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An improved surrogate method for detecting the presence of chaos in gait

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Abstract

It has been suggested that the intercycle variability present in the time series of biomechanical gait data is of chaotic nature. However, the proper methodology for the correct determination of whether intercycle fluctuations in the data are deterministic chaos or random noise has not been identified. Our goal was to evaluate the pseudoperiodic surrogation (PPS) [Small et al., 2001. Surrogate test for pseudoperiodic time series data. Physical Review Letters 87(18), 188,101–188,104], and the surrogation algorithms of Theiler et al. [1992. Testing for nonlinearity in time series: the method of surrogate data. Physica D 58(1–4), 77–94] and of Theiler and Rapp [1996. Re-examination of the evidence for low-dimensional, nonlinear structure in the human electroencephalogram. Electroencephalography and Clinical Neurophysiology 98, 213–222], to determine which is the more robust procedure for the verification of the presence of chaos in gait time series. The knee angle kinematic time series from six healthy subjects, generated from a 2-min walk, were processed with both algorithms. The Lyapunov exponent (LyE) and the approximate entropy (ApEn) were calculated from the original data and both surrogates. Paired t-tests that compared the LyE and the ApEn values revealed significant differences between both surrogated time series and the original data, indicating the presence of deterministic chaos in the original data. However, the Theiler algorithm affected the intracycle dynamics of the gait time series by changing their overall shape. This resulted in significantly higher LyE and ApEn values for the Theiler-surrogated data when compared with both the original and the PPS-generated data. Thus, the discovery of significant differences was a false positive because it was not based on differences in the intercycle dynamics but rather on the fact that the time series was of a completely different shape. The PPS algorithm, on the other hand, preserved the intracycle dynamics of the original time series, making it more suitable for the investigation of the intercycle dynamics and the identification of the presence of chaos in the gait time series.

Introduction

Previous biomechanical investigations have suggested that stride-to-stride (intercycle) variability has chaotic features and the nature of the chaotic structure is an indication of the overall health of the system (Buzzi et al., 2003; Dingwell et al., 2000; Dingwell and Cusamano, 2000; Hausdorff et al., 1995; Lipsitz, 1995; Stergiou et al., 2004a, b). However, further exploration of these initial findings has been hindered by the fact that the identification of chaos in a time series is a very difficult procedure and sometimes purely random signals have been misdiagnosed as chaotic or vice versa (Collins and DeLuca, 1995; Rapp, 1994; Theiler et al., 1992). Thus, methods such as surrogate analysis have been developed to prevent such misdiagnoses (Theiler et al., 1992; Theiler and Rapp, 1996; Rapp, 1994; Stergiou et al., 2004b).

Recently, the surrogate algorithm of Theiler et al. (1992), Theiler and Rapp (1996) has been applied to support the notion that fluctuations in human gait have a deterministic pattern (Stergiou et al., 2004b; Dingwell and Cusamano, 2000; Buzzi et al., 2003). However, Small et al. (2001) have also presented a pseudoperiodic surrogate (PPS) algorithm that preserves the inherent periodic components of human electrocardiogram time- series data while destroying the subtle nonlinear structure. It is possible that this algorithm can be used with gait time series by preserving their essential periodic features and effectively discerning the differences between chaotic fluctuations and random noise. However, such tests have yet to be performed. The purpose of this investigation was to determine which of the two surrogation algorithms can provide a more robust verification of the presence of chaos in gait time series. We hypothesized that the PPS algorithm would be the best algorithm due to the algorithm's ability to preserve intracycle dynamics (dynamic patterns within one period of a cyclic pattern) while changing the intercycle dynamics (dynamic patterns between different periods across a cyclic pattern) of the time series.

Methods

Six healthy subjects (mean age = 29 ±7.4 yr, mean mass = 67.73±6.25 kg, mean height = 1.70±0.05 m) walked at their self-selected pace (mean-1.81±0.17 m/s) on a treadmill for 2 min (116.17±22.80 footfalls) while three-dimensional sagittal knee kinematics were captured (60 Hz) using Peak Motus optical capture system (Peak Performance, Centennial, CO). Subjects completed informed consent forms as required by the University's Institutional Review Board. Surrogates of the respective knee angle time series from all subjects were generated based on both the PPS (Small et al., 2001) and Theiler algorithms (Theiler et al., 1992; Theiler and Rapp, 1996). Theiler's algorithm reorganizes the phases of the complex conjugate pairs in the frequency domain such that surrogate contains linearly filtered independent and identically distributed noise. That means that the data are merely shuffled across the entire time series according to a random number generator with the same mean and variance of the original signal.

The PPS algorithm generates a surrogate that follows the same vector field as the original time series, but is contaminated with dynamic noise, which results in the data being shifted within each period of the cycle, but not between cycles. In this case, dynamic noise is a nonconstant source of variation, such that the signal varies randomly across the entire signal. The PPS algorithm requires that the user defines the embedding dimension, the time lag, and the noise radius for each data set (Table 1). The embedding dimension and time lag are parameters that identify the topology of the original data series (Stergiou et al., 2004b) and the noise radius (ρ) defines the amount of noise in a surrogate

Table 1
Group means and standard deviations for the time lag, the embedding dimension and the ρ values used to calculate LyE values for our data

	Time lag	Global embedding dimension	ρ
Mean	9.833	6.333	3.351
SD	2.994	1.033	5.680

(Small et al., 2001). Noise radii that are too large will result in randomly shuffled data as in the traditional method, while noise radii that are too small will produce surrogates that are too similar to the original data (Small et al., 2001). The embedding dimension and time lag were calculated with the tools from Dynamics Software (Applied Chaos, LLC). Noise radius was chosen such that the fine intercycle dynamics were removed, but the intracycle dynamics were preserved. As suggested by Small et al. (2001), we selected a ρ that maximized the number of short segments (length X2) that are the same for the original time series and the surrogate. These segments represent the amount of correlation between the surrogate and original data sets (Small et al., 2001).

The largest Lyapunov exponent (LyE) of each surrogate (Theiler and PPS) and each respective original time series for each subject were calculated using the chaos data analyzer (Sprott and Rowlands, 1995). LyEs quantify the exponential separation of nearby trajectories in the reconstructed state space of the time series (Stergiou et al., 2004b). As nearby points of the state space separate, they diverge rapidly and can produce instability. LyEs from a stable system with little to no divergence will be zero (e.g. sine wave). Alternatively, LyEs for an unstable system that has a high amount of divergence will be positive and relatively high in value (e.g. 0.469 for random data). LyE for chaotic systems lie between the two extremes. For example, the Lorenz attractor has a value of 0.100.

Approximate entropy (ApEn) of the original time series and surrogated time series were calculated using Matlab software available on Physionet (Goldberger et al., 2000). ApEn values were calculated to determine the influence of the respective surrogation methods on the regularity of the time series. ApEn values typically range from 0 to 2. Values closer to 0 are consistent with greater periodicity or regularity (e.g. a sine wave). Conversely, values nearing 2 represent greater irregularity (e.g. random data; Stergiou et al., 2004b).

The group means for the LyE and ApEn values were calculated for each surrogate method and for the original time series. Paired *t*-tests were used to compare the group means of each surrogate with the original time series. In addition, paired *t*-tests were used to compare the group means between the two surrogate methods. All statistical tests were conducted at a 0.05 alpha level.

Results and discussion

Significant differences were found for both LyE and ApEn values between the original and the surrogate time series for both algorithms (Table 2). These results indicated that fluctuations in the original time series had a deterministic structure that was significantly different from random noise. However, inspection of Figs. 1A and C shows that Theiler's algorithm alters the original geometric structure of the time series (the intercycle dynamics). This suggests that the algorithm shuffles the data points across the entire time series without regard for the periodicity of the signal. It stands to reason that the surrogate would be statistically different from the original series. The PPS algorithm did not alter the overall periodicity of the time series (it protected the intracycle dynamics and only changed the intercycle dynamics), indicating that there actually was determinism in the data. Inspection of Figs. 1A and B indicates that the PPS algorithm maintains the essential geometric structure of the gait time series. In fact, the surrogate and the original gait time series appear virtually indistinguishable.

The qualitative evaluation is also supported by the significant differences found for both the LyE and the ApEn values between the two surrogate methods (Table 2). Regarding ApEn, the Theiler algorithm produced much higher values than the Small algorithm. Specifically, the ApEn values from the Theiler algorithm were very close to the highest possible ApEn value (i.e. two for random data). This clearly indicated high irregularity and randomness in the surrogated data. On the contrary, the ApEn values for the Small algorithm were 0.753 on an average. Even though they were significantly larger than those of the original time series, they were small enough to indicate high regularity in the surrogated data. Similar observations can be made with the LyE values where the Theiler algorithm produced much larger values than both the original and the Small surrogated data indicating high divergence and instability, a characteristic of random data. The LyE values from the Small-surrogated data were again close to the original due to the preserved intracycle dynamics. Importantly, they were significantly different from the original indicating determinism in the intercycle dynamics which should be the goal of a surrogation algorithm.

Table 2
Group means and standard deviations for the Lyapunov exponents (LyE) and the approximate entropy (ApEn) from the original and the Theiler and the pseudoperiodic surrogate (PPS) data

	Original	PPS	Theiler
LyE	$0.101^{a,b} \pm 0.015$	$0.136^{b,c} \pm 0.030$	$0.261^{a,c} \pm 0.018$
ApEn	$0.682^{a,b} \pm 0.227$	$0.753^{b,c} \pm 0.247$	$1.728^{a,c} \pm 0.156$

[a]Indicates significance between the original data and PPS-surrogated data ($p = 0.001$ for LyE and $p = 0.01$ for ApEn).
[b]Indicates significance between the original data and Theiler-surrogated data ($p < 0.001$ for both LyE and ApEn).
[c]Indicates significance between the PPS-surrogated data and Theiler-surrogated data ($p < 0.001$ for both LyE and ApEn).

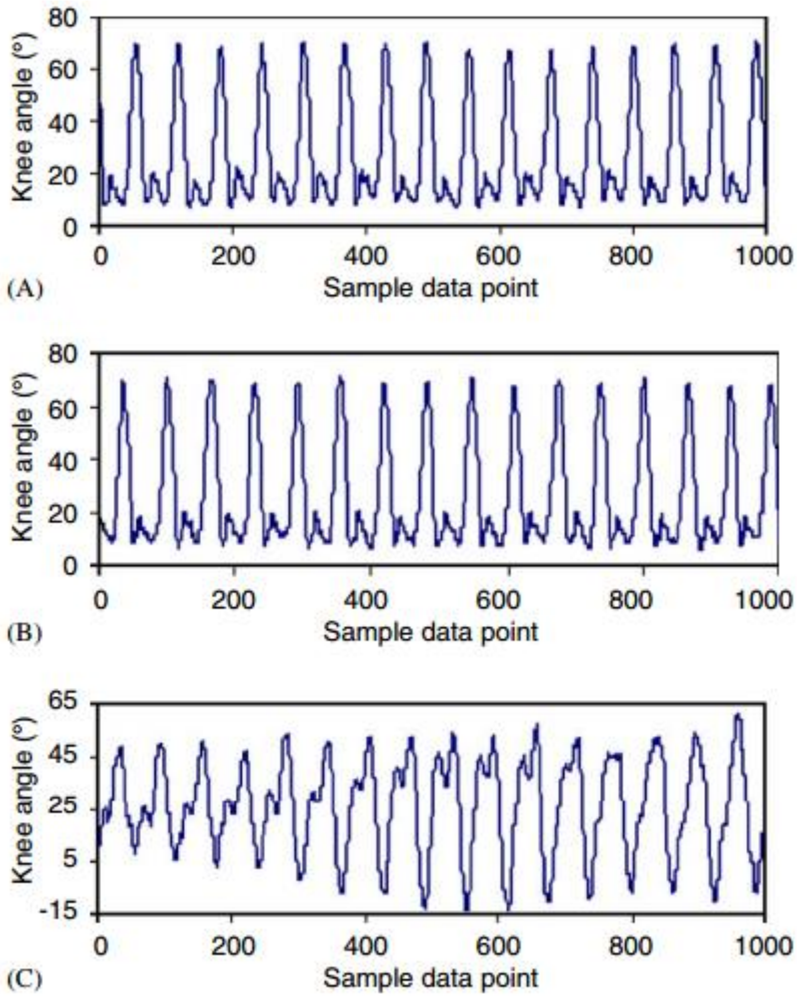

Fig. 1. Knee angle values (°) versus time (s) for the original data series (A), pseudoperiodic surrogate (PPS) (B), and Theiler's surrogate (C) from a representative subject. All time series from all subjects showed similar patterns. The surrogate produced by Theiler's surrogate has lost its temporal structure, while the PPS surrogate maintained its overall temporal geometry, making it a better tool for determining the presence of chaos.

The above results support the notion that the PPS algorithm is more suitable for detecting the presence of subtle chaotic fluctuations that appear in gait. Since there is a cyclic nature to data related to human gait patterns, the detection of determinism using the Theiler algorithm might be a false positive, which would lead to inaccurate classification of the signal. Thus, the PPS algorithm should be adopted in future investigations to rigorously verify that fluctuations in gait patterns are in fact chaotic and not random noise superimposed on top of the time series. This information can be extremely useful in future studies where the association between the presence of chaos in human gait and health of the neuromuscular system is being explored for the development of prognostic and diagnostic biomechanical tools.

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