Scaling Behaviour and Memory in Heart Rate of Healthy Human *

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We investigate a set of complex heart rate time series from healthy human in different behaviour states with the detrended fluctuation analysis and diffusion entropy (DE) method. It is proposed that the scaling properties are influenced by behaviour states. The memory detected by DE exhibits an approximately same pattern after a detrending procedure. Both of them demonstrate the long-range strong correlations in heart rate. These findings may be helpful to understand the underlying dynamical evolution process in the heart rate control system, as well as to model the cardiac dynamic process.

The analysis of time series of physiological significance currently attracts many research groups in physical and biomedical regions. The experts focus not only on the unique physiological functions embedded in the signals, but also on the complex physical characteristics which can help us to understand the underlying mechanism of systems. Recently, several works[1−9] have revealed that heart rate variability of healthy human shares the general principles of other complex systems, like long-range correlations, critical phenomena in nonequilibrium systems, as well as multifractal scaling properties. These complex dynamics of heart rate remains unaltered even after eliminating known behavioral modifiers.[10,11] It is suggested that the origin of heart rate complexity exists in the intrinsic dynamics of the physiological regulatory system. In this Letter, the detrended fluctuation analysis (DFA)[12] and diffusion entropy (DE) method[13,14] are applied to detect the scaling behaviour and memory embedded in heart rate of healthy human.

We analyse three sets of experimental data of heart rate variability from 7 healthy subjects (mean age 25.3 yr, named as samples 1, 2, ..., 7) without any disease affecting the autonomic control of heart rate.[15] Each one was collected in different behaviour states, usual daily activity, experimental exercise, and sleep. The data set consists of the interbeat intervals between consecutive heartbeats measured over 24 h, in which the subjects were initially asked to ride on a bicycle ergometer for 2.5 h, as the exercise state, and maintain their heartbeat intervals at 500–600 ms. After the exercise, the data were continuously measured during usual daily activity in the daytime and sleep at night, with regular sleep schedules.[17] A represen-

tative record of heart interbeat intervals for a healthy subject is shown in Fig. 1, which is classified into four behaviour states: (a) constant exercise, (b) usual daily activity after the exercise, (c) sleep, and (d) usual daily activity the next morning.

The quantitative methods applied in this study are DFA and DE. In order to keep our description as self-contained as possible, we review the DFA and DE method briefly. Firstly, we describe the operational process of DFA as follows:

(1) We consider a time series p_i, $(1, \ldots, N)$ and N is the length of the series. Determine the 'profile'

$$y(i) = \sum_{k=1}^{i} [p_k - \langle p \rangle], \quad i = 1, \ldots, N, \qquad (1)$$

where

$$\langle p \rangle = \frac{1}{N} \sum_{i=1}^{N} p_i. \qquad (2)$$

(2) Divide profile $y(i)$ into non-overlapping boxes with equal size t (scale of analysis).

(3) Calculate the local trend y_{fit} in each box of size t by a least-square fit of the series, and the detrended fluctuation function is given by

$$Y(k) = y(k) - y_{\text{fit}}(k). \qquad (3)$$

(4) For a given box size t, we compute the rms fluctuation

$$F(t) = \sqrt{\frac{1}{N} \sum_{1}^{N} [Y(k)]^2}, \qquad (4)$$

and repeat the above computation for different box sizes t (different scales) to provide a relationship between $F(t)$ and t.
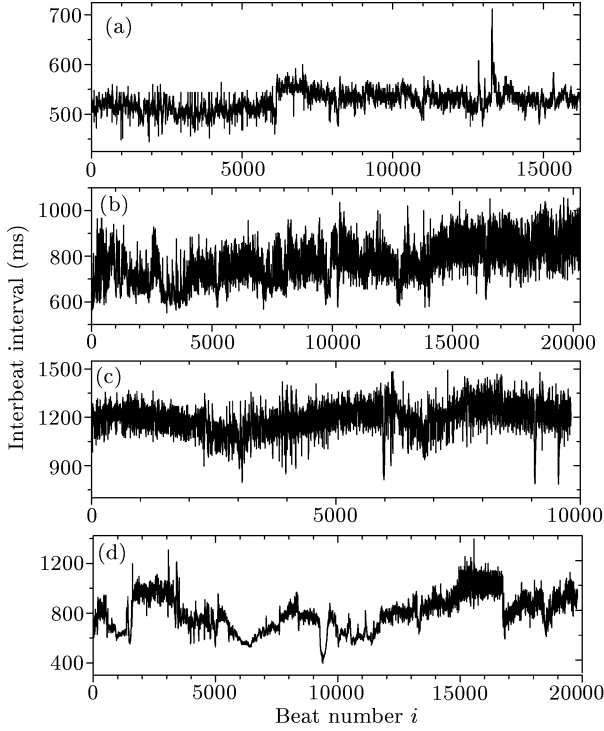

Fig. 1. A representative example of heart interbeat interval fluctuation of healthy human during four physical states: (a) constant exercise, (b) usual daily activity after the exercise, (c) sleep, and (d) usual daily activity the next morning.

We plot $F(t) \sim t^\alpha$ in different box size t, and obtain the scaling exponent α, representing the correlation degree of the signal. If $\alpha = 0.5$, there is no correlation and the signal is an uncorrelated signal (white noise); if $\alpha < 0.5$, the signal is anti-correlated; if $\alpha > 0.5$, there is positive correlation in the signal.

Successively, we briefly review the DE method innovated by the authors in the literature.[13,14] It means that a time series is converted into a diffusion process described by the probability distribution $p(x,t)$ of the diffusing variable x. It is expected to fit the scaling property

$$p(x,t) = \frac{1}{t^\delta} F\left(\frac{x}{t^\delta}\right) \qquad (5)$$

with the 'degree of anomaly' measured by the distance of the scaling parameter δ from the ordinary value 0.5. Here δ deviating from 0.5 also suggests that the waiting time of process does not decay in an exponential form, indicating that the memory exists in the system.[4,16] The memory of the system determines the long-range correlations of output. It is straightforward to prove that the Shannon entropy of a process fitting the scaling condition of Eq. (5) reads

$$S(t) = -\int_{-\infty}^{+\infty} P(x,t) \log_{10}[P(x,t)] dx. \qquad (6)$$

A simple algebraic leads to

$$S(t) = A + \delta \log_{10}(t), \qquad (7)$$

where

$$A = -\int_{-\infty}^{+\infty} F(y) \log_{10}[F(y)] dx, y = \frac{x}{t^\delta}, \qquad (8)$$

and its explicit form is not related to the scaling estimation. The DE method may be more efficient than the calculation of the second moment of the probability distribution. In particular, when the distribution density under study departs from the ordinary Gaussian case and the function $F(y)$ has slow tails with an inverse power-law nature, the second moment is a divergent quantity.[18,19] Diverging quantity is made to be finite by the unavoidable statistical limitation because of the finite records of empirical data. In this case, the second moment analysis would yield misleading results, determined by the statistical inaccuracy, while the method based on Eq. (7) yields a correct result. It has a theoretic relation $\delta = \frac{1}{3-2\alpha}$ with scaling exponent α.[20]

We compute a normalized time series with zero mean and unit variance of sequential heart interbeat intervals, b_i, where i is the beat number. Then, the scaling behaviour obtained with DFA in each of the behaviour states is shown in Fig. 2. For the usual daily activity [Figs. 2(b) and 2(d)], the scaling behaviour approximately conforms to monofractal scaling property with a slope 1, which implies the $1/f$ scaling in the power spectrum and long-range strong correlated behaviour in a wide range of scales. On the other hand, a crossover scaling behaviour exists in the constant exercise [Fig. 2(a)] and sleep [Fig. 2(c)] states, where the scaling value decreases as the range of scales t increases. It demonstrates a breakdown of the long-range correlated behaviour in these states with higher (exercise) and lower (sleep) heart rates.

In order to further confirm the underlying memory of the healthy human heart rate, we apply the DE method to quantify the interbeat interval fluctuations. As mentioned above, we consider a normalized time series with zero mean and unit variance. To generate a diffusive process, we integrate the time series b_i, $(1, \ldots, N)$ with different sliding windows of size t

$$x_k(t) = \sum_{j=k}^{k+t} b_j, \quad k = 1, 2, \ldots, N - t + 1. \qquad (9)$$

and obtain a diffusive trajectory with $N - t + 1$ particles in a fixed t, where $x_k(t)$ is imagined as the position of particle. After pretreatment, we are ready to estimate the entropy of this diffusive process. Figure 3 describes the result yielded by the DE method. The heart interbeat interval fluctuation in four behaviour states exhibits approximate scaling behaviour

with slope 1 at small scales. However, the effect of nonstationary trend contributes to be indistinguish- able scaling behaviour at large scales, where the entropy increases more quickly than scales.
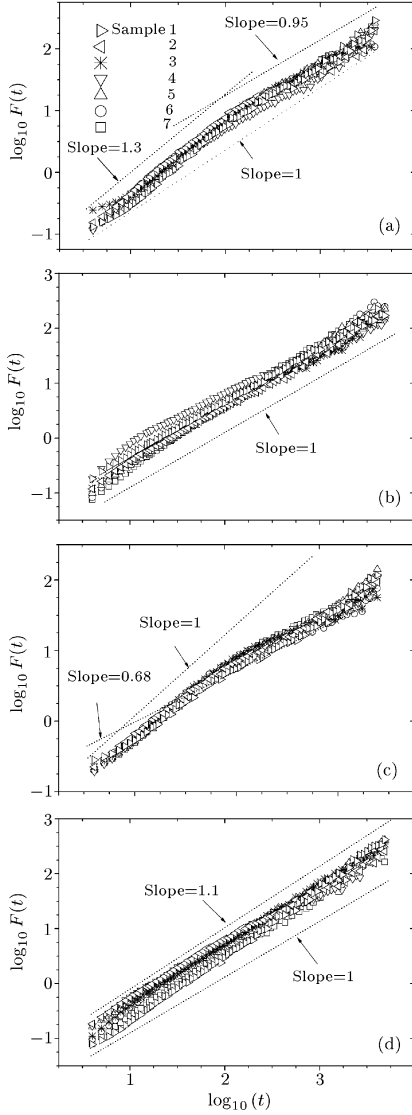

Fig. 2. The DFA results of seven records from healthy subjects during four physical states: (a) constant exercise, (b) usual daily activity after the exercise, (c) sleep, and (d) usual daily activity the next morning.
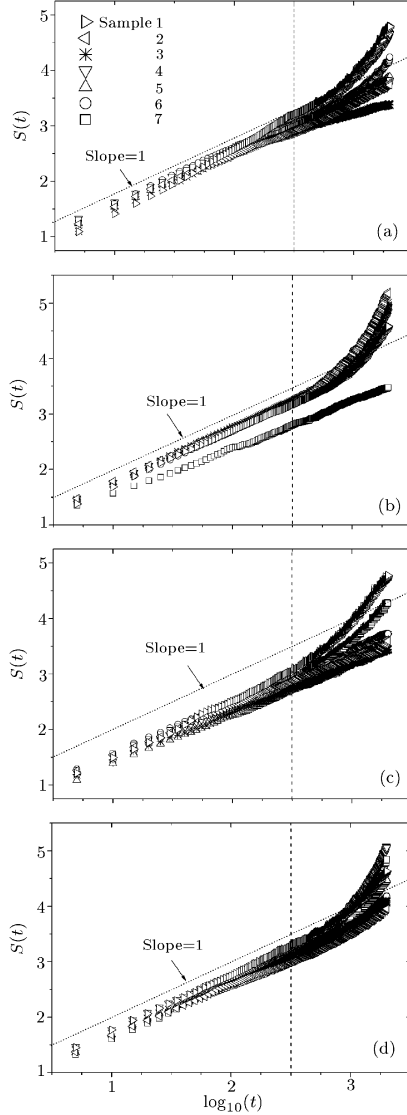
Fig. 3. The DE results of seven records from healthy subjects during four physical states: (a) constant exercise, (b) usual daily activity after the exercise, (c) sleep, and (d) usual daily activity the next morning.

Fig. 4. The DE results of seven records from healthy subjects after detrending the nonstationary trend effect during four physical states: (a) constant exercise, (b) usual daily activity after the exercise, (c) sleep, and (d) usual daily activity the next morning.
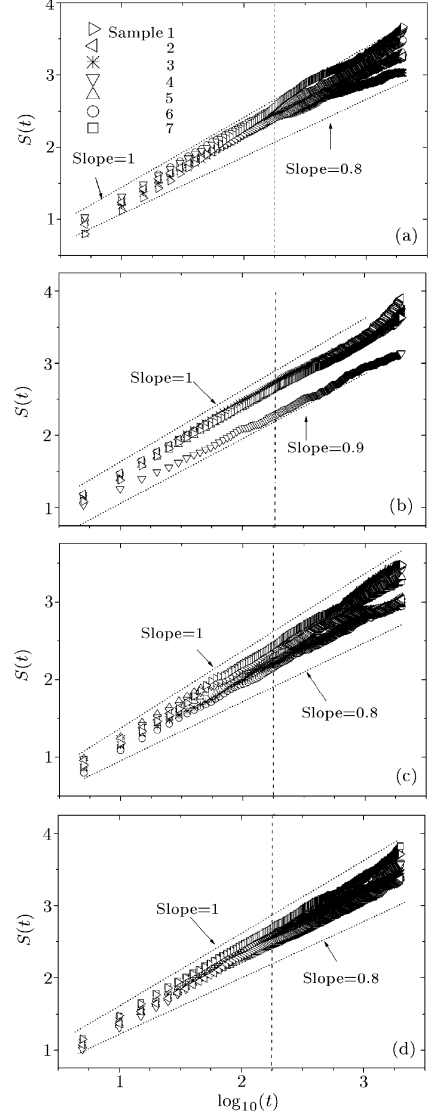
To make these data suitable for the illustration of the memory at all scales as follows, we introduce a method based on the Fourier transform to detrend the nonstationary trend in the whole but not the local temporal domain.[22] The normalized temporal series is transformed to Fourier space. We then use invert Fourier transform to obtain temporal series with cutoff coefficient of the Fourier space. We consider the curtailed interbeat interval fluctuation as the trend and subtract it from original series. The detrended heart interbeat interval fluctuation is computed by the DE method. In comparison with Fig. 3, the scaling be-

haviour behaves distinctly and more accurately at the large scales after detrending the nonstationary trend, as shown in Fig. 4, but the scaling behaviour at small scales does not change essentially, as well as with approximate slope 1. The explanation may be such that nonstationary trend just effect the analytic result of diffusion entropy at low frequency domain (large temporal domain), and filtering procedure weakens the trend effect.[23−25] In comparison with the DFA result, the scaling behaviour conforms to approximate monofractal scaling property with slope 1. All the four behaviour states suggest that the heart rate is a
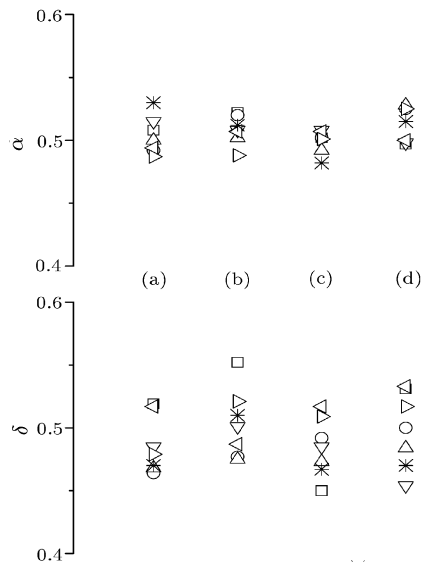
process where the memory is important.

Fig. 5. The scaling exponents of seven records from healthy subjects after randomly shuffling data during four physical states: (a) constant exercise, (b) usual daily activity after the exercise, (c) sleep, and (d) usual daily activity the next morning.

Last but not least, to test that the long-range correlations and memory is not caused by spurious artifact but genuine properties of heart rate, we shuffle the each point of interbeat interval fluctuation for seven records from healthy subjects in four behaviour states. The shuffling operation keeps the distribution of interbeat interval fluctuation unchanged, but destroys the correlation and memory in the time series totally if any. We measure the randomly shuffled data again. They do not show any correlation or memory with giving average exponent ≈ 0.5, as shown in Fig. 5.

In conclusion, we have demonstrated the memory exist in the heart rate of healthy human, which determines the long-range correlations of output of the system. The healthy human heart rate exhibits variable scaling behaviour between different behaviour states. We have discussed relevant characteristics in the significant behaviour states, showing the breakdown of long-range correlations when the scale increases in

constant exercise and sleep states, while a $1/f$ temporal scale–a hallmark of criticality–observed in the whole scales in usual daily activity. It supports the hypothesis that a healthy human heart rate is controlled to converge continually to a critical state during usual daily activity.[7] We also study estimation of memory covered by the nonstationary trend at large scales based on Fourier filter by the DE method. The result suggests that the memory exist at all the scales and exhibits an approximately same pattern in all the behaviour states. These findings may be helpful to understand the underlying dynamical evolution process in the health human heart rate control system, as well as to model the cardiac dynamic process.

The authors wish to thank Dr M. Ignaccolo for helpful discussion.

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