COMPARISON OF HEARTBEAT SCALING EXPONENT DERIVED FROM LONG- AND SHORT-SEGMENTS AT DIFFERENT WAKE PERIODS

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Abstract:
The heartbeat fluctuations show fractal-like correlations that are associated with highly adaptive cardiovascular regulatory systems. Moreover, the short-range fractal or scaling exponent α_1 extracted from these correlations is a powerful predictor of mortality for subjects with an impaired left ventricular function. In general, the RR-interval data required for this analysis are derived from long-term ECG recordings during free-running conditions. Yet short-term recordings are more likely to be obtained in some practical circumstances. Here we compare the α_1 exponents extracted from RR-interval series (9 am-6 pm) of 51 adults in normal sinus rhythm, and the α_1 calculated from 3 shorted segments of only 700 beats obtained from the same series at 9:00 am, 1:30 pm, and 5:00 pm. We found no significant differences between the scaling exponents derived from the whole 9 hours series and the short segments at 9:00 am and 5:00 pm, but did find significant differences when comparing the whole series with the short segment at 1:30 pm. Thus, only if the time of the day is taken in consideration, short segments of heartbeat data could be used to obtain representative α_1 exponents.

Introduction

To examine autonomic and central dynamics via R-R interval fluctuations or heart rate variability (HRV), new methods from statistical physics have recently been developed [1, 2] so complementing conventional measures to quantify HRV data [3, 4]. Such methods provide clinical useful information [3, 4] as heartbeat fluctuations in healthy subjects show fractal temporal structures, characterised by long-range power-law correlation over time scales [1, 5], which breakdown under pathological conditions [1, 4, 5, 6].

Accordingly, among several HRV measurements, including parameters derived from a linear spectral characterisation and approximate entropy, the short-range fractal like scaling exponent α_1 has showed the best overall independent accuracy in predicting mortality of patients with impaired left ventricular function [1, 4, 7, 8]. This parameter is obtained by Detrended Fluctuation Analysis (DFA), which confers advantages over other fractal methods as it can be applied to non-stationary data, a crucial requirement for analysing HRV data because the heart period fluctuates in response to environmental factors, such as posture or physical activity, but also during controlled manoeuvres that are used to minimise the effects of these conditions [4, 9, 10]. Irregularities in breathing patterns are typical factor producing this behaviour. In fact, it is recognised in some circles that the inhomogenity may also occur as in intrinsic property of HRV data [9, 10]. Conveniently, any invariant scaling characteristics in the heart rate fluctuations obtained by DFA are mostly attributed to the intrinsic heartbeat dynamics with the advantage of not having to rigourously control physical activity or provide external stimulus when collecting data [11].

In general, the RR-interval data required to quantify scaling exponents are derived from long-term ECG recordings collected during free-running conditions [1, 3, 4, 12] that provide enough data to obtain reliable estimations [12]. Yet short-term recordings are more likely to be obtained in some practical circumstances, so becoming important to asses the possibility of obtaining representative α_1 exponents from these recordings.

Methods

We compared the α_1 exponents extracted from RR-interval series (9 am-6 pm) of 51 adults in normal sinus rhythm, and the α_1 calculated from 3 shorted segments of only 700 beats (corresponding to approximately 10 minutes of adult data at rest) obtained from the same series at 9:00 am, 1:30 pm, and 5:00 pm. These data were gathered from the public PhysioBank [13], which includes annotations for identifying the corresponding time of the day. The analysis was limited to such window of observation during the day to avoid the day-night and sleep stage differences in the scaling behaviour of RR-interval data that have been reported elsewhere [11, 14].

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DFA was used to quantify the α_1 exponents as follows [1]. Initially, the original RR interval or HRV series is summed by:

$$Y(k) = \sum_{i=1}^{k} [RR(i) - RR_{ave}] \quad (1)$$

where $Y(k)$ is the kth value of the resulting series (k=1,2,...,N), $RR(i)$ is the ith RR interval, and RR_{ave} is the average RR interval of the entire original series of total length N.

Next, this series is divided into windows, or boxes, of equal numbers of n beats or RR intervals. In each window, the local trend Y_n is obtained by a least-squared line fit. Higher order polynomials may also be used for this fitting procedure, but it has been reported that the inherent deviations at small scales of DFA become stronger with higher detrending orders [15]. The trend is locally subtracted from the summed series to reduce the non-stationary artifacts. The average root-mean-square fluctuation, $F(n)$, is then calculated:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [Y(k) - Y_n(k)]^2} \quad (2)$$

The previous procedure is repeated for all window sizes (time scales). Consequently, the relationship on a double-log graph between these fluctuations $F(n)$ and time scales n can be approximately evaluated by a linear model: $F(n) \sim n^{\alpha}$ (see Figure 1). A resulting slope, or scaling exponent α, of 0.5 indicates white noise and the absence of long-range correlations, whilst an exponent of 1 reflects the behaviour of a $1/f^{\beta}$ process ($\beta = 1$) having persistent fractal correlations. The scaling or fractal exponent α, is usually estimated by the slope of the double-log plot covering the short (α_1 4 to 11 beats [3]) or long-range ($\alpha_2 > 11$ beats [3]). Given the duration of our analysed RR-interval short segments (having 700 beats), only results for the short-range scaling exponent α_1 were explored here as no reliable estimation for α_2 would be obtained [12].

Results

Using a Wilcoxon signed rank test, we found no significant differences between the scaling exponents derived from whole 9 hours series (α_1 median 1.3229) and the short segments at 9:00 am (α_1 median 1.3220, p-value 0.4820) as well as 5:00 pm (α_1 median 1.2688, p-value 0.0704), but did find significant differences when comparing the whole series with the short segment at 1:30 pm (α_1 median 1.1898, p-value 0.0048).

It is convenient to describe that α_1 values above 1 appear to result from the typical relatively smooth oscillations associated with respiration that dominate the short-range dynamics, as suggested in Ref. [1].

Figure 2 includes notched box plots to show the scaling exponents α_1 derived from all 9 hours series and short segments at 9:00 am, 1:30 pm as well as 5:00 pm. Table 1 summarizes results of the Wilcoxon test.

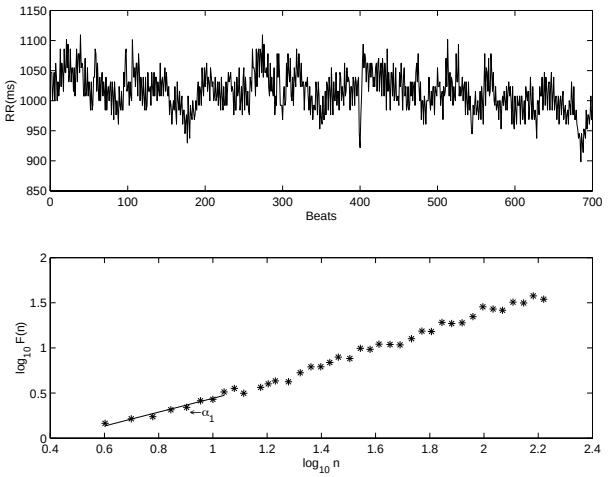

Figure 1: Typical results obtained by applying DFA to an RR-interval short segment of 700 beats. Whereas n indicates the number of beats or RR intervals, $F(n)$ stands for the average root-mean-square fluctuation and α_1 indicates the short-range scaling exponent.

Table 1: Wilcoxon signed rank test results between the scaling exponents derived from whole 9 hours series and the 700 beats short segments at 9:00 am, 1:30 pm as well as 5:00 pm.

	α_1 **median**	**p-value**
9 hours series	1.3229	
Segment at 9:00 am	1.3220	0.4820
Segment at 1:30 pm	1.1898	0.0048
Segment at 5:00 pm	1.2688	0.0704

Discussion

Perkiomaki et. al. [16] have also found that short-term 10 minutes ECG recordings are sufficient to obtain representative individual data about the α_1 exponent of 24-hours RR-interval series in both healthy subjects and postinfarction patients.

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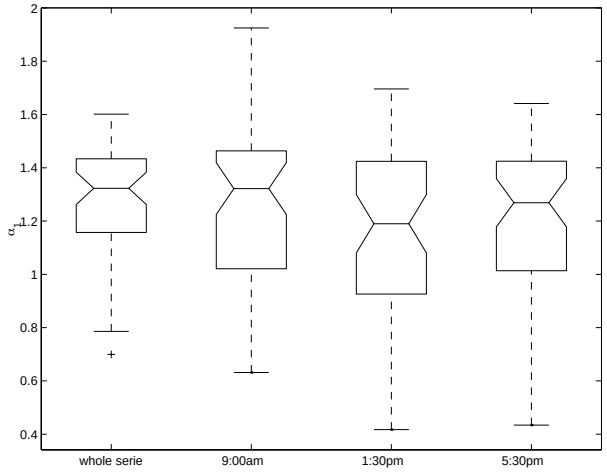

Figure 2: Notched box plots showing the α_1 exponents derived from all 9 hours series and segments at 9:00 am, 1:30 pm as well as 5:00 pm.

Such study was motivated by recognising the importance of measuring α_1 as this becomes more powerful predictor of mortality than other conventional measures of HRV data. However, Hu et. al. [17] have recently reported that the scaling exponent exhibit a significant circadian rhythm, having a sharp peak at approximately 10:00 am that is independent from scheduled behaviour and mean heart rate. As they estimated the scaling exponent over the range of *n* from 20 to 400 beats (instead of 4 to 11 as we reported here), caution should be taken when comparing their with our results. Yet the changes in α_1 during wake hours (Figure 2) may also be related to the involved circadian phase. More to the point, the scaling exponents for signals comprised of mixed segments have been found to be dominated by segments having higher scaling exponents [18], even when their relative fraction in the signal is small. Thus, the scaling exponent derived from the whole 9 hours series analysed here should mainly reflect the higher exponents values of segments like that at 9:00 am (Table 1). Clearly, this should point to the importance of performing local estimations of α_1 at different times of the day, as we believe that potential information like the variation in the exponents of segment at 1:30 pm, which even reveals cases with uncorrelated dynamics, cannot be detected by estimating a global α_1.

Conclusions

Given that our results are in accordance with studies reporting good comparability between the scaling exponents obtained from long- and short-term recordings, but also with other reports showing that the scaling exponent involves changes related to circadian factors [16, 17], we conclude that only if the time of the day is taken in consideration, short segments of heartbeat data could be used to obtain representative α_1 exponents.

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