_{LF}	0.95 ± 0.12	1.21 ± 0.21	0.85 ± 0.38
ΔRR	α_{HF}	0.88 ± 0.24	0.42 ± 0.16	0.22 ± 0.07
	α_{LF}	0.40 ± 0.13	0.37 ± 0.18	0.13 ± 0.13
Δ^dRR	α_{HF}	1.25 ± 0.30	0.71 ± 0.26	0.29 ± 0.13
	α_{LF}	0.65 ± 0.17	0.69 ± 0.28	0.26 ± 0.27
	d	0.46 ± 0.09	0.59 ± 0.16	0.78 ± 0.12
Night period				
Series	Exponent	N	C	T
RR	α_{HF}	1.33 ± 0.15	1.15 ± 0.26	0.76 ± 0.30
	α_{LF}	1.07 ± 0.10	1.26 ± 0.21	0.99 ± 0.43
ΔRR	α_{HF}	0.57 ± 0.15	0.36 ± 0.12	0.25 ± 0.07
	α_{LF}	0.35 ± 0.09	0.39 ± 0.16	0.19 ± 0.17
Δ^dRR	α_{HF}	1.05 ± 0.18	0.81 ± 0.25	0.39 ± 0.19
	α_{LF}	0.81 ± 0.12	0.94 ± 0.33	0.45 ± 0.39
	d	0.34 ± 0.07	0.38 ± 0.16	0.67 ± 0.17

Finally, the scaling exponents α_{HF} and α_{LF} are used for discriminating purposes. The results are presented in Tables 2 and 3. During the nighttime, the scaling exponents obtained from Δ^dRR have the highest discriminatory power, 76.7% for α_{HF} and 63.3% for α_{LF}, among the three patient groups. During the daytime, the scaling exponent α_{HF} of Δ^dRR also has the highest discriminatory power, 86.7%. It is noteworthy that the discriminatory power exponent α_{LF} is generally lower than that of α_{HF} and this exponent takes highest values during daytime. Consequently, when the two exponents are combined their discriminatory power does not improve: during daytime the highest value is 83.3% and during nighttime is 80.0%. Therefore, this study suggests that using solely the exponent α_{HF} over the fractionally differenced series leads to discrimination among the 3 groups of patients.

4. Conclusions

This study contributes to the assessment of heart rate dynamics and risk stratification by proposing to compute only one scaling exponent that characterizes the high frequency (HF) over the series of fractional differences. In fact, the fractional differences remove the long term correlations enhancing the high frequency information. Consequently, the scaling exponent in the HF has a higher discriminatory power among the three groups of subjects.

Table 2. Multiple comparison results of Kruskal-Wallis rank sum test and percentage of correct assignments for the 3 groups (healthy N, subjects affected by congestive heart failure C and transplanted patients T) during 6 hours of the day and night periods. The symbol $\surd$ indicates significant differences at 10% level.

Day period		Multiple comparison			
Series	Exponent	N-C	N-T	C-T	% Correct assignm.
RR	α_{HF}	...	$\surd$	...	60.0
	α_{LF}	$\surd$	...	$\surd$	63.3
ΔRR	α_{HF}	...	$\surd$	...	80.0
	α_{LF}	...	$\surd$	$\surd$	60.0
Δ^dRR	α_{HF}	$\surd$	$\surd$	$\surd$	86.7
	α_{LF}	...	$\surd$	$\surd$	56.7
Night period		Multiple comparison			
Series	Exponent	N-C	N-T	C-T	% Correct assignm.
RR	α_{HF}	...	$\surd$	...	56.7
	α_{LF}	...	...	...	53.3
ΔRR	α_{HF}	...	$\surd$	...	66.7
	α_{LF}	...	...	$\surd$	53.3
Δ^dRR	α_{HF}	...	$\surd$	$\surd$	76.7
	α_{LF}	...	...	$\surd$	63.3

Table 3. Percentage of correct classification among the three groups of patients, when the exponents α_{HF} and α_{LF} are combined.

Series	Day period	Night period
RR	76.7	60.0
ΔRR	80.0	73.3
Δ^dRR	83.3	80.0

Acknowledgements

Research funded by *FEDER* through the programme COMPETE and by the Portuguese Government through the FCT - Fundação para a Ciência e a Tecnologia under the projects PEst-C/MAT/UI0144/2011, PEst-C/MAT/UI4106/2011 and PEst-OE/MAT/UI4080/2011.

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