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Complexity, Coordination, and Health: Avoiding Pitfalls and Erroneous Interpretations in Fractal Analyses

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Complexity, Coordination, and Health: Avoiding Pitfalls and Erroneous Interpretations in Fractal Analyses

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Key words: *fractal fluctuations; 1/f noise; stability; health; complexity.*

Summary. *Background and Objective. The analysis of fractal fluctuation has become very popular because of the close relationships between health, adaptability, and long-range correlations. 1/f noise is considered a "magical" threshold, characterizing optimal functioning, and a decrease or conversely and increase of serial correlations, with respect to 1/f noise, is supposed to sign a kind of disadaptation of the system. Empirical results, however, should be interpreted with caution. In experimental series, serial correlations often present a complex pattern, resulting from the combination of long-range and short-term correlated processes. We show, in the present paper, that an increase in serial correlations cannot be directly interpreted as an increase in long-range correlations.*

Material and Methods. Eleven participants performed four walking bouts following 4 individually determined velocities (slow, comfortable, high, and critical). Series of 512 stride intervals were collected under each condition. The strength of serial correlation was measured by the detrended fluctuation analysis. The effective presence of 1/f fluctuation was tested through ARFIMA modeling.

Results. The strength of serial correlations tended to increase with walking velocity. However, the ARFIMA modeling showed that long-range correlations were significantly present only at slow and comfortable velocities.

Conclusions. The strength of correlations, as measured by classical methods, cannot be considered as predictive of the genuine presence of long-range correlations. Sometimes systems can present the moderate levels of effective long-range correlations, whereas in others cases, series can present high correlation levels without being long-range correlated.

Introduction

When a biological system is repeatedly observed during the repeated performance of a given task, the series of outcomes presents fluctuations around the mean value. These fluctuations have been for a long time considered as insignificant, attributed to random perturbations, and discarded by smoothing or averaging.

A number of recent studies, however, showed that fluctuations in repetitive performance possess interesting properties and, especially, present typical serial correlations. More precisely, a number of studies have evidenced the presence of long-range, or fractal correlations, in the series of performances collected in different experimental situations, for example in the time intervals produced in finger tapping (1), or in forearm oscillations (2), in the step durations during walking or running (3, 4), or in the relative phase between the two effectors in bimanual coordination tasks (5). Long-range correlations are characterized by the presence of persistent dependence in the series and are revealed by a very slow, power-law decay of the autocorrelation function over time (6). Fig. 1 shows an example of autocorrelation function obtained from a long-range correlated series.

Long-range correlations are also characterized by the presence of scaling laws that could be expressed in the frequency or in the time domain. In the frequency domain, the typical scaling law states that squared amplitude (i.e., power) is an inverse power function of frequency, with an exponent β. This property is revealed by a negative linear slope in the log-log power spectrum. For a fractal process, the slope is close to minus one, suggesting that power is roughly proportional to period. This property led to the popular denomination of $1/f$ noise for characterizing this kind of fluctuations. Fig. 2 depicts the log-log power spectrum typically obtained from a long-range correlated series.

The value of the slope, however, can vary, and series can be characterized by a spectral exponent, β, defined as the negative of the slope. $\beta=1$ for perfect $1/f$ noise, but long-range correlations occur in

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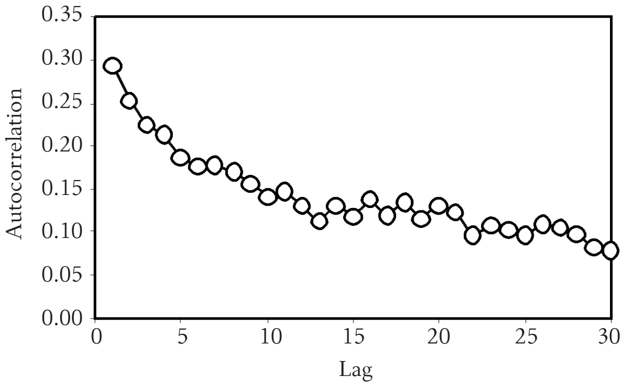

Fig. 1. Typical autocorrelation function of a fractal time series

The autocorrelation function presents a very slow decay over time.

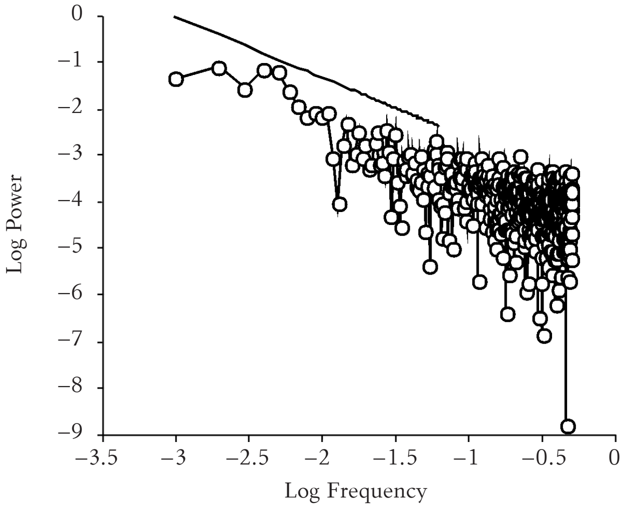

Fig. 2. Log-log representation of the power spectrum of a fractal time series

The presence of long-range correlations is revealed by the negative linear regression slope.

the range $\beta=0.5$ to $\beta=1.5$ (7). Note that the absence of correlation in the signal is revealed by an exponent β close to zero. In contrast, larger values of the spectral exponent reveal more predictable signals.

Fractal fluctuations are closely related to health. Their presence is considered the hallmark of young, healthy, and adaptive systems, and typically, an extinction of long-range correlations is observed in the elderly and in patients suffering from neurodegenerative diseases. These alterations of fractal properties have been observed, for example, by Hausdorff and colleagues (8) in the domain of walking. Series of step durations present fractal properties in young and healthy subjects, but become more random in the elderly and patients with Huntington's disease.

The real origin of fractal fluctuation remains in debate. The most convincing point of view states that long-range correlation reflects the presence of complex interdependence within the system under study, among a wide number of subsystems acting at different time scales. This so-called "interaction-dominant" view suggests that fractal correlations emerge from the coordination among these different time scales, and as such sign the complexity of the system (9).

Consequently, one could conceive a direct link among health, coordination, and complexity. A healthy system is supposed to present this complex coordination among its constitutive components. Deficiency can then be revealed in two opposite ways: (i) the system presents a number of independent subcomponents. In this case, the outcome series become random, less ordered over time; and (ii) the system is dominated by a restricted set of subcomponents: the outcome series become more ordered and predictable.

Fractal fluctuations are often described as an optimal compromise between disorder and order. $1/f$ noise (i.e., $\beta=1$) is often considered a "magic" threshold, characterizing optimal functioning. A decrease of β toward 0 is conceived as a deviation toward disorder and randomness, and conversely, an increase toward 2 is analyzed as a deviation toward order and predictability. Goldberger et al. (10) gave interesting examples, concerning fluctuations in heartbeat. They showed that heartbeat series presented $1/f$ fluctuations in healthy subjects. In contrast, patients with severe congestive heart failure presented highly predictable, quasi-sinusoidal series, interpreted as a shift toward order. In contrast, a patient with a cardiac arrhythmia produced an erratic heart rate, interpreted as a shift toward randomness.

More generally, the presence of $1/f$ noise is supposed to represent the hallmark of stability, flexibility, and adaptability in a given system. On this basis, the assessment of the fractal exponent and its alteration under specific experimental conditions and/or in specific populations has become an important challenge in research.

Empirical results, however, should be interpreted with caution. It is important to keep in mind that serial correlations in empirical series reflect both long-range correlations, arising from the functional complexity of the system, and short-range correlations that could be induced, for example, by local corrective processes. For example, Hausdorff et al. (4) showed that stride interval series collected during walking presented long-range correlations. However, when participants were asked to walk in synchrony with a metronome, this fractal behavior disappeared and series looked uncorrelated. This result could be interpreted as a kind of loss of complexity in the system, becoming overridden by the rhythm imposed by the metronome. However, Delignières and Torre (11) showed that correlations did not disappear in metronomic series: these series actually exhibit slightly antipersistent correlations, and the authors showed that this correlation pattern resulted from the combination of $1/f$ fluctuations, still at work in the system, and a process of continuous coupling to the metronome that tended to induce negative correlations in stride intervals.

A second interesting example was evidenced in tapping tasks. Chen et al. (12) showed that when participants performed tapping in synchrony with the metronome, the series of asynchronies to the metronome was long-range correlated. In a second paper (13), the authors analyzed serial correlations in synchronization and in syncopation tapping. In the second condition, participants had to tap in between two successive metronome beats. The authors showed that the strength of fractal correlations significantly increased from synchronization to syncopation and concluded that long-range correlation tended to increase with task difficulty. Delignières et al. (14), however, proposed another interpretation. They showed that the increase in correlation was due to the superimposition of a short-range process, devoted to the estimation of the duration of the following half-period of the metronome.

These examples show that an increase or conversely a decrease in correlation can be due to the superimposed presence of short-range processes. Interpretations in terms of loss of complexity, shifts toward randomness or order, should be used with caution, at least after considering alternative hypotheses.

The presence of long-range correlation in empirical series is generally considered based on the strength of correlations, as measured by classical methods. The results provided by these methods, however, cannot be considered as predictive of the genuine presence of long-range correlation in the analyzed series. In others words, correlations in a series could be exclusively due to short-range processes, and as such no interpretation in terms of complexity or coordination within the system could be in that case sustainable.

In the following part of this article, we present an experiment that aimed at illustrating these principles. Serial correlations in stride intervals and relative phase series during walking at different speeds were analyzed. Jordan et al. (3) showed that the relation between correlation strength and walking speed followed a U-shape pattern: correlations presented a moderate value at preferred speed, but tended to increase as speed decreased or conversely as speed increased. Our aim in the present experiment was to check whether these increases in correlation strength corresponded to genuine increases in long-range correlation.

Material and Methods

Participants. Eleven volunteers (7 men and 4 women; mean age, 22±2.2 years) were involved in the experiment. All were in good health; none of them had neuromuscular troubles or late trauma in the lower limbs. They all gave their informed consent and were not paid for their participation.

Apparatus. The study was performed on a Medical Development S 2500 treadmill (speed range, 1.5–25 km/h; smallest increment in speed, 0.1 km/h). Heel strikes were detected from force-sensitive soles, connected to a recording device (CPU 196, LIRMM). An Excel routine was used to convert the original data in time series of stride intervals (i.e., the interval between two successive right heel strikes) and relative phases (i.e., the phase difference between the two legs, computed at each right heel strike).

Procedure. First, the preferred walking speed of each participant was determined. The preferred speed was presented as "the speed the most natural one could walk for hours without feeling tired." The preferred speed was determined as follows: participants first walked at a speed of 2.5 km/h during 30 seconds, and then the speed of the treadmill was increased by 0.1 km/h every 10 seconds until participants indicated that they were on their preferred speed. The speed was then increased by 1.5 km/h and decreased gradually by 0.1 km/h every 10 seconds, until the preferred walking speed was re-established. This process was repeated 3 times, with a 2-minute break between each trial. The preferred walking speed was then estimated by averaging the 6 speed values indicated by the participant.

Then the walk-run transition speed was determined: first participants walked at 6 km/h during 30 seconds, and then speed was increased by 0.1 km/h every 10 seconds. Participants were asked to not resist if they felt running more comfortable. The speed at which transition occurred was recorded, and the procedure was repeated 8 times. The transition speed was then estimated by averaging the last 5 values reported.

During the second part of the experiment, participants performed 4 trials corresponding to 4 different speeds: slow speed, preferred speed, fast speed, and transition speed. The preferred walking speed and transition speed have been previously defined. Slow speed corresponded to 80% of preferred speed, and fast speed was determined by averaging the preferred and transition speeds. The order of the 4 conditions was randomized for each participant, and a 5-minute rest was given between trials. The duration of each trial was determined in order to allow collecting series of 512 successive stride intervals (i.e., between 8 and 12 minutes, depending of the effective speed).

Data Analysis. First, the detrended fluctuation analysis (15), a method that allows assessing the strength of serial correlations in the series, was applied. The analyzed series $x(t)$ is first integrated, by computing the accumulated departure from the mean of the whole series for each *t*:

$$X(k) = \sum_{i=1}^{k} \left[x(i) - \bar{x} \right] \quad (1)$$

This integrated series is then divided into nonoverlapping intervals of length *n*. In each interval, a least squares line is fit to the data (representing the trend in the interval). The series $X(t)$ is then locally detrended by subtracting the theoretical values $X_n(t)$ given by the regression. For a given interval length *n*, the characteristic size of fluctuation for this integrated and detrended series is calculated by the following formula:

$$F = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left[X(k) - X_n(k) \right]^2} \quad (2)$$

This computation is repeated over all possible interval lengths from $n=10$ to $n=256$. Typically, *F* increases with interval length *n*. A power law is expected, as:

$$F \propto n^{\alpha} \quad (3)$$

Where α is expressed as the slope of a double logarithmic plot of *F* as a function of *n*. $1/f$ fluctuations are revealed by exponents α close to 1, and uncorrelated series by exponents close to 0.5.

The ARMA/ARFIMA modeling procedure was then applied, a method that allows statistically attesting for the effective presence of long-range dependence in the series (16). This method consists of fitting 18 models to the series, 9 ARMA models and 9 ARFIMA models, the latter differing from the former by the inclusion of a fractional integration parameter. The method selects the best model based on a goodness-of-fit criterion (Bayesian Information Criterion) based on a trade-off between accuracy and parsimony. Two complementary criteria were used for attesting for the presence of long-range correlations: (i) the number of series that were better fitted by an ARFIMA rather than an ARMA model; and (ii) the mean sum of weights captured by ARFIMA models (the weight of a model is derived from the value of the goodness-of-fit criterion and represents the probability that this model was the best among the 18 candidate models for a given series). Torre et al. (16) proposed to accept the hypothesis of long-range correlation if at least of 90% of analyzed series are best fitted by an ARFIMA model, and if the mean sum of ARFIMA weights exceeds 0.90. The fitting of models was conducted using the ARFIMA package (17) for the matrix computing language Ox (18).

Results

The results of these analyses are presented in Table. As previously evidenced in many papers (3, 4), stride interval series presented exponents α close to 1, suggesting the presence of strong long-range correlations. In contrast, relative phase presented low exponents, close to 0.5, suggesting rather low levels of serial correlation in the series.

Table. Analysis of Stride Interval Series During Walking at Different Speeds

	Walking Speed			
	Slow	Preferred	Fast	Transition
α DFA				
Relative phase	0.64	0.71	0.61	0.58
Stride intervals	0.84	0.81	0.91	0.93
Mean ARFIMA weight				
Relative phase	0.86	0.72	0.82	0.94
Stride intervals	0.95	0.93	0.75	0.74
ARFIMA as the best model				
Relative phase	8/11	5/11	7/11	11/11
Stride intervals	11/11	10/11	8/11	7/11

Series were analyzed with the detrended fluctuation analysis that measures the strength of correlations in the series and by the ARMA/ARFIMA modeling procedure that assesses the effective presence of long-range correlation in the series.

ARFIMA modeling, however, gave a completely different picture (Table). Stride interval series presented a convincing indication for the genuine presence of fractal correlation only at slow and preferred speeds, with the mean ARFIMA weights superior to 0.90 and most series being best fitted by ARFIMA models. At fast and transition speeds, in contrast, ARFIMA modeling did not allow to clearly attest the presence of long-range correlations in stride interval series.

On the other hand, one could observe that relative phase, at transition speed (which presented the lowest α exponent), presented a very high mean ARFIMA weight, and all series were best fitted by ARFIMA models.

Discussion

Discussing the details of these results, in terms of the evolution of serial correlations when approaching the transition speed in walking, is out of the scope of the present paper. We would like to restrain our present message at a methodological level.

Often researchers limit their investigations to the application of classical methods, such as spectral analysis or DFA, and are satisfied by the obtaining of results suggesting the presence of long-range correlations in the analyzed series (i.e., a slope close to −1 in the log-log power spectrum or a slope close to 1 in the DFA diffusion plot). These methods, however, allow testing for the presence of serial correlations in the series, but not for the effective presence of long-range correlations. As stated by Wagenmakers and colleagues (19), the presence of (short- or long-range) correlations in an empirical series is more the rule than the exception, and a relevant null hypothesis for testing for the presence of long-range correlations should consider the possible short-range nature of serial correlation. This is the null hypothesis that is tested by the ARFIMA/ARMA procedure we used in the present experiment. In contrast, the null hypothesis accounted for by DFA or spectra analysis is that of the absence of correlation in the signal.

Generally, one accepts the assumption that the strength of correlations in a series reflects the presence of long-range correlations. The present paper suggests that the results provided by fractal analyses should be interpreted with caution. 1/*f* fluctuations could be contaminated by various short-range correlated processes, and such a result could be misinterpreted and lead to erroneous conclusions. Our experimental results show that sometimes systems can present the moderate levels of effective long-range correlations, whereas in others cases, series can present high correlation levels without being long-range correlated. Measuring the strong correlations in a series does not guarantee that these correlations are long-range in nature.

Conclusions

Time series analyses and, especially fractal methods, are currently particularly appealing for researchers. These approaches allow revealing the new properties of the systems under study and questioning traditional theories. The fractal framework, considering 1/*f* fluctuations as an optimal compromise between order and disorder, suggests the adoption of new points of view concerning various key topics, including health, adaptability, flexibility, or learning. These methods can appear easy to apply and their results easy to interpret in terms of deviation from the optimal 1/*f* noise. However, a number of methodological points remain in debate, and a deeper theoretical elaboration seems to be necessary in order to avoid erroneous interpretation.

Statement of Conflict of Interest
The authors state no conflict of interest.

Kompleksiškumas, koordinacija ir sveikata: siekiant išvengti klaidingų interpretacijų fraktalinėje analizėje

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Raktažodžiai: fraktaliniai svyravimai, 1/f triukšmas, stabilumas, sveikata, kompleksiškumas.

Santrauka. *Įvadas ir tyrimo objektas.* Fraktalų svyravimų analizė itin populiarėja dėl glaudaus ryšio tarp sveikatos, gebėjimo adaptuotis ir ilgalaikės koreliacijos. 1/f triukšmas yra laikomas „magiškąja" riba, apibūdinančia optimalų funkcionavimą, sumažėjimą arba atvirkščiai – nagrinėjamų požymių koreliacijų padidėjimą, atitinkamai esant 1/f triukšmui, reiškiantį tam tikrą sistemos deadaptaciją. Tačiau empiriniai duomenys turėtų būti aiškinami atsargiai. Eksperimentinėse sekose nuosekli koreliacija dažnai atskleidžia kompleksinę struktūrą, sąlygojamą ilgalaikių ir trumpalaikių koreliuojamųjų procesų. Įrodome, kad padidėjusi nuosekli koreliacija negali būti tiesiogiai prilyginama padidėjusiai ilgalaikei koreliacijai.

Tirtųjų kontingentas ir tyrimo metodai. 11 dalyvių atliko keturias ėjimo serijas keturiais individualiai nustatytais greičiais (lėtas, patogus/optimalus, didelis ir kritinis). Kiekviena skirtingo greičio serija sudaryta iš 512 žingsnių intervalo. Nagrinėjamų sekų koreliacijos stiprumas buvo matuojamas betrendės fliuktuacinės analizės (DFA) metodu. 1/f svyravimas buvo išbandytas, panaudojant ARFIMA modelį.

Rezultatai. Nagrinėjamų sekų koreliacijų stiprumas didėjo atitinkamai didėjant ėjimo greičiui. Tačiau, panaudojus ARFIMA modelį, nustatyta, kad ilgalaikė koreliacija patikimai stipri tik esant lėtam ir patogiam/optimaliam ėjimo greičiams.

Išvados. Koreliacijos stiprumas, matuojamas klasikiniais metodais, negali būti laikomas patikimu ilgalaikės koreliacijos prognozavimo požymiu. Kartais sistemos gali išreikšti vidutinio stiprumo lygio ilgalaikę koreliaciją, o kitais atvejais nagrinėjamose sekose gali būti nenustatyta ilgalaikė koreliacija, tačiau gali atitikti stiprią koreliaciją.

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