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Long-range correlation properties in motor timing are individual and task specific

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Abstract $1/f^{\beta}$ noise represents a specific form of (long-range) correlations in a time series that is pervasive across many sensorimotor variables. Recent studies have shown that the precise properties of the correlations demonstrated by a group of test participants may vary as a function of experimental conditions or factors characterizing the group. Our purpose in the present study was to clarify whether long-range correlations affect sensorimotor performance generally or in a task-specific manner and whether each individual produces characteristic long-range correlations that are reliable across several runs of the same task. We analyzed the series of time intervals produced by 43 participants in two timing tasks: unimanual rhythmic tapping and circle drawing. We found that a participant's $1/f^{\beta}$ properties in tapping were not related to the $1/f^{\beta}$ properties in circle drawing. However, within each task, individual differences were reliable, and a Cronbach's alpha of .59 showed a high degree of within-subjects reproducibility of the long-range correlations. Thus, long-range correlations represent a consistent and distinctive characteristic of individuals performing a particular task, rather than a ubiquitous generic property of sensorimotor time series. The implications of these results are discussed from both a theoretical and a methodological perspective.

Keywords $1/f$ noise · Individual characteristic · Reproducibility · Serial long-range correlation · Timing

In sensorimotor experiments conducted in psychology or behavioral neurosciences, the response of an individual is often assessed over several iterations under similar experimental conditions. Such series of repeated performances are likely to be correlated, meaning that the performance at time *t*, or iteration number *n*, is related to the previous responses. Actually, uncorrelated fluctuations appear to be more an exception than the rule (Slifkin & Newell, 1998). A vibrant interdisciplinary literature has shown that serial correlations in a number of variables are not transient (i.e., the current response being dependent on the few immediately preceding responses) but persist over a long time (i.e., the current response depends on the whole "history" of the series). Such so-called *long-range correlations* have been observed in a number of various systems and behaviors, including, for example, human self-esteem (Delignières, Fortes, & Ninot, 2004), reaction time (Van Orden, Holden, & Turvey, 2003), word naming (Kello, Anderson, Holden, & Van Orden, 2008), rhythmic movement timing (Gilden, Thornton, & Mallon, 1995), rhythmic coordination (Torre, 2010; Torre & Delignières, 2008), repetitive force production (Sosnoff, Valantine, & Newell 2009; Wing, Daffertshofer, & Pressing, 2004), gait (Hausdorff, Peng, Ladin, Wei & Goldberger 1995), and heart rate (Peng, Havlin, Stanley, &

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Goldberger, 1995), as well as neural activity (Linkenkaer-Hansen, Nikouline, Palva, & Ilmoniemi, 2001).[1] In such time series approaches, participants have to produce uninterrupted sequences of repeated performances at regular time intervals (e.g., answering a questionnaire for self-esteem twice a day for 512 days, producing force pulses every 3 s for 250 times, etc.). Researchers are then interested in the information that the measure-to-measure dynamics contain about the underlying system. In general, it is considered that long-range correlations are a universal statistical property that emerges from complex systems (i.e., systems with multiple interdependent components ranging between the microscopic and macroscopic levels and acting at multiple time scales) allowed to fluctuate on their own (Kello, Beltz, Holden, & Van Orden, 2007, Van Orden et al., 2003).

Long-range correlated series belong to the family of *fractal* processes. Such processes are composed of a (theoretically) infinite continuum of high-frequency and low-amplitude fluctuations nested within low-frequency and high-amplitude fluctuations. This specific so-called *scaling* structure entails persistent long-range correlations in the time series. Basically, the term *long-range correlation* refers to the presence of positive autocorrelations that remain substantially high over large time lags, so that the autocorrelation function of the series exhibits a slow asymptotic decay, (theoretically) never reaching zero. The strength or persistence of the long-range correlations contained in experimental time series can be assessed by several well-established methods (e.g., power spectral analysis, detrended fluctuation analysis, rescaled range analysis). In this family of long-range correlated, or fractal, processes, $1/f$ noise represents a specific process at the frontier between stationary[2] and nonstationary time series. $1/f$ noise is defined by an inverse-proportional relationship between the amplitudes and the frequencies of the fluctuations that compose the series. When applying power spectral analysis, this serial structure yields a typical linear regression in the bilogarithmic spectrum, with a slope close to 1. Usually, researchers adopt the notation $1/f^{\beta}$ noise, where β (the spectral index) corresponds to the negative of the slope in the log-log power spectrum. While β equals 1 in the strict definition of $1/f$ noise (the relationship between frequencies and amplitudes of fluctuations is inversely proportional), researchers generally consider a broader definition of $1/f^{\beta}$ noise, for $0.5 < \beta < 1.5$ (e.g., Koverda & Skocov, 2000; Milotti, 1995). This means that the persistence of correlations can vary within the category of $1/f^{\beta}$ noise: The higher β is, the more persistent the long-range correlations are. Note that the spectral index β corresponds to the specific exponents provided by the alternative methods of analysis (e.g., detrended fluctuations analysis) through simple linear relationships.

While $1/f^{\beta}$ noise or long-range correlations are found almost everywhere, their behavioral significance remains unclear. The literature provides some evidence for the fact that long-range correlation properties may change as a function of the context of performance of a task (e.g., synchronization to acoustic or visual stimuli, Chen, Ding, & Kelso, 2001; running at different speeds, Jordan, Challis, & Newell, 2007), and as a function of different group-matching factors (e.g., age, Iyengar, Peng, Morin, Goldberger, & Lipsitz, 1996; pathology, Goldberger et al., 2002, Hausdorff et al., 1997). However, to our knowledge, only one study in the area of cognition and motor behavior has addressed the question of interindividual differences (Madison, 2004), and no study has addressed the combined influence of the task and the individuals. Therefore, we ask a very simple question in the present article. Do individuals demonstrate characteristic long-range correlations that affect sensorimotor performance very generally or in a task-specific manner? This is an issue of the reproducibility or reliability of long-range correlation properties—that is, the extent to which the serial correlation structure demonstrated by an individual producing a series of repeated performances for a given task represents (or predicts) the structure of the fluctuations in another series for the same task and for a different task.

There are two major implications concerning whether the reliability of long-range correlations is individual or task specific. The first implication has to do with the experimental designs used to investigate psychological functions and dysfunctions from the perspective of serial long-range correlations. Indeed, common statistical analyses rely on the assumption that the individuals who constitute an experimental group do not significantly differ with respect to the long-range correlation properties they demonstrate. For instance, clinical studies contrasting independent groups have shown that the long-range correlation properties in the variables under focus allow discrimination between healthy participants and patients for several pathological dysfunctions (e.g., heartbeat intervals in cardiac failures, Iyengar et al., 1996; stride intervals in Huntington's disease, Hausdorff et al., 1997; reaction times in attention deficit disorders, Gilden & Hancock, 2007). In such

[1] Event-based timing, associated with discontinuous movements, is thought to involve an effector-independent representation of the time intervals to produce; the cognitive events that delimit the successive intervals trigger the motor responses. Emergent timing, associated with continuous movement, is assumed to not involve such a hierarchical organization; temporal regularity emerges from the intrinsic dynamics of the effector system, with the modulation of some (not directly temporal) parameters, such as the oscillator's stiffness.

[2] A time series is deemed perfectly stationary if its mean and variance do not change over time. On account of the persistent positive of correlations, long-range correlated series exhibit locally persistent trends and can be considered to be *weakly* stationary (Brophy, 1968).

clinical approaches, assessing the power of prediction of serial correlations about the future occurrence or evolution of disease is among the promising lines of research on long-range correlation properties. In this view, investigating the fine interindividual differences, instead of studying the long-range correlations in groups matched on a given pathology, might help improve the predictive power of long-range correlations that characterize the clinical evolution of the patient.

The second implication of the present work relates to basic choices in the approach to theories and models for studying serial performance. Indeed, depending on the research questions and the different levels of observation adopted (e.g., analyzing different macroscopic and/or microscopic variable(s) and their possible relationships), several investigations have drawn different conclusions about the processes and systems' organization that are considered to underlie long-range correlations in behavior. Currently, it is not clear to what extent one should consider that the long-range correlation is a universal product of complex systems (whatever their nature) or that long-range correlations can be generated by multiple processes and organizations specific to each task, individual, system, and so forth and, as such, deserve somewhat unique accounts (Torre & Wagenmakers, 2009).

To address whether long-range correlations are reliable and/or task specific, we used a very simple timing experiment comprising two unimanual rhythmic movement tasks that differed only in the motor execution modalities: rhythmic tapping (i.e., discontinuous movements) and rhythmic circle drawing (i.e., continuous movements). Despite their apparent similarity, these two tasks are known to involve distinct timing processes—event-based timing, associated with discontinuous movements, and emergent timing, associated with continuous movements—that differ with respect to the forms of interplay between the information used for temporal regulation and the motor implementation (see note 1). Consistent evidence for this distinction has been provided by neurophysiological and behavioral studies (e.g., Delignières, Lemoine, & Torre, 2004; Ivry, Spencer, Zelaznik, & Diedrichsen, 2002; Spencer, Zelaznik, Diedrichsen, & Ivry, 2003; Zelaznik, Spencer, & Ivry, 2002) and allows for the strong assumption that performance in the two tasks is driven by different neuropsychological processes. We expected to find that both the tasks and the individual participants significantly affect the long-range correlation properties. Independence of these two factors would support the hypothesis that individuals have characteristic long-range correlation properties that may affect movement and cognition very generally. In contrast, obtaining an effect of interaction between the two factors would signify that the long-range correlation properties are characteristic of an individual performing a specific task.

Method

Participants Forty-three college-aged (18–23 years) volunteers (25 men and 18 women) took part in the experiment. All of them were undergraduate students and were recruited via the introductory psychology research participation for course credit program. The informed consent procedures were approved by the Purdue University Committee for the Use of Human Research Subjects (IRB).

Apparatus The apparatus consisted of a 79-cm-high wooden table, upon which a standard letter size (8.5 × 11 in.) piece of paper was placed 5 cm from the edge of the table, relative to where a participant sat. The sheet of paper contained a circle (7.5-cm diameter). A small (1-cm diameter) target zone was printed on the circle at the point farthest away from the participant (12 o'clock). A plastic transparency sheet was taped over the paper. For the circle-drawing timing task, the participants traced circles using a 2 H wood drawing pencil. One receiver (23 × 13 × 11 mm) from a Polhemus Liberty-8 magnetic motion capture system was placed 1 cm above the writing tip of the pencil. For the tapping timing task, a receiver was taped to the nail of the index finger.

For the synchronization phase of each run, a wave file was generated by MATLAB® to produce a series of 20-ms 800-Hz "beeps." The stimulus offset asynchrony was 480 ms, yielding a 500-ms period between tone onsets.

Tasks and procedure Participants were required to produce sequences of regularly timed movements, using their dominant hand, under two experimental conditions. The required movement frequency was 2 Hz (500-ms time intervals). The first task consisted of producing repetitive taps on the table, using the index finger. The second task consisted of drawing circles smoothly and continuously by following the circular template with the pencil; emphasis was put on regular movement timing, rather than on spatial accuracy of the circle shape. Both timing tasks were performed using the synchronization-continuation paradigm. For each task there were 16 beeps, spaced 500 ms apart, following which the participant continued to tap/draw circles for a period long enough to produce at least 550 time intervals. For the tapping task, participants had to tap their index finger down in synchrony with the metronome beat. For the circle-drawing task, they were instructed to pass the pencil through the target zone on the beat. Participants performed nine runs for each of the two tasks.

The experiment was divided into two separate sessions conducted over 2 days. Participants performed nine runs (i.e., synchronization-continuation timing sequences) per session. A break of 5 min was administrated between the successive runs. Tapping was always performed first in a session. Half the participants performed five runs tapping and four runs circle drawing in session 1 and four runs tapping and five runs of circle drawing in Session 2. The other participants performed the tasks in the reverse order.[3]

Data analysis Because of failings in the recording that occurred for a few participants, we discarded the first and last runs performed in each task so as to homogenize the variance of the experimental data available for all the participants. We trimmed the continuation portion of the time series so that each run analyzed had 512 time intervals. These 512 intervals constituted the middle portion of the continuation time series. For each series, we computed the mean and standard deviation.

To assess the long-range correlation properties, we used the detrended fluctuation analysis (DFA) in a standard way (for details on the method, see Peng et al., 1993). The DFA exploits the diffusion properties of the time series, assessing the relationship between the mean amplitude of fluctuations and the size of the window within which the fluctuations are observed. Basically, the series is first integrated and divided into nonoverlapping intervals of equal lengths. After a linear detrending within each interval is considered, the mean standard deviation $F(n)$ is determined. This computation is repeated and averaged for all possible interval lengths n ranging between 10 and 256 points. For fractal series, a power relationship between $F(n)$ and n, characterized by a scaling exponent $\alpha \in [0, 2]$, is expected. The results of the analysis are represented in a so-called diffusion plot [$\log(F(n))$ as a function of $\log(n)$]. A linear diffusion plot is thus expected, and α is given by the slope of the regression line. For $\alpha \in [0, 1]$, the series can be considered fractional Gaussian noises (i.e., stationary series), and for $\alpha \in [1, 2]$, the series are fractional Brownian motions (i.e., nonstationary series). "Perfect" $1/f$ noise corresponds to $\alpha = 1$. According to the current definition of $1/f^{\,\beta}$ noise in the literature, and given the linear relationship that exists between the spectral indexes β and the exponents provided by DFA, series can be considered to contain $1/f^{\,\beta}$ noise, or persistent long-range correlations for α ranging from 0.75 to 1.25.

The aim of our statistical design was to assess the respective effects of the task (is there a significant difference between the mean α exponents obtained for the two experimental tasks?) and the participants (do the different participants yield specific mean exponents?) and the possible interaction between the two factors. Therefore, we used a two-way task (2)×participant (43) ANOVA, with repeated measures on the second factor. In this design, the seven runs performed by each participant on each task are considered as statistical "subjects" in order to provide each cell (1 participant in one task) with the variance required for the analysis. Since the two tasks are assumed to be responsible for the generation of specific levels of α, this statistical design considers that the task effect expresses repeatedly in the performances of the 43 participants. That is, each participant represents one of the 43 levels of the repeated measures factor participant. This design is reversed with respect to classical repeated measures ANOVAs, where the characteristics of each participant express repeatedly at different times. Finally, the reproducibility of the long-range correlation properties demonstrated by the participants was assessed by the Cronbach's alpha coefficient.

Results

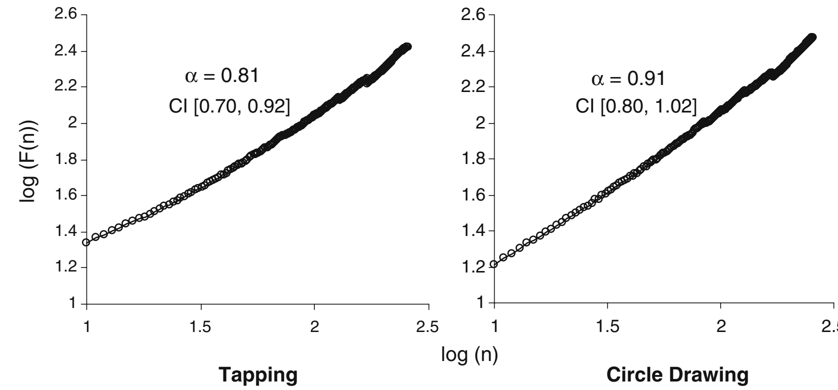
The mean of the series of produced time intervals was 497 ms (SD = 33) and 497 ms (SD = 36) in the tapping and circle-drawing tasks, respectively. The mean standard deviation was 33 ms (SD = 10) and 26 ms (SD = 9), respectively.

DFA yielded a mean α exponent of .81 (±.16) for tapping and .91 (±.17) for circle drawing. Figure 1 displays the averaged diffusion plots obtained in tapping and circle drawing. The ANOVA on the α exponents showed significant main effects for both the task, $F(1, 12) = 71.012$, $p < .001$ (see Fig. 2), and the participant, $F(42, 504) = 2.948$, $p < .001$, factors. The long-range correlations were stronger in the circle-drawing than in the tapping task, and the strength of correlations also varied across individuals. Moreover, the interaction between task and participant was significant, $F(42, 504) = 1.994$, $p < .001$. A Fisher's LSD post hoc test showed that 269 of 903 (i.e., 30% of the total number) of the interindividual differences were significant. Figure 2 illustrates the interaction effect; it displays the mean α exponents demonstrated by the participants in tapping and circle drawing, as well as the dispersion around the mean α of the individual exponents obtained for the seven runs on the two tasks. Figure 3 illustrates the resemblance of the time intervals series produced by the same participant and the difference between the series produced by different participants on the same task.

For an alternative way to understand the interaction effect, we conducted two complementary analyses. First, we tested for linear correlation between the mean individual α exponents in tapping and circle drawing. As is shown in Fig. 4, there was no significant correlation, r = .19, 95% CI [0.11, 0.51], p = .214, between the long-range correlation properties demonstrated by the participants in

[3] Keele and Hawkins (1982) argued that because there will be order effects across practice, the practice order should be fixed so that individual-difference correlations are not masked by order effects. Moreover, Zelaznik and Rosenbaum (2010) showed that the order of tasks does not change the correlation pattern in a significant fashion.

Fig. 1 Averaged diffusion plots and the corresponding mean α exponents obtained with the detrended fluctuation analysis for the series of time intervals produced in tapping (left) and circle drawing (right). The values in brackets show the 95% Masson and Loftus within-subjects confidence intervals



the two tasks. Second, we computed the percentages of total variance in the set of α exponents that were accounted for by the task and the participant factors separately and by the joint effects of the two factors. The maximum variance in the exponents was accounted for by considering the individuals performing a specific task; indeed, 8.16% of the variance was accounted for by the task factor alone, 15.74% by the participant factor alone, and 34.55% by the combination of the two factors.

Finally, we evaluated the reproducibility of the exponents across the repetitions performed by the participants in each of the two tasks. The Cronbach's alpha was .56 in tapping and .61 in circle drawing (M = .59).

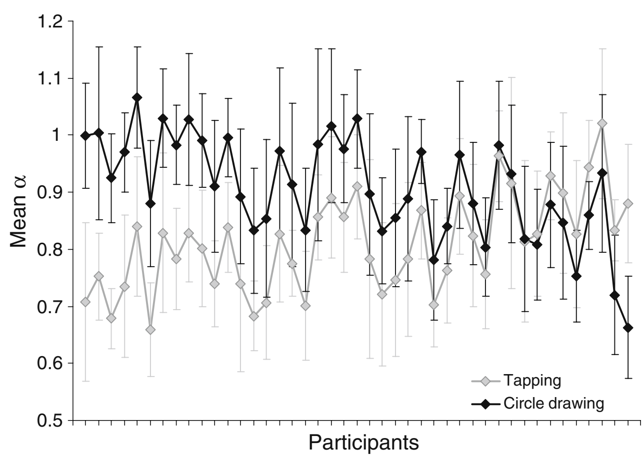


Fig. 2 Average α exponents obtained per participant in tapping (gray) and circle drawing (black). This figure illustrates our statistical results. To facilitate the reading of the figure, the participants were ordered along the individual mean differences (mean $\alpha_{\text{Circle drawing}}$ mean α_{Tapping}). The error bars represent confidence intervals. In particular, one can observe the following. (1) The exponents obtained in circle drawing are globally higher than those obtained in tapping. (2) The participants produce specific levels of serial correlations, as indicated by the matching shapes of the two curves. For example, participant 5 produces globally higher α exponents than does participant 6. (3) The hierarchy of the α exponents produced by the 43 participants differs between tapping and circle drawing, since, for example, participant 41 shows the highest mean α in tapping, while participant 5 shows the highest mean exponent in circle drawing. Moreover, the crossing of the two curves shows that some participants produce higher α exponents in circle drawing than in tapping, while other participants do the opposite. This interaction between the participant and task effects is confirmed by the absence of significant correlation between the α exponents obtained in tapping and circle drawing

Discussion

We discovered that the long-range correlations produced are individual specific. Within a task, individuals differ in their long-range correlation behavior, and the long-range correlations are reliable. However, the individual differences in the time series generated by the circle-drawing timing task are not the same as those in the tapping timing task. In other words, the $1/f^{\beta}$ phenomenon is also task specific. Following a short discussion specific to the present results, we lay out some methodological, theoretical, and clinical considerations deriving from our findings.

Although the goal of the two tasks was basically the same (producing a regular series of time intervals), the different processes of timing and executing the movement affected the sequential structure of the timing performances. Our participants constituted a random sample from a population of individuals who could not have been distinguished with respect to any specific criterion relative to their timing ability. However, the analysis showed that the individuals could be consistently differentiated with respect to their long-range correlation properties. Madison (2004) showed an effect of the participants on the serial correlation properties obtained on a tapping task, but this result does not allow determining whether the long-range correlation captures a general purpose nature of the participants cognitive–motor organization or whether processes are assembled in a unique fashion for each individual performing on a particular task. In the present study, the effect of interaction between the task and the participants indicates that, although there were significant interindivid-

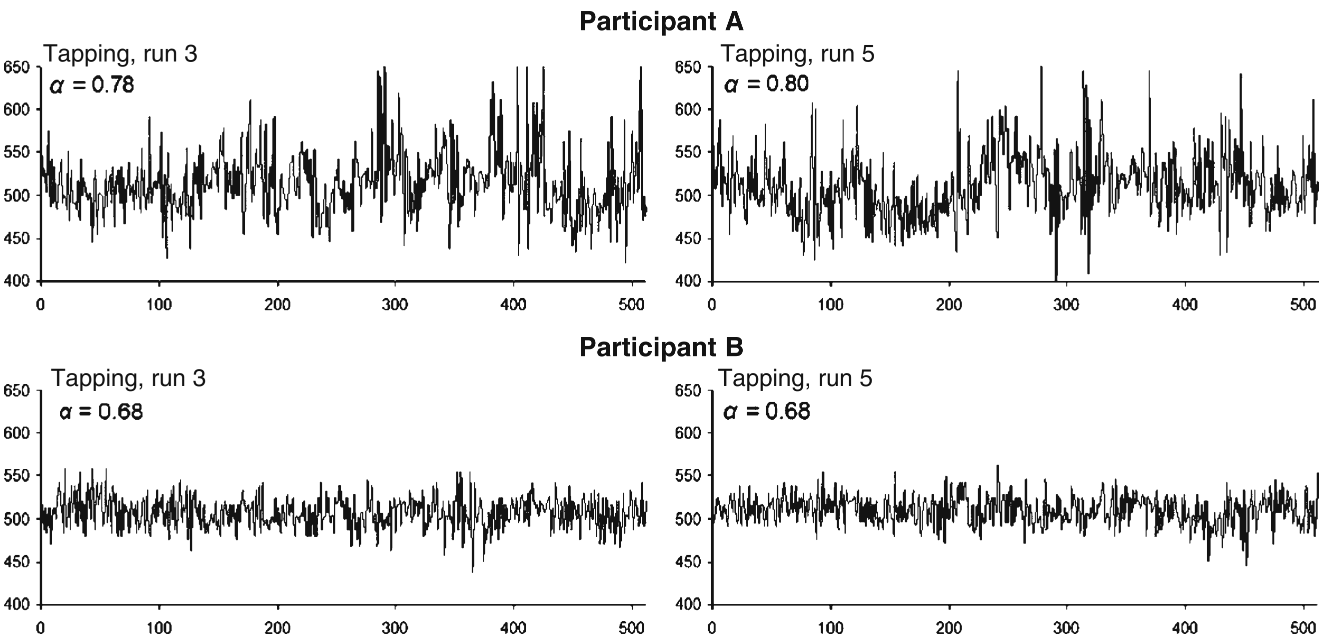


Fig. 3 Example of time interval series produced by 2 participants in the tapping task. The figure illustrates the interindividual differences and within-individual consistency of the serial correlations produced. Within the same task, two timing series produced by the same participant exhibit very similar correlation structures (characterized by similar α exponents), while the structure differs (dissimilar α) between the series produced by different participants

ual differences in the long-range correlation properties produced, these differences were not consistent across the two tasks. This result thus supports the idea that the long-range correlations observed emerge from a unique assembly of cognitive–motor processes for each individual performing on a particular task, instead of reflecting some general characteristic of individuals. Accordingly, we suggest that to account for the maximum variance within a set of long-range correlation properties obtained from any given experiment, researchers should consider the individuals performing a specific task. Finally, we obtained a Cronbach's alpha of .59 that demonstrates a consistent within-subjects reproducibility of the long-range correlations in serial performance. This intraindividual consistency was measured over 2 days in the present experiment, which allows one to consider our results with confidence. All in all, our results converge to support the idea that empirical long-range correlations represent a consistent characteristic of individuals performing within a particular task, but this "signature" is not generic across tasks.

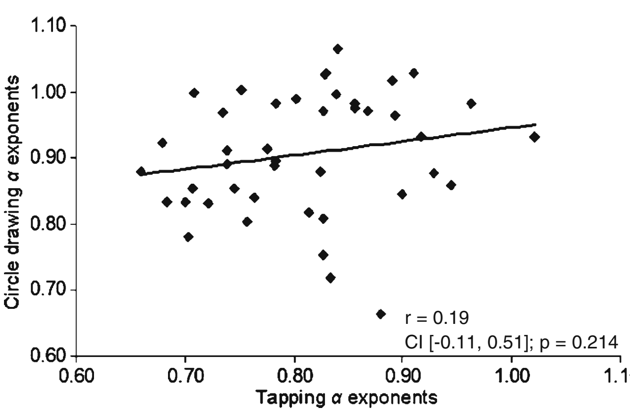


Fig. 4 Correlations between the individual average α exponents demonstrated in the tapping and the circle-drawing tasks, showing the absence of a significant correlation

There are methodological issues that one needs to consider when dealing with data that might exhibit long-range correlations. It is important to note that use of DFA makes certain assumptions about homoscedasticity (finiteness of variance) and monofractality (as opposed to multifractality—i.e., multiple scaling regimes contained in the time series) in the data. Recent work by Ihlen and Vereijken (2010) has shown that distributions such as the ones reported in the present study might not satisfy the above-mentioned requirements for using DFA. The value of the α exponent calculated using our methods could be considered an aggregation, or average estimation, of multiple scaling exponents of the series. One would expect the consistency of the intraindividual long-range correlation properties to be lower using multifractal methods. Applying more sensitive multifractal methods might help future investigations to unravel the multiple factors that are likely to influence the long-range correlation properties produced. Without a specific hypothesis about the influence of such factors, however, the estimations provided by DFA represent an appropriate level of analysis.

On a more theoretical level, the intraindividual consistency of long-range correlation properties could be interpreted in terms of generic *regulatory behavior* implemented by each participant in the two different timing tasks. For instance, a consistently high α exponent in 1 participant might reflect a general tendency to perform more unsystematic and delayed corrections in maintaining the time intervals, as opposed to a participant with a consistently low α. Indeed, late regulations would imply that the time interval values are allowed to drift to a greater extent before being corrected. Consequently, the time series would present larger persistent trends, resulting in a higher α exponent. However, the interrun variation of the long-range correlation properties observed for 1 participant is determined by numerous individual-specific factors that may influence the timing sequence produced (e.g., cardiac or respiratory rhythms, attentional focus fluctuating between the temporal and spatial accuracy demands of the task, "cognitive" strategies to maintain a regular rhythm, neuromuscular and proprioceptive factors). Testing the influence of multiple factors that contribute to the overall long-range correlations across individuals and tasks will be an important future research avenue.

Finally, pertaining to more clinical considerations, we see that beyond the gross classification of time series as $1/f^{\beta}$ noise, the fine variations of long-range correlations appear to be very specific to the particular system dynamics, codetermined by the task constraints and individual dispositions. This finding suggests that focus on notions such as effort (e.g., Correll, 2008), stress, habits, or expertise (e.g., Wijnants, Bosman, Hasselman, Cox, & Van Orden 2009), which directly specify the particular relationship between a given individual and a given task, might provide very useful contributions to the understanding of long-range correlations in human performance. Clinical studies have shown that serial long-range correlation properties can help distinguish between groups of healthy participants and patients in the context of cardiac or neurobehavioral pathologies (e.g., Gilden & Hancock, 2007; Hausdorff, 2009; Iyengar et al., 1996). Some researchers have even argued for the potential predictive power of long-range correlation properties about particular health risks (fall risk in elderly persons, occurrence of heart attack; see Herman, Giladi, Gurevich, & Hausdorff 2005; Mäkikallio et al., 2001). The present results open new perspectives in this direction when one considers that the fine interindividual differences and/or differential evolutions of the long-range correlation properties before any apparent dysfunction might help in identifying individual predispositions to develop given pathologies.

In conclusion, in this study, we have shown the combined influence of the task and the individuals on the long-range correlation properties in serial performance. Our results support the idea that the long-range correlations specifically capture the dynamics that arise from the particular interaction between a participant and the situation in which the participant is performing. The correlation properties of a participant in one task do not allow for predicting the correlations for a different participant or another task. From this perspective, the challenge of future investigations will be more in the direction of how to explain and model the individual-specific long-range correlation (or $1/f^{\beta}$) properties than of how to model the long-range correlations themselves.

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