**Diffusion entropy analysis on the stride interval fluctuation of human gait**

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In this paper, the diffusion entropy technique is applied to investigate the scaling behavior of stride interval fluctuations of human gait. The scaling behavior of the stride interval of human walking at normal, slow and fast rate are similar; with the scale-invariance exponents in the interval [0.663, 0.955], of which the mean value is 0.821 ± 0.011. Dynamical analysis of these stride interval fluctuations reveals a self-similar pattern: Fluctuation at one time scale are statistically similar to those at multiple other time scales, at least over hundreds of steps, while the healthy subjects walk at their normal rate. The long-range correlations are observed during the spontaneous walking after the removal of the trend in the time series using a Fourier filter. These findings uncover that the fractal dynamics of stride interval of human gait are normally intrinsic to the locomotor systems.

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I. INTRODUCTION

Recently, it has been recognized that in many natural sequences the elements are not positioned randomly, but exhibit long-range correlations and fractal dynamics. Prominent examples include noncoding DNA sequences, human heartbeat, human brain electroencephalogram, teenagers’ births in Texas, and financial time series. The common feature of all these diverse systems with long-range correlations is that scaling behavior decay by a power law, where a characteristic scale is absent, and the scaling behavior is usually rather robust and universal.

The scaling behavior in complex systems is not only interesting in physical sense, but also provides an intrinsic description of the system, and highlights the system dynamical mechanism. Several useful variance-based methods, such as the probability moment method and the fluctuation approach as well as the de-trended fluctuation approach, are proposed to detect the scale-invariance properties. However, these variance-based methods have two basic shortcomings. One is that the scale-invariance property can be detected but the value of the exponent cannot be obtained accurately. The other is that for some processes, like the Lévy flight, the variance tends to infinite and these methods are unavailable at all. Although the infinite can not be reached due to the finite records of empirical data, clearly we will obtain misleading information about the dynamics under these conditions.

The dynamics of human gait is relative to locomotor system’s synthesizing inputs from the motor cortex, the basal ganglia and the cerebellum, as well as feedback from the vestibular, visual and proprioceptive sources. Therefore, to investigate the scaling behavior of the stride interval fluctuations of human gait is very interesting with both the physical and physiological communities. By using some recently proposed approaches for nonlinear data, some scientists studied the statistical characters of the stride interval fluctuations of human gait [10, 11, 12, 13, 14, 15, 16, 17]. Hausdorff et al. [10, 11] demonstrated that the stride interval time series exhibits long-range correlations, suggesting that the human gait displays a self-similar activity. Subsequent studies, by West et al and Goldberger et al [12, 13, 14, 15], supported the above conclusion, and several dynamics models are established to mimic the human gait [18, 19]. Furthermore, Perc [17] found that the human gait process possesses some typical properties like a deterministic chaotic system. In this paper, we apply the diffusion entropy (DE) technique to accurately detect and obtain the scaling property of stride interval fluctuations of human gait on a Fourier analysis.

II. DIFFUSION ENTROPY TECHNIQUE BASED ON FOURIER ANALYSIS

To overcome the mentioned shortcomings in the variance-based methods, Grigolini et al. [8, 9] designed the approach named diffusion entropy analysis (DEA). To keep our description as self-contained as possible, we briefly review the DEA method.

Consider a complex system containing a large amount of particles. The scale-invariance property in the diffusion process of this system can be described mathematically with the probability distribution function as

\[ P(x, t) = \frac{1}{t^{\delta}} F\left(\frac{x}{t^{\delta}}\right), \]

where \( x \) is the displacements of the particles in the complex system and \( \delta \) the scale–invariance exponent. The
Consequently, the Shannon entropy can be defined as
\[ S(t) = -\int_{-\infty}^{+\infty} P(x,t) \log_{10}[P(x,t)] dx. \] (3)
A simple algebraic leads to
\[ S(t) = A + \delta \log_{10}(t), \] (4)
where
\[ A = -\int_{-\infty}^{+\infty} F(y) \log_{10}[F(y)] dx, \quad y = \frac{x}{\delta}. \] (5)

The DEA method has been used to analysis many time series in different research fields, such as the solar induced atmosphere temperature series [22], the intermittency time series in fluid turbulence [23], the spectra of complex networks [24], the output spike trains of neurons [25], the index of financial market [26], and so on.

### III. DATA ANALYSIS

Herein, we map a time series to a diffusive process and introduce the DE technique to investigate the time series of stride interval fluctuations of human gait, which is obtained from healthy subjects who walked for 1 hour at their normal, slow and fast paces [27]. The data contains the stride interval fluctuations of ten young healthy men, given an arbitrary ID (s01, s02, s03, ⋯, s10). Participants have no history of any neuromuscular, respiratory, or cardiovascular disorders and are taking no medication. Mean age is 21.7 yr (range 18–29 yr). Height is 1.77 ± 0.08 (SD) m, and weight is 71.8 ± 10.7 (SD) kg. All the subjects provided informed written consent. Subjects walked continuously on level ground around an obstacle free, long (either 225 or 400 meters), approximately oval path and the stride interval is measured using ultra-thin, force sensitive switches taped inside one shoe. A typical example is shown in Fig. 1.

The stride interval significantly decreased and the velocity significantly increased with each chosen walking rate, as expected. The mean stride intervals of the three subjects are 1.3 ± 0.2 s, 1.1 ± 0.1 s, and 1.0 ± 0.1 s during the slow, normal, fast walking trials, respectively. And the mean velocities are 1.0 ± 0.2 m/s, 1.4 ± 0.1 m/s, and 1.7 ± 0.1 m/s during the slow, normal, and fast walking, respectively. The mean velocity increases by an average of 77% from slow to fast walking. A wide range of walking rates are obtained, enable us to test for the effects of walking rate on the scaling behavior indicating the long-range correlations.

The locomotor control system maintains the stride interval at an almost constant level throughout the 1 hour walking. Nevertheless, the stride interval fluctuations is in a highly complex, seemingly random fashion. In order to truly uncover the scaling behavior of the stride interval fluctuation of human gait, we study all the 30 samples.
classifying into three subjects: Fast, normal, and slow. The scaling behaviors of the three classes of subjects, obtained by using DE analysis, are shown in Fig. 2A, 2B and 2C, respectively. Each figure contains 10 samples, of which the time scale is from 10 to 300. The results indicate that the stride interval time series is not completely random (uncorrelated), instead, it exhibits the scale-invariance property and long-range correlation at all the three walking rates.

Furthermore, Fig. 3 illustrates the dependence of $\delta$ on self-determined walking rate for all three subjects. For the 29 samples of 30 1-h trials, except one samples s108 of the slow subject (see Fig. 2C), the scale-invariant exponents $\delta$ is around $0.821 \pm 0.011$ (range 0.663 to 0.955). Thus for all subjects at all rates, the stride interval time series displayed scaling behavior and long-range power law correlations.

There are a strong similarity of $\delta$ on chosen walking rate: $\delta$ is $0.829 \pm 0.011, 0.827 \pm 0.011, 0.809 \pm 0.013$ during the fast-, normal-, slow-walking trails, respectively (see Fig. 3). In principle, the estimation of $\delta$ depends on the fitting range $(t_1, t_2)$. It is preferable to have $t_2 \gg t_1$. However, due to the finite size of data, a larger $t_2$ may lead to a bigger error in $\delta$ [28]. In this paper, all the results are obtained by linear fitting within the region (10, 300).

**IV. CONCLUSION**

In summary, by means of the DE method we investigate the scaling behavior embedded in the time series of stride interval fluctuation. Scale-invariance exponents of the three subjects are almost the same, being in the interval of $[0.663, 0.955]$, of which the mean value is $0.821 \pm 0.011$. Dynamical analysis of these step-to-step fluctuations reveals a self-similar pattern: Fluctuation at one time scale are statistically similar to those at multiple other time scales, at least over hundreds of steps, while the healthy subjects walk at their normal rate. The long-range correlation is observed during the spontaneous walking by removal of the drift or trend in the time series. Thus the above features uncover the fractal dynamics of spontaneous stride interval are normally intrinsic to the locomotor system.
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