Assessing Complexity of Heart Rate Variability in People with Spinal Cord Injury using Local Scale Exponents

Fuyuan Liao, Ian Brooks, Chang-Wei Hsieh, Ian M. Rice, Maria M. Jankowska and Yih-Kuen Jan

Abstract—**Detrended fluctuation analysis (DFA) has been widely used to study dynamics of heart rate variability (HRV), which provides a quantitative parameter, the scaling exponent α, to represent the correlation properties of RR interval series. However, it has been demonstrated that HRV exhibits complex behavior that cannot be fully described by a single exponent. This study aimed to investigate whether local scale exponent $\alpha(t)$ with t being the time scale can reveal new features of HRV that cannot be reflected by DFA coefficients. To accurately estimate $\alpha(t)$, we developed an approach for correcting $\alpha(t)$ at small scales and verified the approach using simulated signals. We studied HRV in 12 subjects with spinal cord injury and 14 able-bodied controls during sitting and prone postures. The results showed that $\alpha(t)$ provides complementary views of HRV, suggesting that it may be used to evaluate the effects of SCI-induced autonomic damage on HRV.**

Key words— Heart rate variability, spinal cord injury, local scale exponent.

I. Introduction

Heart rate variability (HRV) represents one of the most promising markers of autonomic activity [1, 2] and has shown a great potential for evaluating the remaining autonomic functions of the cardiovascular system in people with spinal cord injury (SCI) [3, 4]. Various methods have been developed to quantify HRV, including time domain, frequency domain, and nonlinear methods [1, 2]. Spectral analysis of HRV reveals two characteristic frequencies: the low frequency (LF, 0.04-0.15 Hz) and the high frequency (HF, 0.15-0.4 Hz). The HF of HRV reflects vagal modulation, and the LF is considered to be jointly mediated by sympathetic and vagal nerves [3, 4]. The ratio of LF to HF power is widely used as an index of sympathovagal balance for assessing cardiovascular regulation. However, heart rate (HR) fluctuations exhibit scale-invariant patterns over a wide range of time scales that cannot be described by time and frequency domain methods [5]. Hence, scale independent measures have been introduced to study the integrated control of HR.

Detrended fluctuation analysis (DFA) [6] is one of the most commonly used scale independent method. DFA provides a quantitative parameter, the scaling exponent α, to represent the correlation properties of time series [6]. Usually, the properties of RR interval (RRI) series are described by two scaling exponents: a short-term (4-11 beats) exponent α_1 and a long-term (>11 beats) exponent α_2 α_2[7]. A growing number of studies have suggested that $\alpha_1$can yield prognostic information that cannot be provided by conventional measures [8]. However, there is evidence that HRV exhibits complex behavior that cannot be fully described by a single exponent [9]. Some authors therefore proposed to use a whole spectrum of local scale exponents $\alpha(t)$ to describe HR dynamics with t being the time scale [10-12]. However, we found that $\alpha(t)$ at small scales cannot be estimated accurately using the existed methods. This problem is intrinsic to the DFA method [13] and was ignored in the previous studies [10, 12].

This study aimed to investigate whether $\alpha(t)$ reveals new features of HRV that cannot be reflected by DFA coefficients. To accurately estimate $\alpha(t)$, we developed an approach for correcting $\alpha(t)$ at small scales based on a previous study by Kantelhardt et al. [14]. Then we applied the approach to HRV data collected from subjects with SCI and able-bodied (AB) controls during sitting and prone postures. We hypothesized that $\alpha(t)$ would reveal important features of HRV in people with SCI that are not reflected by DFA coefficients.

II. Methods

A. Subjects

Twenty six participants were recruited into this study, including 12 subjects with SCI and 14 AB controls. Their demographic data are shown in Table1. The SCI group included 7 subjects with lesion level at C4-T5 (6 incomplete and 1 complete) and 5 subjects with lesion level at T6-T12 (2 incomplete and 3 complete). All participants with SCI were in a stable clinical condition (the injury event occurred more than 6 months before the time of the study). None of the participants had any diagnosed cardiovascular or neurological diseases that might affect autonomic cardiovascular control.

B. Data Acquisition

Room temperature was maintained at about 23°C. Each participant was asked to stay in the laboratory for at least 30 min to acclimate to the room temperature. When the subject sat in the wheelchair, a three-lead Biopac ECG monitor (ECG100C, Biopac Systems; Goleta, CA) was used to record

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the ECG signals for 10 min with a sampling rate of 1,000 Hz. Then the subject was transferred to a mat table in a prone position for 10 min recording. By using the AcqKnowledge software (Biopac Systems), the RRIs were derived from the

TABLE I. DEMOGRAPHIC DATA OF THE ENROLLED PARTICIPANTS

	SCI	Controls
Number of subjects	12	14
Gender, M/F	9/3	7/7
Age, yr	35.1±11.9	26.1 ± 5.8
Body mass index, kg/m2	25.8 ± 4.9	23.5 ± 2.8
Duration of injury, yr	6.7 ± 5.9	/

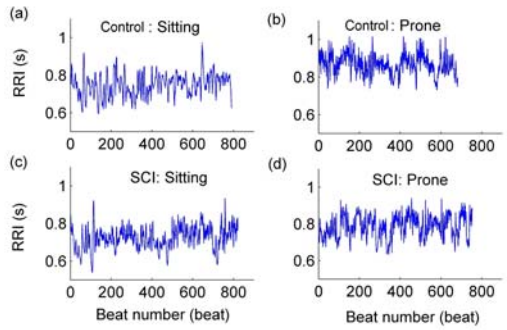

Fig. 1. Changes in RRI in response to the postural change in an AB control (a and b), and a person with SCI (c and d).

ECG signal for later processing. This study was approved by a university institutional review board. Fig. 1 shows examples of RRIs in an AB control and a subject with SCI during sitting and prone postures.

C. Detrended Fluctuation Analysis (DFA)

The DFA method applied to RRI series has been described elsewhere [6]. Briefly, given a series of RRIs, $\{x(i), i = 1, \dots, N\}$, it is first integrated after mean subtraction

$$y(k) = \sum_{i=1}^{k}(x(i) - \langle RR \rangle), \tag{1}$$

where ⟨RR⟩ is the mean of the series. Then, the integrated series $y(k)$ is divided into boxes of n RRIs. In each box, the local trend, $y_n(k)$, is estimated by a least-square fit of $y(k)$ using a polynomial function. The root-mean square function

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

is calculated for box sizes $n \geq 4$. A power-law between $F(n)$ and n indicates the presence of scaling: $F(n) \sim n^{\alpha}$. The parameter α, called scaling exponent, represents the correlation properties of the signal. For RRI series, α typically includes a short-term (4-11 beats) scaling exponent α_1 and a long-term (>11 beats) scaling exponent α_2 [7].

D. Local Scale Exponent

A local scale exponent is defined as the derivative of $\log[F(n)]$ with respect with to $\log(n)$

$$\alpha(n_k) = \frac{log[F(n_{k+1})] - log[F(n_k)]}{log(n_{k+1}) - log(n_k)}, \tag{3}$$

where $\{n_k\}$ is a set of box sizes spaced evenly on a log scale. This definition is similar to that given by Castiglioni et al. [12]. It has been demonstrated that the $\log[(F(n)]$-$\log(n)$ plot deviates from scaling at small scales [14, 15]. Hu et al. [15] reported that locally estimated α, α_{loc} (by local fitting of $F(n)$), yields $\alpha_{loc} > \alpha$ if $\alpha < 1$ and $\alpha_{loc} < \alpha$ if $\alpha > 1$. We found that $\alpha(n)$ defined by (3) can be overestimated for either $\alpha < 1$ or $\alpha > 1$ (see Fig. 2). This inconsistency may be due to the different definitions of α_{loc} by Hu et al. [15] and $\alpha(n)$ by (3).

To address the above problem, Kantelhardt et al. [14] introduced a correction function

$$K^{1/2}(n) = \frac{\langle [F(n)]^2 \rangle^{1/2}/n^{1/2}}{\langle [F(n')]^2 \rangle^{1/2}/n'^{1/2}}, \tag{4}$$

where $\langle \cdot \rangle$ denotes the average over different configurations, and n' is a specific box size. The modified fluctuation function is given by [14]

$$F_{mod}(n) = F(n)/K^{1/2}(n). \tag{5}$$

Because $K^{\alpha}(n)$ depends only weakly on α, $K^{1/2}(n)$ can be used in all cases and can be obtained by analyzing the corresponding shuffled data. Kantelhardt et al. [14] suggested that n' has to be large (n'>50) but must remain significantly smaller than the record length N and that $n' \approx N/20$ seems to be a reasonable number.

In practice, however, it may be difficult to determine an optimal box size n', because the correction function $K^{1/2}(n)$ depends on both the shuffled data and n'. This problem is aggravated in the case of short record lengths. Moreover, we found that the modified function $F_{mod}(n)$ can lead to smaller values of $\alpha(n)$ at small scales than the expected ones. Hence, we suggest to use a set of box sizes $\{n_{k'}\}$, rather than a single one, for computing the correction function, where $\{n_{k'}\}$ is a subset of $\{n_k\}$. Empirically, $\{n_{k'}\}$ can be chosen as a set of successive box sizes such that $\alpha(n_{k'})$ of the shuffled data show a plateau. The correction function can therefore be rewritten as

$$K^{1/2}(n_k) = \frac{\langle [F_{shuff}(n_k)]^2 \rangle^{1/2}/{n_k}^{1/2}}{\langle \langle [F_{shuff}(n_{k'})]^2 \rangle^{1/2}/{n_{k'}}^{1/2} \rangle}, \tag{6}$$

where the outer angle brackets in the denominator denotes the average over $\{n_{k'}\}$. The modified fluctuation function is given by

$$F_{mod}(n_k) = F(n_k)\left[1 + \frac{1}{K^{1/2}(n_k)}\right]/2. \tag{7}$$

We tested the proposed approach using three typical signals: Guassian white noise, $1/f$ noise, and Brownian noise, whose expected values of α are 0.5, 1, and 1.5, respectively. The simulated series were generated by using inverse discrete Fourier transform [16], having the same length of 750 points. This length is roughly equivalent to the lengths of the HRV data series. In the calculation of $F(n)$, linear fitting was performed. Fig. 2 compares corrected α(n) obtained by using (7) and the original $\alpha(n)$ obtained by using (3). Obviously, the proposed approach substantially improves estimations of $\alpha(n)$ at small scales.

E. Application to HRV Data

The time duration of a box size depends on the mean RRI, which was generally shorter in the sitting posture compared to the prone posture, especially in AB controls. To compare local scale exponents of HRV between the sitting and prone

postures and among different subjects, we converted the box sizes $\{n_k\}$ to time scales $\{t_k\}$ by [10]

$$t_k = n_k \times \langle RR \rangle. \quad (8)$$

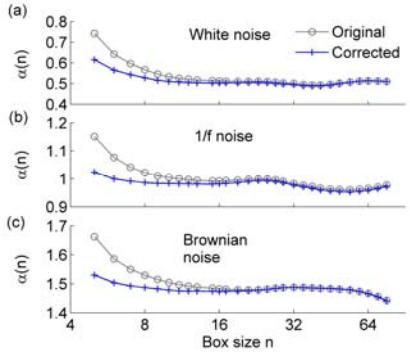

Fig. 2. Corrected $\alpha(n)$ (7) and corresponded original values (3) for simulated (a) Gaussian white noise, (b) $1/f$ noise, and (c) Brownian noise. The results were obtained by averaging over 10 simulated series of 750 points. The simulated series were generated by using inverse discrete Fourier transform. In the calculation of F(n), linear fitting was performed.

Then the spectrum $\alpha(t_k)$ was linearly interpolated to obtain a new spectrum $\alpha(t_i)$ with $\{t_i\}$ evenly distributed between 4 s and 60 s on a log scale. The choice of the smallest time scale 4 s was depended on the mean RRI. For most of our data sets, mean RRI ranges between 0.6 s and 1 s. Thus, the time scale corresponding to the smallest box size of 4 RRIs ranges between 2.4 s and 4 s. On the other hand, the largest time scale depends on the length of data series [15]. The choice of 60 s as the largest time scale was based on the observation that the log$[F(t_k)]$-log(t_k) plot may deviate from scaling at scales larger than 60 s.

F. Statistical Analysis

The Wilcoxon signed-ranked test was used to examine the differences of α_1 and α_2, and $\alpha(t_i)$ between sitting and prone postures. The Wilcoxon rank-sum test was used to examine the differences in these measures between subjects with SCI and AB controls.

III. RESULTS

A. DFA coefficients

α_1 was significantly higher in the sitting posture than in the prone posture in AB controls ($p<0.05$) but not in subjects with SCI (Fig. 3). In the sitting posture, α_1 was significantly higher in controls than in subjects with SCI (Fig. 3a). Unlike α_1, α_2 showed only slight changes after the postural change in either control or SCI group (Fig. 3b) and no significant differences were observed between two groups.

B. Local Scale Exponent

Fig. 4 presents the local scale exponents $\alpha(t)$ over AB control and SCI groups as means ± SE. In controls in both the sitting and prone postures, $\alpha(t)$ monotonically decreased with scale at the shorter scales and then showed a plateau (Fig. 4a). At the scales shorter than 14 s, $\alpha(t)$ was significantly higher in the sitting posture than in the prone posture (Fig. 4a), while at the scales larger than 20 s, $\alpha(t)$ showed similar behaviors between two postures. In subjects with SCI, $\alpha(t)$ maintained relative constant at all scales. No differences were observed between two postures (Fig. 4b). In the sitting posture, $\alpha(t)$ in subjects with SCI was significantly lower at scales shorter than 6 s and tended to be higher at lager scales (Fig. 4c). In the prone posture, $\alpha(t)$ at scales between 8 s and 12 s was significantly higher in subjects with SCI than in controls (Fig. 4d).

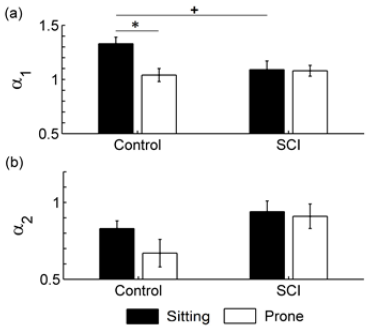

Fig. 3. DFA coefficients α_1 (short-term) and α_2 (long-term) in AB controls and subjects with SCI. Values are means ± SE. *p<0.05 for within-subjects test; $^{+}$p<0.05 for between-subjects test. (a) α_1 in control and SCI groups. (b) α_2 in the two groups.

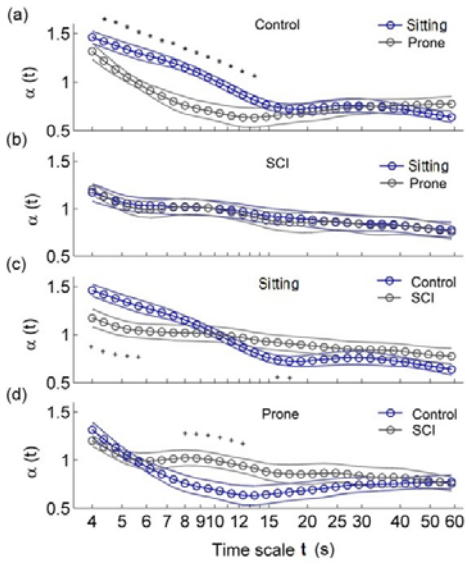

Fig. 4. Local scale exponent $\alpha(t_i)$ in AB controls and subjects with SCI. Values are presented as means ± SE. *p<0.05 for within-subjects test; +p<0.05 for between-subjects test. (a) Comparisons of $\alpha(t_i)$ in control group between two postures. (b) Comparisons of $\alpha(t_i)$ in SCI group between two postures. (c) Comparison of $\alpha(t_i)$ in the sitting position between two groups. (d) Comparisons of $\alpha(t_i)$ in the prone position between two groups.

IV. DISCUSSIONS

The main findings of this study are: 1) local scale exponent $\alpha(t)$ in AB controls monotonically decreased with scale at small scales in both the sitting and prone postures but maintained relatively constant in subjects with SCI (Fig. 4a, b); 2) in the sitting posture, $\alpha(t)$ at small scales was lower in subjects with SCI than in controls (Fig. 4c); and 3) in the prone posture, $\alpha(t)$ at moderate scales was higher in subjects with SCI than in controls. Our findings support our hypothesis that $\alpha(t)$ can reveal important features of HRV in subjects with SCI that are not reflected by DFA coefficients. This approach may be used to investigate the effects of

SCI-induced autonomic damage on HRV.

DFA is considered to be a useful tool for evaluating HRV in people with SCI [17]. Our results showed that in the sitting posture, α_1 significantly increased in AB controls but not in subjects with SCI (Fig. 3). It has been suggested that the LF to HF ratio and DFA coefficients provide similar characterizations of HRV [18]. Willson et al. [18] suggested that α_1 is related to $2/[1+(\mathrm{HF}/\mathrm{LF})]$. Platisa et al. [19] observed an approximated linear relationship between α_1 and $\ln(\mathrm{LF}/\mathrm{HF})$. Thus, the results of α_1 suggested that sympathovagal balance in controls increased in the sitting posture and decreased in the prone posture but showed only small changes in subjects with SCI.

Unlike DFA coefficients, $\alpha(t)$ provides information about time scales at which the correlation properties of HRV differed between AB controls and subjects with SCI. In AB controls, $\alpha(t)$ at t between 5 s and 14 s was significantly higher in the sitting posture than in the prone posture (Fig. 4a). Supposing that the mean RRI is 0.8 s (Fig. 1), the scales between 5 s and 14 s correspond to 6-17 beats. This range of beat number may spread across the ranges of observation window sizes over which α_1 and α_2 are calculated. As shown in Fig. 3b, α_2 in controls in the sitting posture tended to be higher than in the prone posture but the differences did not reach a significant level. The reason might be that α_2 was calculated over a wide range of observation window sizes, while in major parts of the range, $\alpha(t)$ exhibited similar behavior under two conditions (Fig. 4a).

In the sitting posture, $\alpha(t)$ at t<6 s was significantly lower in subjects with SCI than in controls (Fig. 4c). The lower values of $\alpha(t)$ are compatible with lower values of α_1 (Fig. 3a). At t between 6 s and 20 s, $\alpha(t)$ monotonically decreased with t in controls but remained relatively constant in subjects with SCI. These features were not reflected by DFA coefficients.

A limitation of this study is that the subjects with SCI were older than the controls and the SCI group had more male subjects. This may influence the validity of our results [20]. However, the age and sex effect should be a minor confounding variable compared to postural changes [21, 22]. Thus, the difference of $\alpha(t)$ between two groups should be mainly due to abnormal control of HR in SCI patients.

V. CONCLUSION

Our results suggest that local scale exponents reveal important features of HRV in people with SCI that are not reflected by DFA coefficients. This method may be used to investigate the effects of SCI-induced autonomic damage on HRV.

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