Fractal properties and short-term correlations in motor control in cycling: influence of a cognitive challenge

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ABSTRACT

Fluctuations in cyclic tasks periods is a known characteristic of human motor control. Specifically, long-range fractal fluctuations have been evidenced in the temporal structure of these variations in human locomotion and thought to be the outcome of a multicomponent physiologic system in which control is distributed across intricate cortical, spinal and neuromuscular regulation loops.

Combined with long-range correlation analyses, short-range autocorrelations have proven their use to describe control distribution across central and motor components.

We used relevant tools to characterize long- and short-range correlations in revolution time series during cycling on an ergometer in 19 healthy young adults. We evaluated the impact of introducing a cognitive task (PASAT) to assess the role of central structures in control organization.

Autocorrelation function and detrending fluctuation analysis (DFA) demonstrated the presence of fractal scaling. PSD in the short range revealed a singular behavior which cannot be explained by the usual models of even-based and emergent timing.

The main outcomes are that (1) timing in cycling is a fractal process, (2) this long-range fractal behavior increases in persistence with dual-task condition, which has not been previously observed, (3) short-range behavior is highly persistent and unaffected by dual-task.

Relying on the inertia of the oscillator may be a way to distribute more control to the periphery, thereby allocating less resources to central process and better managing additional cognitive demands. This original behavior in cycling may explain the high short-range persistence unaffected by dual-task, and the increase in long-range persistence with dual-task.

1. Introduction

There is growing evidence that the neurophysiological coordination of human motor control can be meaningfully viewed as a dynamic system exhibiting complexity in its timing behavior (Costa, Goldberger, & Peng, 2002; Diniz et al., 2011; Goldberger et al., 2002; Marmelat & Delignières, 2012). As such, human motor control is characterized by emergent dynamical properties that could hardly be understood by only studying the system's different parts in isolation (Dingwell, John, & Cusumano, 2010; Stergiou & Decker, 2011; Warlop, Detrembleur, Stoquart, Lejeune, & Jeanjean, 2018). The coordination among multiple components and at multiple system levels is thought to be at the origin of the complex fractal behavior in signal outputs (Marmelat & Delignières, 2012).

The presence of fractal dynamics implies that control in such systems is distributed rather than localized in given parts (Wijnants, 2014). This is a consequence of the interdependence and cooperation of processes operating simultaneously at multiple timescales (Iyengar, Peng, Morin, Goldberger, & Lipsitz, 1996; Marmelat & Delignières, 2012). The arising absence of a characteristic timescale is considered as an advantage since the dominance of a unique timescale may be a sign of a restricted functional responsiveness, a lack of flexibility (Goldberger et al., 2002; Hausdorff, 2009). In this regard, the field of fractal physiology (Gilden, Thornton, & Mallon, 1995; Goldberger et al., 2002; West, 2010) has demonstrated a greater capacity than classically used reductionist methods to assess movement control strategy, by providing relevant complexity metrics (Eke, Herman, Kocsis, & Kozak, 2002; Nicolini, Ciulla, De Asmundis, Magrini, & Brugada, 2012; Whitacre, 2010; Gilfriche, Deschodt-Arsac, Blons, & Arsac, 2018).

An interesting link was established between signal output complexity and neurophysiological complexity. Especially, time series of rhythmic motor behavior have been characterized within the continuum between two stochastic processes (Mandelbrot & Van Ness, 1968): white noise and Brownian motion, the middle of the continuum being $1/f$ noise, also called fractal fluctuations (Tatom, 1995). In this formalism, cyclic movements exhibiting white noise may indicate no coordination in the supporting neurophysiological network. At the other end of the spectrum, Brownian motion is thought to mark a rigid, non flexible control since the system output widely deviates from its average temporal behavior. A coordinated system ensuring that timing rhythm is both robust and flexible is conceivably midway between a tight and a loose control. This statement has found strong support in experimental works in physiology (Iyengar et al., 1996; Torre & Wagenmakers, 2009; Tulppo et al., 2005), psychology (Gilden et al., 1995; Farrell, Wagenmakers, & Ratcliff, 2006; Pressing & Jolley-Rogers, 1997; Thornton & Gilden, 2005), and behavioral sciences (Nourrit-Lucas, Tossa, Zélic, & Delignières, 2015; Wijnants, 2014), all indicating that the temporal behavior of young and healthy systems exhibits fractal fluctuations. Aging, pathology or mental and mechanical constraints shift the system's temporal output towards less clear fractal properties (Wijnants, 2014).

The presence of fractal fluctuations in motor rhythm during human locomotion has been a matter of interest (Den Hartigh, Marmelat, & Cox, 2016; Den Hartigh, Marmelat, & Cox, 2018; Jordan, Challis, Cusumano, & Newell, 2009; Terrier & Dériaz, 2012). In pioneer works, stride-to-stride fluctuations during walking have been explored (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Hausdorff et al., 1996; Hausdorff, Zemany, Peng, & Goldberger, 1999), comparing fractal dynamics in healthy people to fractal dynamics in people with neurodegenerative diseases or facing different constraints (Hausdorff, 2007). Since then, researchers have paid more and more attention to fractal fluctuations (Stergiou & Decker, 2011). Fractal properties have usually been quantified using the 'scaling exponent' which places the analyzed signal in the monofractal continuum.

Further exploration of motor variability revealed that in many tasks, the overall temporal structure is not only characterized by a fractal component, but is also influenced by a short range component. This component has been shown to bring meaningful information on control organization (Gilden, 2001; Wijnants, 2014). The overall temporal structure is then a blend of a fractal process in the long range and another process in the short range. This short-range process has been explained in some specific motor tasks by the formalism of event-based *vs.* emergent nature of motor timing (Zelaznik, Spencer, & Ivry, 2002), a theory to explain timing generation processes (Delignières, Lemoine, & Torre, 2004; Huys, Studenka, Rheaume, Zelaznik, & Jirsa, 2008; Lewis & Miall, 2003; Spencer, Zelaznik, Diedrichsen, & Ivry, 2003; Torre, Balasubramaniam, & Delignières, 2010). Event-based and emergent timing are two distinct way to generate timing, relying respectively on an explicit cognitive (central) representation of timing and on an implicit bio-mechanical (peripheral) oscillator (Delignières & Torre, 2011; Lemoine, 2007; Delignières, Torre, & Lemoine, 2008). Previous studies have shown that the short-range correlation behavior can in some tasks mark a difference between both modes. As the short-range behavior have been explained by the reliance (or non-reliance) on the dynamical properties of the effector, movement continuity and inertia play a critical role in this range.

In recent years, fractal fluctuations have been observed in the timing of cycling (Warlop, Bollens, Crevecoeur, Detrembleur, & Lejeune, 2013). Cycling on a friction-loaded ergometer imposes a functional interaction between the neuromuscular system and the heavy rotating flywheel, which gives the global oscillating system a great inertia, a factor that could influence control design (Lemoine, 2007).

To better understand neurophysiological control distribution in cycling, the present study added a cognitive challenge to normal cycling. It has been shown for years that simultaneously performing a motor task and a mental task deteriorates performance in one or both tasks (Kang et al., 2009; Szturm et al., 2013). It has been expected that fractal properties could also be impacted by simultaneously performing a cognitive task (Gilden et al., 1995; Gilden, 2001). Yet, such impact is neither trivial nor consistent. Previous works on walking while performing a cognitive task reported either a decrease in fractal scaling exponent (Hausdorff, 2009; Lamoth et al., 2011; Tanimoto, Anan, Sawada, Takahashi, & Shinkoda, 2016) or no change at all (Bollens, Crevecoeur, Detrembleur, Warlop, & Lejeune, 2014; Grubaugh & Rhea, 2014; Hausdorff, 2009; Kiefer, Riley, Shockley, Villard, & Van Orden, 2009). More work is still needed to fully understand the impact of dual-tasking on the temporal structure of motor control output. As such, exploring cycling while adding a cognitive challenge may improve our understanding of neurophysiological control in human locomotion.

In the present work, we analyze short- and long-range fluctuations in cycling with and without a simultaneous cognitive task to better understand control distribution and identify the functional role of cognitive resources. We hypothesized that: (i) like in other locomotor systems, the temporal structure of cycling is fractal (Warlop et al., 2013), (ii) given the biomechanical constraints and the smoothness of the movement, cycling is characterized by positive short range correlations, (iii) a cognitive challenge affects the long-range fractal properties.
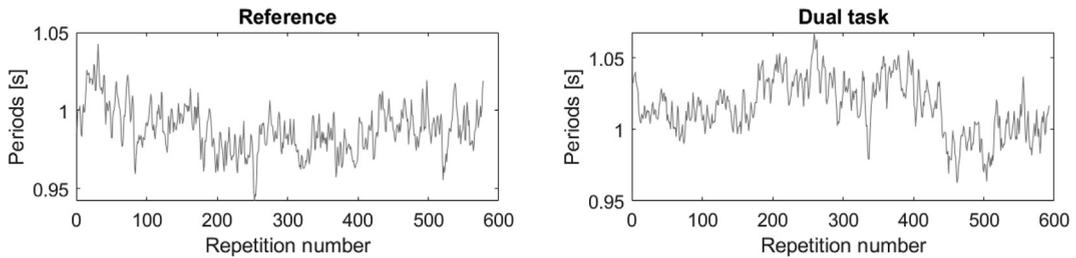
Fig. 1. Example of inter-cycle time series of one subject in normal (reference) and dual-task cycling.

2. Material and methods

2.1. Protocol

19 subjects (15 men and 4 women) aged 24.4 ± 2.7 years participated in the study and gave informed consent. They were asked to cycle on a friction-loaded cycle ergometer with light charge (50 W), for a total of 20 min: 10 min without performing any task (reference situation), and 10 min while performing a cognitive task (dual-task situation), in a randomized order. Each time, they first had to synchronize their pedaling with a metronome at 1 Hz during 1 min (not recorded) and were asked to continue at the same cadence after the metronome was turned off.

The "cognitive task" situation was a Paced Auditory Serial Addition Test (PASAT; Gronwall, 1977). PASAT recruits executive functions and requires attentional functioning, working memory and information processing speed. It has been suggested that the discrepancy in results obtained in fractal modification during dual-tasking in walking may be due to a poor choice of cognitive tasks; in order to avoid this problem here we selected PASAT because it is known to recruit prefrontal cortical networks (Lambourne, Audiffren, & Tomporowski, 2010), and hence to be able to interfere with the motor area (also frontal; Dietrich & Sparling, 2004).

In the PASAT, a list of numbers is given (one every 3 s here) and the subjects have to add the last number they heard to the previous one. The numbers were chosen randomly between 1 and 8 in a way that their sum was to be between 2 and 9. Participants listened to the instructions with earphones and answered aloud. They were informed that their answers were recorded, and the score of the cognitive task was defined as the percentage of good answers.

To record time intervals between pedal strokes, a lightmeter (Light Meter Pod, AD-Instruments) with sampling frequency 1 kHz detected the changes in light when the pedal passed by the sensor. Inter cycle intervals were then extracted using a semi-automated algorithm designed using Matlab 2018a (Mathworks). Examples of obtained time series for one subject are given in Fig. 1.

2.2. Data analysis

All the data were processed using Matlab 2018a (Mathworks), using functions we specifically designed to this end.

The data analysis techniques used here will be described below, and an overview is provided in Table 1.

The time intervals between pedal strokes, generally fluctuating around 1s (as the metronome heard during the first minute encouraged) were resampled at 1 Hz using a cubic spline for the DFA and PSD-based methods that will be developed below, so that the periods and frequencies could be properly expressed in s and Hz rather than respectively trial and inverse-trial numbers.

2.2.1. Long-range correlations

First, to robustly confirm the fact that in normal situation cycling contains fractal properties (Warlop et al., 2013), we visually controlled for the slow decay of the autocorrelation function, and the scaling exponent α was computed with DFA and checked to be close to 1.

Once the presence of long-range correlations is validated, the subtle variations of α can be properly used as a marker of variations in fractal properties.

Autocorrelation decay. The decay of the time series autocorrelation function was qualitatively observed up to lag 30 on the linearly-detrended signal (substraction of a linear fit of the whole signal).

Table 1
Overview of the data analysis methods used and their aim.

Focus	Method	Detects	Quantifies
Long range correlations	Autocorrelation decay	Yes	No
	DFA	Yes	Yes
Short range correlations	Lag-one Autocorrelation	Yes	No
	DWA	Yes	No
	$^{high}PSD_{we}$	Yes	Yes

Detrended Fluctuation Analysis. Detrended Fluctuation Analysis (DFA) is a method to analyze the fractal properties in a signal (Peng et al., 1994). It relies on the monofractal framework, which describes a continuum between white noise and brownian motion (Mandelbrot & Van Ness, 1968). This class of signals is said to exhibit "scaling" properties; a specific power law relation between a characteristic scale and the power in said scale. The power spectral density in such a signal then follows the relation: $P(f) \sim \frac{1}{f^\beta}$ (hence, $log(P(f)) \sim \beta \times log(f)$). DFA has been designed specifically to analyze this type of signals, it computes a scaling exponent α, which in the limit of perfect monofractals of infinite length, is linked to β by the relation $\alpha = \frac{\beta+1}{2}$. Signals described by α close to 1 ($\alpha \in [0.75, 1.25]$), are called 1/f noise, while $\alpha = 0.5$ describes white noise, and $\alpha = 1.5$ describes Brownian motion. DFA has been shown to give identical results as PSD analysis in long signals (Heneghan & McDarby, 2000), but has been preferred for shorter signals, or signals closer to 1/f noise (Delignières, Torre, & Lemoine, 2005; Delignières et al., 2006), that is why it has been preferred here for computing long-range correlations.

DFA algorithm contains several steps, detailed here for an initial signal x of size N:

1. The cumulated sum of the signal x is computed (without its mean to avoid a linear drift):
   $y(k) = \sum_{i=1}^{k} (x(i) - \bar{x})$
2. The time-series y is then divided into non-overlapping boxes of length n and in each box a straight line is fit to the data using least square approximation (representing the trend in each box). The signal constructed with these lines is called y_n.
3. After subtraction of the approximated signal, the root-mean-square fluctuation of the detrended time-series obtained is calculated by:
   $F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2}$
   Steps 2 and 3 are repeated for a range of n (usually for n = 4 to n = N/4).
4. In the case of a scaling phenomenon, F(n) increases with n as a power law:
   $F(n) \sim n^\alpha \Rightarrow log(F(n)) \sim \alpha \times log(n)$

The scaling exponent α is obtained by the slope of the line of $log(F(n))$ *vs.* $log(n)$ (or the line of $F(n)$ *vs.* n in a log–log plot, which is strictly equivalent). Throughout this article, log defines the base 10 logarithm (even though natural logarithm holds for most equations).

For the specific purpose of observing a possible crossover phenomenon, the time-series representing successive pedal-stroke durations, an irregular series by nature, was resampled in the present study at 1 Hz using a cubic spline interpolation. First DFA was computed on all box sizes and the shape of the residuals was studied after the linear fit of log(F(n)) *vs.* log(n). The shape of the residuals allows to check for statistical independence of the residuals, in order to decide on which scales a proper linear fit can be done (Fig. 3). DFA is then applied a second time only on the chosen box size range and the residuals of the linear fit are observed in order to check for the correctness of a linear model (Fig. 4).

It has been remarked that if all the integer values of n in a certain range are selected, a high concentration of data points will be regrouped in the large box sizes (due to the log plot), giving this zone excessive weight for the linear fit. To cope with that problem, box sizes were selected to be a geometric sequence, so that their log is an arithmetic sequence. This choice was made to follow recommendations of "evenly-spaced" DFA (Almurad & Delignières, 2016). The sequence was defined as follows:

- $n(1)$ is the minimum timescale
- $n(2) = n(1) + 1$
- for $i > 2$, $n(i) = n(i-1) \times \frac{n(2)}{n(1)}$ (values of n are then rounded to have integer values of box sizes)

2.2.2. Short-range correlations

Most methods to analyze short-range correlations in motor timing (Table 1) rely on the theoretical models event-based and emergent timing. It is useful to understand them to better understand the subsequent computational methods.

Event-based timing is mostly represented through the model of Wing and Kristofferson, or WK model, (Wing & Kristofferson, 1973; Wing, 1980), wherein each cycle duration is considered to depend on two factors: an internal central explicit timer, and a motor delay so that j-th interval, I_j, is:

$$I_j = C_j + M_j - M_{j-1}$$

where C_j is the j-th timekeeper's interval and M_j is the j-th motor delay.

In emergent timing it has been proposed that motor noise affects the entire period (Delignières et al., 2004), so that the intervals could be modeled using the following equation:

$$I_j = D_j + M_j$$

where D_j are the periods of a self sustained biomechanical oscillator. C_j and D_j are defined as fractal signals (Delignières & Torre, 2011) which dominate in the long range.

Lag-one autocorrelation. Consequently, event-based and emergent timing are often differentiated using lag-one autocorrelation: event-based timing has been associated with negative lag-one autocorrelation (due to the differentiated white-noise term above) while emergent timing possesses null or positive lag-one autocorrelation (due to the white-noise term and the long-range 1/f noise; Delignières & Torre, 2011).

Hence, lag-one autocorrelation, noted $\gamma(1)$, was computed on our time-series.

Detrended Windowed lag-one Autocorrelation. When using lag-one autocorrelation method, the presence of long-range correlations has been shown to corrupt the results by artificially inducing persistence. To tackle this problem, it has been recently proposed to compute lag-one autocorrelations on a detrended moving window, a method called detrended windowed lag-one autocorrelation (DWA), giving an evaluation of the type of timing less impacted by slow trends (Lemoine & Delignières, 2009).

DWA was computed using a 30 data points moving window and a linear detrending (Delignières & Torre, 2011; Lemoine & Delignières, 2009). From the instantaneous value of DWA obtained, noted $w\gamma(1)$, the mean value of $w\gamma(1)$, and the percentage of positive $w\gamma(1)$ were calculated.

Spectral analysis. The models used for emergent timing and event-based timing, describing the whole signal as a blend of short-range and long-range behavior, reveal that the short-range scaling behavior can persist on several small scales, so that observing the scaling on the small scales can be an interesting complementary information to lag-one autocorrelation analysis (Delignières et al., 2004; Lemoine, 2007; Torre et al., 2010). This way, a β value calculated in the high frequencies with a value above 0 (negative slope) signs emergent timing (persistence) while a value below 0 (positive slope) reveals an event-based timing (antipersistence) as illustrated in Fig. 8.

The β value is obtained by computing a modification of the PSD (here using Discrete Fourier Transform) called $^{high}PSD_{we}$ which consists in: (1) removing the mean from the signal, (2) applying a parabolic window (w), (3) operating a bridge detrending (e). The low frequency power estimates (lower than $f_s/8$, f_s being the sampling frequency) are then ignored when fitting a linear function $log(P(f)) \sim \beta \times log(f)$ to the data (low) (Eke et al., 2000; Torre & Wagenmakers, 2009).

The $f_s/8$ limit was originally justified by the need for a separation of short range and long range processes, and the works of Eke et al. (Eke et al., 2000) on improving long range correlation analysis, but has then been used by confusing f_N and f_s (Delignières et al., 2005; Delignières et al., 2008): we think that this limit should rather be considered has having a physiological meaning at the frontier between two different systems working on different frequencies, so as for DFA long range analysis, the PSD was visually examined before determining a frequency-range for short-range analysis (Fig. 6).

While lag-one autocorrelation and DWA both give limited information on the short-range behavior (positive or negative values), spectral analysis fully grasps signal persistence in the short range to explore subtle changes.

It should be noted that a DFA analysis in the short timescales (small boxes) could be similarly performed, however the method is not optimized to this end (by beginning by boxes of size 4 for example), so that short term DFA analysis is generally not performed and won't be used here.

3. Results

3.1. Cognitive task

All subjects performed the cognitive task without notable disengagement. One audio recording was unusable as the sound from the cycle ergometer drowned the sound of the participant's answers. One subjects had a particularly low score due to a misunderstanding of the PASAT (the subject likely summed the wrong numbers). Both subjects were kept as there answer rate seemed sufficiently high (no disengagement).

The other 17 subjects had a score of $85.5 \pm 9.8\%$.

3.2. Long-range correlations

3.2.1. Autocorrelation decay

Qualitatively, Fig. 2 illustrates that the autocorrelation function of the linearly-detrended time intervals decreases slowly in reference situation, suggesting the presence of long-range correlations in cycling.

3.2.2. Detrended Fluctuation Analysis

Both in reference situation and in dual-task, the residuals of a linear fit in DFA on all box sizes reveals what seems to be a scaling zone in the long timescales, as expected (Fig. 3). We inferred that the linear fits could be done in the low frequencies on boxes of size $\geqslant 10$. The residuals of the linear fit on box sizes $\geqslant 10$ indicate the adequacy of a linear fit in those scales (Fig. 4).

Finally, with long-range scaling exponents α close to 1 in reference situation (1.01 ± 0.10), DFA confirms again the presence of long-range correlations.

Though the long-range scaling exponent of periods stays close to 1 for both reference and dual-task condition, a major result of this study is that its value slightly but significantly increases from $\alpha = 1.01 \pm 0.10$ in reference to $\alpha = 1.07 \pm 0.15$ during cognitive task ($P < 0.05$; see Fig. 5), with a small effect size (Cohen's d = 0.14).

We should remind that the choice of the minimal box size for the quantification of this scaling using DFA is not trivial, especially since the smallest boxes (high frequencies) are mostly influenced by the nature of the motor timing (event-based or emergent) and should be ignored when analyzing long-range $1/f$ noise. Here this choice was guided by a prior analysis of the residuals of a linear fit on all box sizes. Some authors, using PSD, advised to look at frequencies lower than $\frac{f_s}{8}$ where f_s is the sampling frequency (Delignières et al., 2005; Delignières et al., 2008), this is rather close to our result as it matches box sizes higher than 8 (Gilfriche et al., 2018).
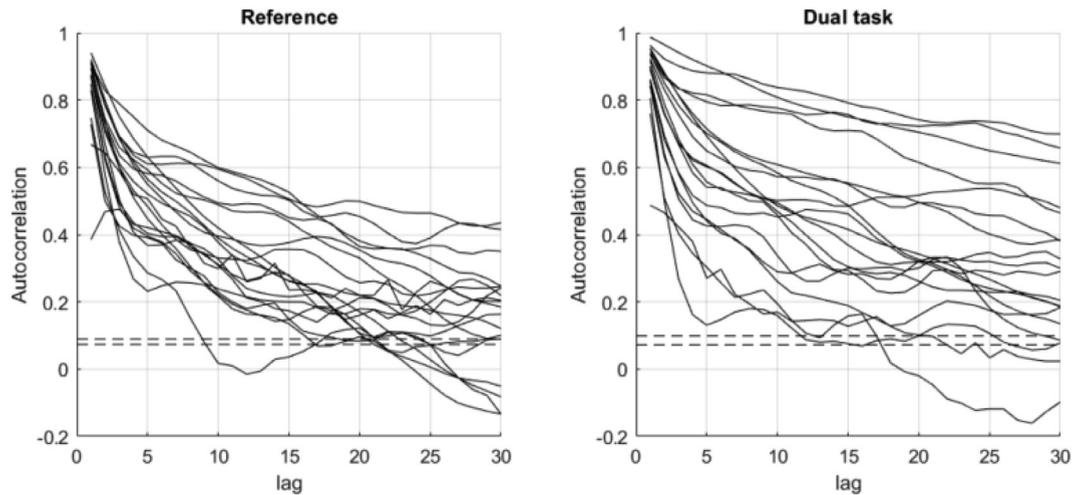
Fig. 2. Autocorrelation function of the detrended time intervals for all subjects in the reference and dual-task situation (full lines, where each line represents a subject), and the 95% confidence intervals associated (dashed lines). Note that the 2 confidence intervals lines define the minimum and maximum values of confidence intervals, which respectively correspond to the subject with the maximum and minimum number of samples (depending on the pedaling speed).

3.3. Short-range correlations

3.3.1. Short-range autocorrelation analysis

In both situations (reference and dual-task), lag-one autocorrelation $\gamma(1)$ was positive in all subjects, Mean $w\gamma(1)$ was positive in all but one subject, and the percentage of positive $w\gamma(1)$ was close to 100% in all but one subject (same atypical subject). .

3.3.2. Power spectral density

From the residuals of a linear fit on the whole PSD graph we chose to analyze the short-range frequencies on frequencies $\geqslant 0.2 Hz$. The residuals of the individual linear fits on these frequency ranges indicate the adequacy of such linear fit (Fig. 6). There is however a visible peak in spectral power around 0.34 Hz in the dual task condition in all subjects (Fig. 6), which still stands out in the residuals of the linear fit.

The short-range PSD scaling analysis on frequencies $\geqslant 0.2 Hz$ showed a short-range β value of 3.38 ± 1.32 in reference situation and 3.81 ± 1.34 in dual-task condition (P = 0.12). These values of $\beta \geqslant 0.5$ confirm yet again the strong short-range persistence in cycling. The value $\beta > 1$ is an original observation (Fig. 8) and will be interpreted in Section 4.3.

4. Discussion

The present quantitative study of temporal fluctuations in ergometer cycling reveals several interesting findings using an exhaustive analysis of the blend of long-range and short-range behaviors. (1) Cycling undoubtedly contains long-range fractal correlations as observed in other locomotor activities in humans. (2) The addition of a cognitive task modifies the properties of long-range correlations, which has not been clearly established in other locomotor tasks. (3) A specific behavior emerges in the short-range fluctuations (strong persistence) that has not been observed to date. Taken together, these results may improve our understanding of control strategies and of the associated neurophysiological system coordination engaged in a cycling task.

4.1. Significance of fractal fluctuations in cycling

In the present study, using methods to assess the presence of long-range fractal fluctuations in physiological signals, namely autocorrelation decay and DFA, we show strong evidence that a fractal temporal structure is definitively a hallmark of motor timing in cycling (Warlop et al., 2013). The emergence of a fractal signal (1/f noise) as output of complex physiological systems is understood as a multilevel process implying coordinated interactions between many elements of the system. Such systems are especially interesting by the way the coordination between sensory, cognitive and motor components takes place across multiple levels, which allows a strong adaptability and flexible stability (Wijnants, 2014). This way of considering control strategy, called interaction-dominant dynamics, is in opposition with more conventional reductionist approaches that attempt to find a key critical structure (Eke et al., 2002), a view called component-dominant dynamics (Wijnants, 2014).

An original finding of the present study is a typical reference value of scaling exponent for cycling based on DFA method ($\alpha = 1.01 \pm 0.10$), which allows to place cycling in the framework of fractal fluctuations that characterize the neurophysiological control of human locomotion. A classical interpretation is that 1/f noise with α closest to 1.0 indicates an optimal coordination within and between interacting components, that constraints like pathology or aging can alter. This way, in response to constraints or
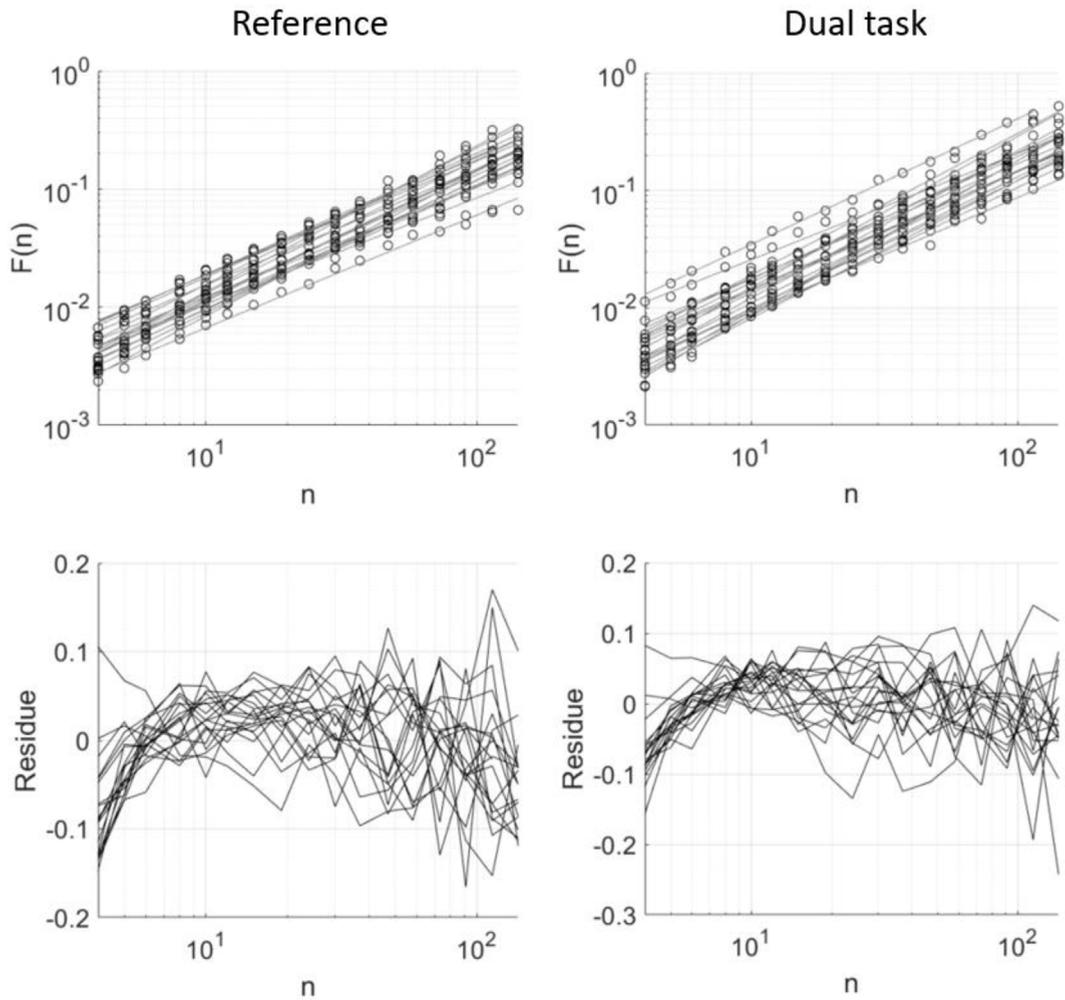
Fig. 3. Detrended Fluctuation Analysis on the time series on all box sizes for all 19 subjects (each line represents a subject) in each experimental situation. The profile of the residuals (no statistical independence) indicates that a linear fit over the entire range of scales is poorly adapted.

perturbations, the scaling exponent moves away from 1.0, as remarked in physiology (Goldberger et al., 2002) and in cognitive science (Wijnants, 2014). However, it has been shown in some studies that things may be more subtle. Particularly, in locomotor tasks like walking and running, the typical unconstrained scaling exponent is rather centered around 0.7–0.8 (Hausdorff et al., 1995; Jordan, Challis, & Newell, 2007; Terrier, Turner, & Schutz, 2005). More than the distance from $\alpha = 1.0$, the relevant information linked to control strategies seems to be the way the signal becomes more persistent or more random when facing constraints (Marmelat & Delignières, 2012; Jordan et al., 2007). Here in the studied population we evidence a significant increase in signal persistence with dual-task situation compared to reference situation (Fig. 5).

4.2. Evidence for a cognitive contribution in fractal fluctuations

By showing the impact of dual-tasking on long-range fractal properties of scaling, we deduced a non-negligible role of a central integration in the control strategy during cycling. The cognitive task presently used, PASAT, recruiting executive functions, disrupted the ordinary behavior of the free-running system as quantified by a higher scaling exponent α, which signifies a more persistent signal (Fig. 5). As cycling is a continuous task, which are believed to rely even less on cognitive control (Lewis & Miall, 2003), this result is not straightforward. By imposing the rhythm of a metronome, Warlop et al. (Warlop et al., 2013) showed a breakdown in long-range fractal fluctuations in cycling and inferred an active central control of locomotion on the generation of long-range autocorrelations. This result was consistent with the previously observed breakdown of fractal features in metronomic walking (Hausdorff et al., 1996). As well, a cognitive task has the potential to alter long-range fractal dynamics in walking (Hausdorff, 2009; Lamoth et al., 2011; Tanimoto et al., 2016). Unfortunately, the effect of a cognitive task reported by different groups can hardly allow a definitive synthetic view of control strategy in dual-task locomotion, because of some discrepancies. Here α slightly increased with dual-tasking in cycling, while precedent studies on walking reported either a decrease in scaling exponent (Hausdorff, 2009; Lamoth et al., 2011;
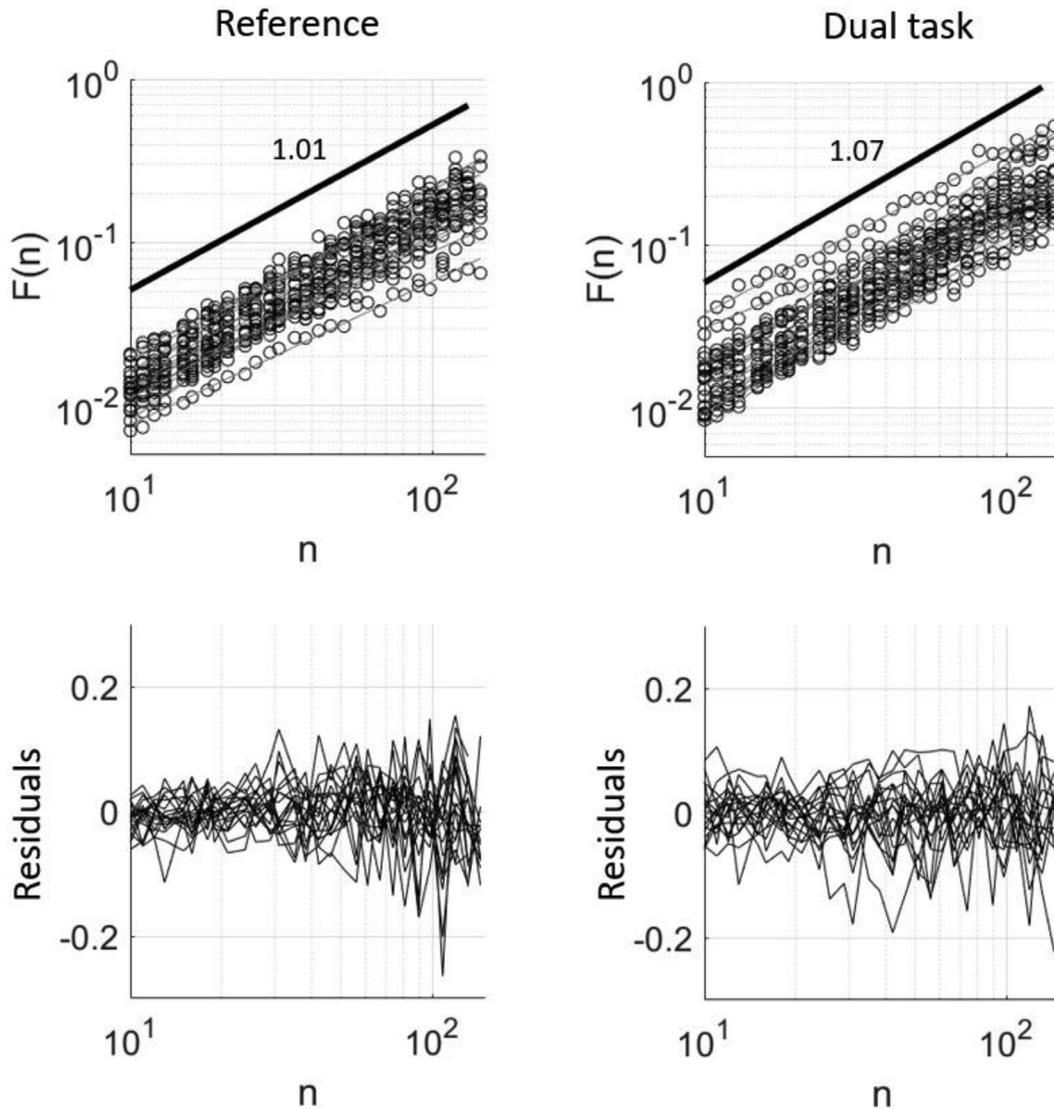
Fig. 4. Detrended Fluctuation Analysis on the time series on box sizes ⩾ 10 (long range) for all 19 subjects (each line represents a subject) in each experimental situation. The profile of the residuals (statistical independence) indicates that the linear fit computed on this box size range is adapted. The thick black lines represent the mean slope across all subjects (offset for clarity).

Tanimoto et al., 2016) or no change at all (Bollens et al., 2014; Grubaugh & Rhea, 2014; Hausdorff, 2009; Kiefer et al., 2009). The theories of interaction-dominant dynamics support the idea that adding an external constraint to a system increases its randomness (Wijnants, 2014; Diniz et al., 2011; Kello, Beltz, Holden, & Van Orden, 2007), which would mean a decrease in α and is once again contrary to our observations.

Three possible reasons, not mutually exclusive, may explain these discrepancies.

First, methodological issues, associated with the range over which long-range correlations are assessed (Wijnants, 2014) and the sensitivity of DFA to box sizes distribution (Almurad & Delignières, 2016; Gilfriche et al., 2018) can alter the reliability of the computed scaling markers in experimental works. In the present study, these issues were taken into account by careful examination of DFA characteristics (Figs. 4), and use of robust methods (evenly-spaced DFA), which certainly improved the reliability of scaling exponent computation by better distinguishing short- and long-range behaviors.

A second, more probable, cause of discrepancy may be that fractal properties variations in dual-task conditions are inherently dependent on the cognitive task, so that the alterations to long-range correlations under external constraints may depend on the type of constraints. Here in the PASAT/cycling dual-task, the observed increase in long-range persistence is not in line with interaction-dominance, which predicts that external constraints reduce long-range persistence (Wijnants, 2014). This opens the door to a deeper investigation about the interaction between constraints typology and complex control network remodeling. To this end, more experimental works may be needed to map changes in fractal behavior with different mental constraints. In this context, the increased
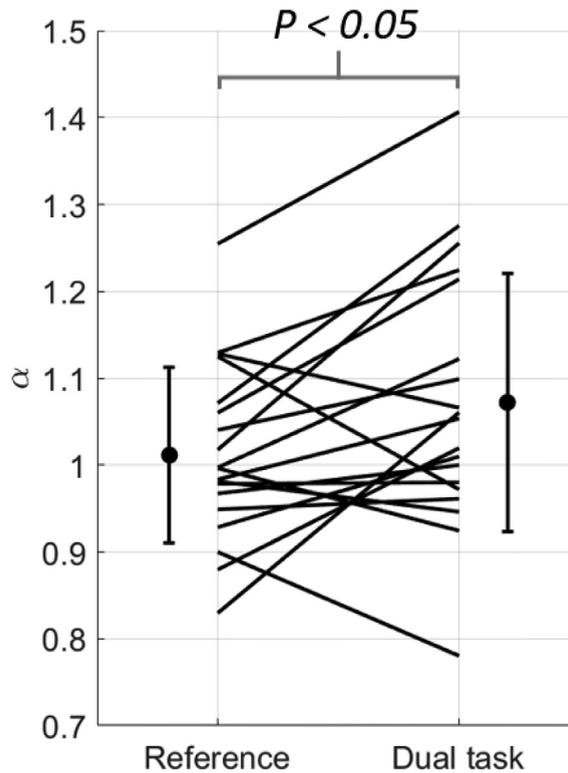
Fig. 5. Long-range scaling exponent α computed with DFA on box sizes $\geqslant 10$, for all subjects in reference and dual-task situations. Individual values as well as mean $\pm$ standard deviation are given. In 14 subjects out of 19, α increased in dual-task.

scaling exponent during dual-tasking observed for the first time in the present study may be specifically associated with the PASAT. This task recruits executive functions and requires attentional functioning, working memory and information processing speed, and this result cannot trivially be extended to any cognitive task.

A third explanation for this discrepancy with previous works (increase in scaling exponent) lies in the peculiarity of the motor task. Indeed, in such complex system wherein control is inherently distributed (as evidenced by long-range fractal correlations), relying on the inertia of the pedaling movement could allow the subjects to reduce the cognitive demand of the motor task by unloading central control towards more peripheral dominance (as will be seen in the following section). This way, the complex control, partly centrally-mediated, would slightly untighten and stabilize around a looser form of control reflected in a higher long-range persistence. Simply put, the mental task distracts the subjects from their primary task (cycling), decreasing their focus on their internal timing, hence drifting more and increasing their long-range persistence. Once again more work is needed to explore this hypothesis.

It is rather clear from Fig. 5 that although the increase in long-range scaling exponent α with dual-tasking is significant, it is not systematic in all subjects. In a few subjects, long-range persistence does not increase or even decreases. One can suppose that this originates in a difference in engagement in the task: less engaged subjects would focus more on their motor timing by cutting on their focus on the PASAT. This hypothesis is rejected here as shown by the absence of correlation between the variation of α and the PASAT score (Fig. 7); at least, the effect is not directly reflected in the PASAT score. Another possibility is that only individuals with a greater capacity to manage dual-tasking increased their focus on the motor task, without decreasing their efficiency in the PASAT. Unfortunately the design of the study does not allow to conclude on that matter.

Much less is known about another fundamental aspect of control, the putative interference of a cognitive task with the behavior of a dynamic oscillator supposed to be a key factor in motor timing of continuous motor tasks. As cycling exhibit clearly such a characteristic, here we paid attention to short-range correlations in order to shed some light on this particular issue and be able to have a more comprehensive view of control strategies in dual-task cycling.

4.3. An unprecedented short-term correlation behavior

Some studies focusing on the temporal structure of variability pointed to a blend of short-term and long-term serial correlations. In the present study, a crossover was similarly observed in cycling time series (Figs. 3). Further explorations using classical lag-one autocorrelation and DWA showed the presence of positive short-range autocorrelations, which are generally associated with emergent timing, expected here due to the smoothness in the rotating movement. A relevant supplementary information came in an original high short-range persistence ($\beta = 3.38 \pm 1.32$ in reference situation; Fig. 6) in our conditions demonstrated by the short-range
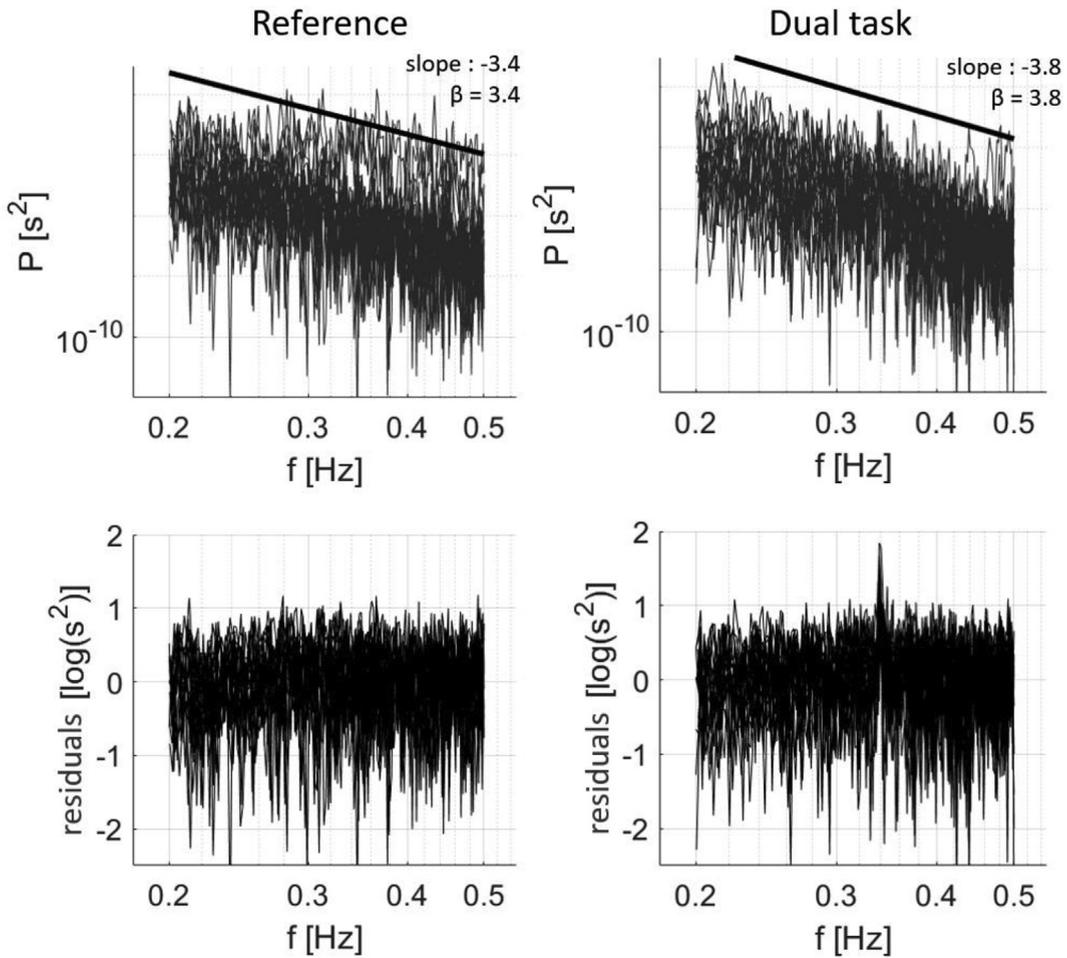
Fig. 6. Top: Power Spectral Density analysis of the time series on frequencies ⩾ 0.2 Hz (short range) for all 19 subjects (each line represents a subject) in each experimental situation. Bottom: residuals of the linear fit. The profile of the residuals (statistical independence) indicates that a linear fit on this frequency range is adapted. Thick black lines represent the mean slope (offset for clarity).
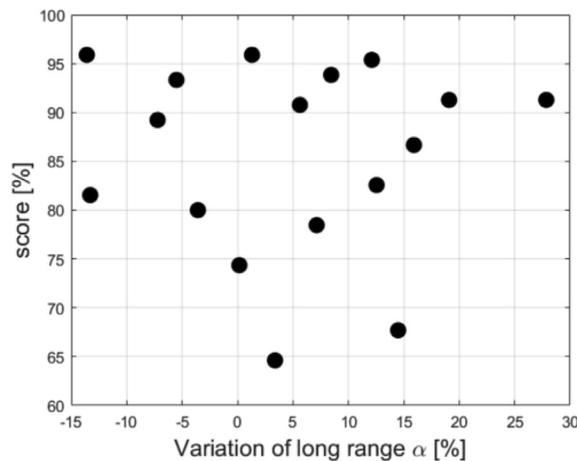

Fig. 7. Correlation between the percentage of variation of α with dual tasking and the score in the 17 subjects with exploitable PASAT results.

PSD analysis, which does not match currently used models of emergent timing (wherein $\beta \leq 1$; Fig. 8). Thus, this result uncovers a new short-term correlation behavior which has not been reported before to our knowledge, and therefore deserves further comments.

Short-range characteristics have been a matter of interest to assess the contribution of the motor subsystems in control strategies.
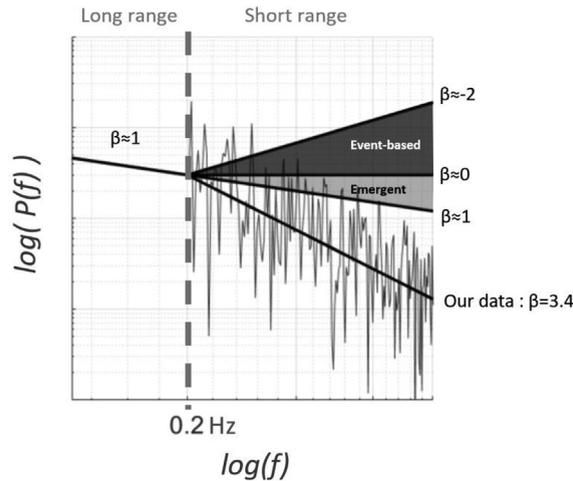
Fig. 8. Example of the high frequency ($\geqslant 0.2Hz$) PSD of one typical subjects in reference situation, placed beside the classical zones associated with event-based and emergent timing.

It is understood that cycling exhibits a singular timing. We expect that this unusual behavior typical of cycling signs a motor characteristic not engaged in other human movements studied to date. In our conditions of cycling on a friction loaded cycle ergometer, the heavy rotating flywheel likely plays a critical role in a motor subsystem composed of a generator (skeletal muscles) and heavy parts with large inertia: legs and flywheel, linked via the feet on the pedals. It allows the subjects to rely on the large inertia of this bio-mechanical oscillator, which does not require any quick adjustment by the neurophysiological system to maintain the desired rhythm. Under this hypothesis, high short-range autocorrelations are the natural consequence of the persistence of the rotating flywheel.

Although the theory behind the emergent timing/ event-based timing distinction lies in cognitive considerations (Delignières & Torre, 2011), the association of such mechanisms with the short-range correlations in the output time-series has been a post hoc task-specific models. This way, the use of previous domain-specific models to any motor task is not straightforward. Our observations of a highly persistent signal in the short timescales ($\leqslant 5$ pedal strokes), inconsistent with the usual event-based and emergent models of short-range correlations, can feed new task-specific models (putatively covering the field of human locomotion) and promote the development of a more general framework in motor control theory.

As an additional piece of knowledge, our study shows the absence of effect of a cognitive challenge on timing control in the short-range. This component has generally been associated with a dominance of motor components of the whole system for which we show here great persistence associated with high inertia. It is therefore not surprising that a cognitive challenge, mobilizing central resources, would not be reflected in this component of the temporal structure of variability. In a more general way, this could point to a global strategy to allocate a great part of the distributed control towards the motor component when supported by the environment, in order to minimize cognitive resource recruitment for timing generation and ensure cognitive availability for dual-task.

4.4. Impact of the periodicity in the cognitive task

Interestingly enough, the cognitive task used here is repetitive at a constant period (3s cycle of the delivered numbers during the PASAT), which could alter the periodicity of cycling variability through a cyclic stimulation. Indeed, it has been shown that cognitive time duration assessments, typically behaving like $1/f$ noise, could spontaneously couple with a periodic driver through a process called entrainment, while keeping an underlying fractal scaling (Amon, Pavlov, & Holden, 2018).

Such a phenomenon, driven by the PASAT process, appears in our conditions in the short-range, as revealed by a peak in the PSD graph around 0.34 Hz during dual-tasking, corresponding to the 3s period between two successive instructions (Fig. 6). Thus, we observe a process similar to previous works (Amon et al., 2018), but in the short-range rather than in the long-range localized control.

It was suggested that one advantage of $1/f$ noise could be the capacity to adaptatively lock to any periodic driver. Here, though we have no means of showing whether it occurs through entrainment (strong anticipation) or local correction, we show that a similar coupling can occur even in the short range in a strongly persistent scaling (rather than $1/f$ scaling). Future studies may find it interesting to delve deeper into this subject.

5. Conclusion and perspectives

The present study aimed at exploring neurophysiological control strategies in cycling by exploring concomitantly short- and long-range timing behaviors. The presence of fractal fluctuations in the long range during cycling was evidenced and could be definitively considered as a hallmark of temporal fluctuations in cycling. This property reveals that a complex distributed and coordinated system underlies control, which is considered to be an asset to face perturbations thanks to many degrees of freedom for system

responsiveness (flexibility). Contrary to previous works, our study evidenced that dual-tasking could increase long-range persistence, which may reveal a special characteristics of the cognitive task (PASAT), of the motor task (continuity and great inertia), or of the combination of both. A peculiar short-term process was observed here in cycling, revealing that the interface between the locomotor system and an external oscillator with great inertia can lead to an original control distributions across central and peripheral instances. Collectively, these results invite to explore more thoroughly both short- and long-range persistence in different motor and cognitive situations to better understand the neurophysiology of human locomotor control. For example, future works may find it interesting to explore more thoroughly the effect of inertia by testing a similar motor tasks with different loads. Other endeavors may aim at upgrading the current models of timing generation for them to include such peculiar short-range inertia phenomenon (Delignières et al., 2008).

Such explorations may be interesting in applied contexts. The population here was young and healthy and might represent a reference from which elderly or diseased populations could be compared. The response to dual-tasking helps discriminating frailty in such populations (Kang et al., 2009), and the fact that cycling on an ergometer is safe for fallers offers new ways of exploring neurophysiological functions in relation with psychological or physiological defects. The fractal approach of physiological complexity also has the potential to reveal the effect of training and motor learning (Nourrit-Lucas et al., 2015), a domain in which the cycle ergometer is now obviously relevant for fractal analysis.

Grants

References

Almurad, Z. M. H., & Delignières, D. (2016). Evenly spacing in detrended fluctuation analysis. *Physica A: Statistical Mechanics and its Applications, 451*, 63–69. https://doi.org/10.1016/j.physa.2015.12.155.

Amon, M. J., Pavlov, O. C., & Holden, J. G. (2018). Synchronization and fractal scaling as foundations for cognitive control. *Cognitive Systems Research, 50*, 155–179. https://doi.org/10.1016/j.cogsys.2018.04.010.

Bollens, B., Crevecoeur, F., Detrembleur, C., Warlop, T., & Lejeune, T. M. (2014). Variability of human gait: Effect of backward walking and dual-tasking on the presence of long-range autocorrelations. *Annals of Biomedical Engineering, 42*, 742–750. https://doi.org/10.1007/s10439-013-0961-9.

Costa, M., Goldberger, A. L., & Peng, C.-K. (2002). Multiscale entropy analysis of complex physiologic time series. *Physical Review Letters, 89*, 068102 https://doi.org/10.1103/PhysRevLett.89.068102.

Delignières, D., Lemoine, L., & Torre, K. (2004). Time intervals production in tapping and oscillatory motion. *Human Movement Science, 23*, 87–103. https://doi.org/10.1016/j.humov.2004.07.001.

Delignières, D., Ramdani, S., Lemoine, L., Torre, K., Fortes, M., & Ninot, G. (2006). Fractal analyses for 'short' time series: A re-assessment of classical methods. *Journal of Mathematical Psychology, 50*, 525–544. https://doi.org/10.1016/j.jmp.2006.07.004.

Delignières, D., & Torre, K. (2011). Event-based and emergent timing: dichotomy or continuum? a reply to repp and steinman (2010). *Journal of Motor Behavior, 43*, 311–318. https://doi.org/10.1080/00222895.2011.588274.

Delignières, D., Torre, K., & Lemoine, L. (2005). Methodological issues in the application of monofractal analyses in psychological and behavioral research. *Nonlinear Dynamics, Psychology, and Life Sciences, 9*, 435–461.

Delignières, D., Torre, K., & Lemoine, L. (2008). Fractal models for event-based and dynamical timers. *Acta Psychologica, 127*, 382–397. https://doi.org/10.1016/j.actpsy.2007.07.007.

Den Hartigh, R.J.R., Marmelat, V., & Cox, R.F.A. (2016). Fractal scaling and complexity matching in ergometer rowing. Poster session presentation at the 14th European Workshop on Ecological Psychology.

Den Hartigh, R. J. R., Marmelat, V., & Cox, R. F. A. (2018). Multiscale coordination between athletes: Complexity matching in ergometer rowing. *Human Movement Science, 57*, 434–441. https://doi.org/10.1016/j.humov.2017.10.006.

Dietrich, A., & Sparling, P. B. (2004). Endurance exercise selectively impairs prefrontal-dependent cognition. *Brain and Cognition, 55*, 516–524. https://doi.org/10.1016/j.bandc.2004.03.002.

Dingwell, J. B., John, J., & Cusumano, J. P. (2010). Do humans optimally exploit redundancy to control step variability in walking? *PLoS Computational Biology, 6*, e1000856 https://doi.org/10.1371/journaltitle.pcbi.1000856.

Diniz, A., Wijnants, M. L., Torre, K., Barreiros, J., Crato, N., Bosman, A. M. T., Hasselman, F., Cox, R. F. A., Van Orden, G. C., & Delignières, D. (2011). Contemporary theories of 1/f noise in motor control. *Human Movement Science, 30*, 889–905. https://doi.org/10.1016/j.humov.2010.07.006.

Eke, A., Herman, P., Kocsis, L., & Kozak, L. R. (2002). Fractal characterization of complexity in temporal physiological signals. *Physiological Measurement, 23*, R1–38. https://doi.org/10.1088/0967-3334/23/1/201.

Eke, A., Herm'n, P., Bassingthwaighte, J. B., Raymond, G. M., Percival, D. B., Cannon, M., Balla, I., & Ikrényi, C. (2000). Physiological time series: Distinguishing fractal noises from motions. *Pflugers Arch, 439*, 403–415. https://doi.org/10.1007/s004249900135.

Farrell, S., Wagenmakers, E.-J., & Ratcliff, R. (2006). 1/f noise in human cognition: Is it ubiquitous, and what does it mean? *Psychonomic Bulletin & Review, 13*, 737–741.

Gilden, D. L. (2001). Cognitive emissions of 1/f noise. *Psychological Review, 108*, 33–56. https://doi.org/10.1037/0033-295X.108.1.33.

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science, 267*, 1837–1839. https://doi.org/10.1126/science.7892611.

Gilfriche, P., Deschodt-Arsac, V., Blons, E., & Arsac, L. M. (2018). Frequency-specific fractal analysis of postural control accounts for control strategies. *Frontiers in Physiology, 9*. https://doi.org/10.3389/fphys.2018.00293.

Goldberger, A. L., Amaral, L. A. N., Hausdorff, J. M., Ivanov, P. C., Peng, C.-K., & Stanley, H. E. (2002). Fractal dynamics in physiology: Alterations with disease and aging. *Proceedings of the National Academy of Sciences of the United States of America, 99*(Suppl 1), 2466–2472. https://doi.org/10.1073/pnas.012579499.

Gronwall, D. M. (1977). Paced auditory serial-addition task: A measure of recovery from concussion. *Perceptual and Motor Skills, 44*, 367–373. https://doi.org/10.2466/pms.1977.44.2.367.

Grubaugh, J., & Rhea, C. K. (2014). Gait performance is not influenced by working memory when walking at a self-selected pace. *Experimental Brain Research, 232*, 515–525. https://doi.org/10.1007/s00221-013-3759-y.

Hausdorff, J. M. (2007). Gait dynamics, fractals and falls: finding meaning in the stride to stride fluctuations of human walking. *Human Movement Science, 26*, 555–589. https://doi.org/10.1016/j.humov.2007.05.003.

Hausdorff, J. M. (2009). Gait dynamics in parkinson's disease: Common and distinct behavior among stride length, gait variability, and fractal-like scaling. *Chaos, 19*, 026113 https://doi.org/10.1063/1.3147408.

Hausdorff, J. M., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of

human gait. *Journal of Applied Physiology, 78*, 349–358. https://doi.org/10.1152/jappl.1995.78.1.349.

Hausdorff, J. M., Purdon, P. L., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1996). Fractal dynamics of human gait: Stability of long-range correlations in stride interval fluctuations. *Journal of Applied Physiology, 80*, 1448–1457. https://doi.org/10.1152/jappl.1996.80.5.1448.

Hausdorff, J. M., Zemany, L., Peng, C., & Goldberger, A. L. (1999). Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children. *Journal of Applied Physiology, 86*, 1040–1047. https://doi.org/10.1152/jappl.1999.86.3.1040.

Heneghan, C., & McDarby, G. (2000). Establishing the relation between detrended fluctuation analysis and power spectral density analysis for stochastic processes. *Physical Review E, 62*, 6103–6110. https://doi.org/10.1103/PhysRevE.62.6103.

Huys, R., Studenka, B. E., Rheaume, N. L., Zelaznik, H. N., & Jirsa, V. K. (2008). Distinct timing mechanisms produce discrete and continuous movements. *PLoS Computational Biology, 4*, e1000061 https://doi.org/10.1371/journaltitle.pcbi.1000061.

Iyengar, N., Peng, C. K., Morin, R., Goldberger, A. L., & Lipsitz, L. A. (1996). Age-related alterations in the fractal scaling of cardiac interbeat interval dynamics. *American Journal of Physiology, 271*, R1078–1084. https://doi.org/10.1152/ajpregu.1996.271.4.R1078.

Jordan, K., Challis, J. H., Cusumano, J. P., & Newell, K. M. (2009). Stability and the time-dependent structure of gait variability in walking and running. *Human Movement Science, 28*, 113–128. https://doi.org/10.1016/j.humov.2008.09.001.

Jordan, K., Challis, J. H., & Newell, K. M. (2007). Walking speed influences on gait cycle variability. *Gait Posture, 26*, 128–134. https://doi.org/10.1016/j.gaitpost.2006.08.010.

Kang, H. G., Costa, M. D., Priplata, A. A., Starobinets, O. V., Goldberger, A. L., Peng, C.-K., Kiely, D. K., Cupples, L. A., & Lipsitz, L. A. (2009). Frailty and the degradation of complex balance dynamics during a dual-task protocol. *Journals of Gerontology. Series A, Biological Sciences and Medical Sciences, 64*, 1304–1311. https://doi.org/10.1093/gerona/glp113.

Kello, C. T., Beltz, B. C., Holden, J. G., & Van Orden, G. C. (2007). The emergent coordination of cognitive function. *Journal of Experimental Psychology: General, 136*, 551–568. https://doi.org/10.1037/0096-3445.136.4.551.

Kiefer, A. W., Riley, M. A., Shockley, K., Villard, S., & Van Orden, G. C. (2009). Walking changes the dynamics of cognitive estimates of time intervals. *Journal of Experimental Psychology: Human Perception and Performance, 35*, 1532–1541. https://doi.org/10.1037/a0013546.

Lambourne, K., Audiffren, M., & Tomporowski, P. D. (2010). Effects of acute exercise on sensory and executive processing tasks. *Medicine and Science in Sports and Exercise, 42*, 1396–1402. https://doi.org/10.1249/MSS.0b013e3181cbee11.

Lamoth, C. J., van Deudekom, F. J., van Campen, J. P., Appels, B. A., de Vries, O. J., & Pijnappels, M. (2011). Gait stability and variability measures show effects of impaired cognition and dual tasking in frail people. *Journal of NeuroEngineering and Rehabilitation, 8*, 2. https://doi.org/10.1186/1743-0003-8-2.

Lemoine, L. (2007). Phd thesis- implication des processus de timing événementiels et émergents dans la gestion des aspects temporels du mouvement,http://www.theses.fr/120522284.

Lemoine, L., & Delignières, D. (2009). Detrended windowed (lag one) autocorrelation: a new method for distinguishing between event-based and emergent timing. *The Quarterly Journal of Experimental Psychology (Hove), 62*, 585–604. https://doi.org/10.1080/17470210802131896.

Lewis, P. A., & Miall, R. C. (2003). Distinct systems for automatic and cognitively controlled time measurement: evidence from neuroimaging. *Current Opinion in Neurobiology, 13*, 250–255. https://doi.org/10.1016/S0959-4388(03)00036-9.

Mandelbrot, B. B., & Van Ness, J. W. (1968). Fractional brownian motions, fractional noises and applications. *SIAM Review, 10*, 422–437. https://doi.org/10.1137/1010093.

Marmelat, V., & Delignières, D. (2012). Strong anticipation: Complexity matching in interpersonal coordination. *Experimental Brain Research, 222*, 137–148. https://doi.org/10.1007/s00221-012-3202-9.

Nicolini, P., Ciulla, M. M., De Asmundis, C., Magrini, F., & Brugada, P. (2012). The prognostic value of heart rate variability in the elderly, changing the perspective: From sympathovagal balance to chaos theory. *Pacing and Clinical Electrophysiology, 35*, 622–638. https://doi.org/10.1111/j.1540-8159.2012.03335.x.

Nourrit-Lucas, D., Tossa, A. O., Zélic, G., & Delignières, D. (2015). Learning, motor skill, and long-range correlations. *Journal of Motor Behavior, 47*, 182–189. https://doi.org/10.1080/00222895.2014.967655.

Peng, C. K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., & Goldberger, A. L. (1994). Mosaic organization of DNA nucleotides. *Physical Review E, 49*, 1685–1689. https://doi.org/10.1103/PhysRevE.49.1685.

Pressing, J., & Jolley-Rogers, G. (1997). Spectral properties of human cognition and skill. *Biological Cybernetics, 76*, 339–347. https://doi.org/10.1007/s004220050347.

Spencer, R. M. C., Zelaznik, H. N., Diedrichsen, J., & Ivry, R. B. (2003). Disrupted timing of discontinuous but not continuous movements by cerebellar lesions. *Science, 300*, 1437–1439. https://doi.org/10.1126/science.1083661.

Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: Is there a connection? *Human Movement Science, 30*, 869–888. https://doi.org/10.1016/j.humov.2011.06.002.

Szturm, T., Maharjan, P., Marotta, J. J., Shay, B., Shrestha, S., & Sakhalkar, V. (2013). The interacting effect of cognitive and motor task demands on performance of gait, balance and cognition in young adults. *Gait Posture, 38*, 596–602. https://doi.org/10.1016/j.gaitpost.2013.02.004.

Tanimoto, K., Anan, M., Sawada, T., Takahashi, M., & Shinkoda, K. (2016). The effects of altering attentional demands of gait control on the variability of temporal and kinematic parameters. *Gait Posture, 47*, 57–61. https://doi.org/10.1016/j.gaitpost.2016.04.005.

Tatom, F. B. (1995). The relationship between fractional calculus and fractals. *Fractals, 03*, 217–229. https://doi.org/10.1142/S0218348X95000175.

Terrier, P., & Dériaz, O. (2012). Persistent and anti-persistent pattern in stride-to-stride variability of treadmill walking: Influence of rhythmic auditory cueing. *Human Movement Science, 31*, 1585–1597. https://doi.org/10.1016/j.humov.2012.05.004.

Terrier, P., Turner, V., & Schutz, Y. (2005). GPS analysis of human locomotion: further evidence for long-range correlations in stride-to-stride fluctuations of gait parameters. *Human Movement Science, 24*, 97–115. https://doi.org/10.1016/j.humov.2005.03.002.

Thornton, T. L., & Gilden, D. L. (2005). Provenance of correlations in psychological data. *Psychonomic Bulletin & Review, 12*, 409–441.

Torre, K., Balasubramaniam, R., & Delignières, D. (2010). Oscillating in synchrony with a metronome: serial dependence, limit cycle dynamics, and modeling. *Motor Control, 14*, 323–343.

Torre, K., & Wagenmakers, E.-J. (2009). Theories and models for 1/f(beta) noise in human movement science. *Human Movement Science, 28*, 297–318. https://doi.org/10.1016/j.humov.2009.01.001.

Tulppo, M. P., Kiviniemi, A. M., Hautala, A. J., Kallio, M., Seppänen, T., Mäkikallio, T. H., & Huikuri, H. V. (2005). Physiological background of the loss of fractal heart rate dynamics. *Circulation, 112*, 314–319. https://doi.org/10.1161/CIRCULATIONAHA.104.523712.

Warlop, T., Detrembleur, C., Stoquart, G., Lejeune, T., & Jeanjean, A. (2018). Gait complexity and regularity are differently modulated by treadmill walking in parkinson's disease and healthy population. *Frontiers in Physiology, 9*. https://doi.org/10.3389/fphys.2018.00068.

Warlop, T. B., Bollens, B., Crevecoeur, F., Detrembleur, C., & Lejeune, T. M. (2013). Dynamics of revolution time variability in cycling pattern: voluntary intent can alter the long-range autocorrelations. *Annals of Biomedical Engineering, 41*, 1604–1612. https://doi.org/10.1007/s10439-013-0834-2.

West, B. J. (2010). Fractal physiology and the fractional calculus: A perspective. *Frontiers in Physiology, 1*. https://doi.org/10.3389/fphys.2010.00012.

Whitacre, J. M. (2010). Degeneracy: A link between evolvability, robustness and complexity in biological systems. *Theoretical Biology and Medical Modelling, 7*, 6. https://doi.org/10.1186/1742-4682-7-6.

Wijnants, M. L. (2014). A review of theoretical perspectives in cognitive science on the presence of scaling in coordinated physiological and cognitive processes. *Nonlinear Dynamics*. https://doi.org/10.1155/2014/962043.

Wing, A. M. (1980). The long and short of timing in response sequences. In G. E. Stelmach, & J. Requin (Eds.). *North-Holland volume 1 of Tutorials in Motor Behavior.* .

Wing, A. M., & Kristofferson, A. B. (1973). The timing of interresponse intervals. *Perception & Psychophysics, 13*, 455–460. https://doi.org/10.3758/BF03205802.

Zelaznik, H. N., Spencer, R. M. C., & Ivry, R. B. (2002). Dissociation of explicit and implicit timing in repetitive tapping and drawing movements. *Journal of Experimental Psychology: Human Perception and Performance, 28*, 575–588. https://doi.org/10.1037/0096-1523.28.3.575.