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Maximum Lyapunov exponent revisited: Long-term attractor divergence of gait dynamics is highly sensitive to the noise structure of stride intervals

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ABSTRACT

Background: The local dynamic stability method (maximum Lyapunov exponent) can assess gait stability. Two variants of the method exist: the short-term divergence exponent (DE), and the long-term DE. Only the short-term DE can predict fall risk. However, the significance of long-term DE has been unclear so far. Some studies have suggested that the complex, fractal-like structure of fluctuations among consecutive strides correlates with long-term DE. The aim, therefore, was to assess whether the long-term DE is a gait complexity index.
Methods: The study reanalyzed a dataset of trunk accelerations from 100 healthy adults walking at preferred speed on a treadmill for 10 min. By interpolation, the stride intervals were modified within the acceleration signals for the purpose of conserving the original shape of the signal, while imposing a known stride-to-stride fluctuation structure. Four types of hybrid signals with different noise structures were built: constant, anti-correlated, random, and correlated (fractal). Short- and long-term DEs were then computed.
Results: The results show that long-term DEs, but not short-term DEs, are sensitive to the noise structure of stride intervals. For example, it was that observed that random hybrid signals exhibited significantly lower long-term DEs than hybrid correlated signals did (0.100 vs 0.144, i.e. a 44% difference). Long-term DEs from constant hybrid signals were close to zero (0.006). Conversely, short-term DEs of anti-correlated, random, and correlated hybrid signals were closely grouped (2.49, 2.50, and 2.51).
Conclusions: The short-term DE and the long-term DE, although they are both computed from divergence curves, should not be interpreted in a similar way. The long-term DE is very likely an index of gait complexity, which may be associated with gait automaticity or cautiousness. Consequently, to better differentiate between short- and long-term DEs, the use of the term attractor complexity index (ACI) is proposed for the latter.

1. Introduction

Analysis of the nonlinear variability of human locomotion has attracted growing interest over the past decade [1]. This approach postulates that decoding nonlinear dependence among consecutive gait cycles (strides) can help to better understand gait control. A popular nonlinear method is the local dynamic stability (LDS) of the gait [2–5]. LDS is derived from the maximum Lyapunov exponent, which is used to highlight the deterministic chaos in nonlinear systems. Gait LDS has been proven particularly useful for detecting patients at risk of falling [6].

The majority of LDS studies use the Rosenstein's algorithm that computes the distance between trajectories of an attractor reflecting the gait dynamics [3,4]. A logarithmic divergence curve is then built to assess the exponential divergence rate—the divergent exponent (DE)—by means of linear fitting over a given range. Two ranges have been proposed: a short-term range over 0–1 or 0–0.5 stride (the short-term DE), and a long-term range over 4–10 strides (the long-term DE) [4]. Puzzling results have been found when these two LDS indexes are used together to assess fall risk: both indexes most often vary in opposite directions [7,8]. Further theoretical and experimental studies have shown that only the short-term DE is a valid gait stability measure [2,9,10]. However, it is not excluded that the long-term DE is associated with other gait features given its responsiveness to various conditions [11–13].

Another approach for studying nonlinear gait variability is the analysis of the noise structure of stride-to-stride fluctuations. In healthy individuals, basic gait parameters, such as stride interval, stride length and stride speed, fluctuate among strides within a narrow range of 2%–4% [14]. It has been shown that these fluctuations are not random,

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but exhibit long-range correlations and a scale-free, fractal-like pattern [14–16]. This particular noise structure is observed in many different physiological signals, and is considered a hallmark of the complexity of living-beings [17]. Interestingly, this fractal structure can be altered when external cues are used to intentionally drive the steps, such as synchronizing gait to a metronome, or by following marks on the floor [16].

In 2009, Jordan et al. [18] analyzed both gait stability and complexity in treadmill walking and running. They observed a strong correlation (r = 0.80) between a measure of gait complexity (the scaling exponent of stride intervals) and the long-term DE. In 2012, Sejdic et al. [12] assessed the noise structure of stride intervals as well as the LDS (short-term and long-term DEs) during normal walking with and without external cueing (metronome walking). The results showed that, with auditory cueing, the long range-correlations of stride intervals changed to anti-correlated patterns along with a substantial decrease of long-term DEs, but with no change of short-term DEs. Similarly, in 2013 [4], we analyzed the gait stability and complexity of treadmill walking, confirming that both long-term DE and the noise structure of stride intervals were similarly modified by external cueing. A significant correlation between scaling exponents and long-term DEs (r = 0.57) was also observed. In summary, the long-term DE seems more associated with the noise structure of stride intervals than with local stability and fall risk. Complex fluctuations that occur over dozens of consecutive strides seem to induce a less dampened divergence curve, resulting in a higher long-term DE.

The current study's objective was to further explore whether the long-term DE should be interpreted as an index of gait complexity rather than an index of gait instability. To this end, stride intervals of natural gait acceleration signals were replaced with artificial time series exhibiting known noise structure. The hypothesis was that higher long-term DEs were associated with a more complex variability of stride-to-stride fluctuations. It was also assumed that short-term DEs were, in contrast, not sensitive to the noise structure of stride intervals.

2. Methods

2.1. Setting

A large, anonymized dataset of acceleration signals obtained from our previous studies was re-analyzed [19,20]. In short, 100 healthy individuals aged between 20 and 69 years walked at preferred speed on a treadmill for five minutes in two sessions, separated by one week. A 3D accelerometer, attached to the sternum, recorded the trunk acceleration.

2.2. Data pre-processing

Each of the two-hundred acceleration signals was pre-processed using Matlab (R 2017a; Mathworks, Natick, MA, USA). First, the vertical signal was selected and normalized to zero mean (i.e. removal of the constant gravity component). Based on the walking cadence assessed using spectrum analysis, 500 steps (250 strides) were extracted from the 5-minute signal, which was then resampled to a constant length of 25,000 samples. A custom peak-detection algorithm found the local maxima, which corresponded to heel strikes (Fig. 1A, B). One in two of these maxima delimited each stride and constituted the original time series of stride intervals. The standard deviation (SD) and the coefficient of variation (CV = SD / mean × 100) characterized the variability magnitude among the stride intervals. Finally, the detrended fluctuation analysis (DFA) determined the noise structure of the stride-interval time series. DFA can detect self-similarity, and hence correlation structure, in non-stationary times series [4,21]. The slope of a line-fit in a log-log plot of scales vs fluctuations is the scaling exponent. The evenly spacing method [22] was used, with box sizes between 6 and N/2, i.e. 125. If the scaling exponent is smaller than 0.5, the noise is deemed anti-correlated. Random noise has a scaling exponent of about 0.5. Correlated noise exhibit a scaling exponent lying between 0.5 and 1.

2.3. Signal selection

Using a simple algorithm to look for local maxima may produce spurious stride intervals due to the sporadic presence of two close acceleration peaks of similar intensity around heel strike. This phenomenon is mainly related to idiosyncratic gait pattern and suboptimal sensor placement (upper trunk). Therefore, we excluded the poorly configured signals that corresponded to at least one of these two criteria: 1) an average CV of stride intervals greater than 8%; or 2) a scaling exponent below 0.5. The interval time series of the included signals, therefore, had a noise structure and magnitude similar to the commonly admitted values, i.e. a CV around 3%, and a scaling exponent around 0.7 [16].

2.4. Artificial times series

For each included acceleration signal, we built three computer-generated time series with the same length (i.e. 250 points), mean, and SD as the original stride-interval time series, but with different noise structures (i.e. anti-correlated, random and correlated structures) (Fig. 1C). The random time series were generated by the Matlab random number generator (*normrnd)*. Correlated and anti-correlated time series were generated with an autoregressive fractionally integrated moving average (ARFIMA) noise simulator [23]. Based on the time-series theory introduced by Box & Jenkins [24], ARFIMA models can simulate processes with long-range correlations among consecutive samples [25]. DFA was applied to measure the actual scaling exponent of the artificial time series.

2.5. Hybrid signals

Each acceleration signal was combined with the corresponding artificial time series to form the hybrid signals. We sought to preserve the shape of the original signal, while altering the duration of each stride according to the artificial time series. To this end, each stride in the original signal was lengthened or shortened by adding or removing points by interpolation (Fig. 1D). The stride intervals in the original signal were replaced by the intervals in the artificial times series. We used the shape-preserving piecewise cubic interpolation algorithm (*pchip*) provided by the Matlab function *interp1*. As a result, three hybrid signals with identical shape, but different noise structures for stride intervals, were obtained. A fourth hybrid signal was also generated by equalizing the duration of each stride to the mean stride interval (constant signal).

2.6. Attractor divergence curves and divergence exponents

Divergence curves and DEs were computed following the habitual method applied in our lab [4]. Multi-dimensional attractors were constructed based on the delay embedding theorem. A global false nearest neighbors (GFNN) algorithm determined an attractor dimension of five common for all signals. Individualized time delays were assessed by the average mutual information (AMI) of each signal [mean delay (SD): 7.3 sample (2.6)]. Logarithmic divergence curves were built with the Rosenstein's algorithm. The time axis (x-axis) was normalized by stride intervals. The average curves are presented in Fig. 2. The exponential divergence rate was computed for three time-scales: across the span of 0–0.5 stride (short-term DE), 2–4 strides, and 4–10 strides (long-term DEs).