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## 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.

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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.

*Keywords:* 

Motor timing, Fractal, Timing nature, Cycling

#### 1 1. Introduction

There is growing evidence that the neurophysiological coordination of hu-2 man motor control can be meaningfully viewed as a dynamic system exhibit-3 ing complexity in its timing behavior (Costa et al. (2002); Diniz et al. (2011); Goldberger et al. (2002); Marmelat & Delignières (2012)). As such, human 5 motor control is characterized by emergent dynamical properties that could 6 hardly be understood by only studying the system's different parts in isola-7 tion (Dingwell et al. (2010); Stergiou & Decker (2011); Warlop et al. (2018)). The coordination among multiple components and at multiple system levels 9 is thought to be at the origin of the complex fractal behavior in signal outputs 10 (Marmelat & Delignières (2012)). The presence of fractal dynamics implies 11 that control in such systems is distributed rather than localized in given parts 12 (Wijnants (2014)). This is a consequence of the interdependence and coop-13 eration of processes operating simultaneously at multiple timescales (Ivengar 14 et al. (1996); Marmelat & Delignières (2012)). The arising absence of a char-15 acteristic timescale is considered as an advantage since the dominance of a 16 unique timescale may be a sign of a restricted functional responsiveness, a 17 lack of flexibility (Goldberger et al. (2002); Hausdorff (2009)). In this re-18 gard, the field of fractal physiology (Gilden et al. (1995); Goldberger et al. 19 (2002); West (2010)) has demonstrated a greater capacity than classically 20 used reductionist methods to assess movement control strategy, by provid-21 ing relevant complexity metrics (Eke et al. (2002); Nicolini et al. (2012); 22 Whitacre (2010); Gilfriche et al. (2018)). 23

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 fluc-

tuations (Tatom (1995)). In this formalism, cyclic movements exhibiting 29 white noise may indicate no coordination in the supporting neurophysiologi-30 cal network. At the other end of the spectrum, Brownian motion is thought 31 to mark a rigid, non flexible control since the system output widely deviates 32 from its average temporal behavior. A coordinated system ensuring that tim-33 ing rhythm is both robust and flexible is conceivably midway between a tight 34 and a loose control. This statement has found strong support in experimen-35 tal works in physiology (Ivengar et al. (1996); Torre & Wagenmakers (2009); 36 Tulppo et al. (2005)), psychology (Gilden et al. (1995); Farrell et al. (2006); 37 Pressing & Jolley-Rogers (1997); Thornton & Gilden (2005)), and behav-38 ioral sciences (Nourrit-Lucas et al. (2015); Wijnants (2014)), all indicating 30 that the temporal behavior of young and healthy systems exhibits fractal 40 fluctuations. Aging, pathology or mental and mechanical constraints shift 41 the system's temporal output towards less clear fractal properties (Wijnants 42 (2014)).43

The presence of fractal fluctuations in motor rhythm during human lo-44 comotion has been a matter of interest (Den Hartigh et al. (2016, 2018); 45 Jordan et al. (2009); Terrier & Dériaz (2012)). In pioneer works, stride-to-46 stride fluctuations during walking have been explored (Hausdorff et al. (1995, 47 1996, 1999), comparing fractal dynamics in healthy people to fractal dynam-48 ics in people with neurodegenerative diseases or facing different constraints 49 (Hausdorff (2007)). Since then, researchers have paid more and more atten-50 tion to fractal fluctuations (Stergiou & Decker (2011)). Fractal properties 51 have usually been quantified using the "scaling exponent" which places the 52 analyzed signal in the monofractal continuum. 53

Further exploration of motor variability revealed that in many tasks, the 54 overall temporal structure is not only characterized by a fractal component, 55 but is also influenced by a short range component. This component has 56 been shown to bring meaningful information on control organization (Gilden 57 (2001); Wijnants (2014)). The overall temporal structure is then a blend of 58 a fractal process in the long range and another process in the short range. 59 This short-range process has been explained in some specific motor tasks by 60 the formalism of event-based vs. emergent nature of motor timing (Zelaznik 61 et al. (2002)), a theory to explain timing generation processes (Delignières 62 et al. (2004); Huys et al. (2008); Lewis & Miall (2003); Spencer et al. (2003); 63 Torre et al. (2010)). Event-based and emergent timing are two distinct way to 64 generate timing, relying respectively on an explicit cognitive (central) repre-65 sentation of timing and on an implicit bio-mechanical (peripheral) oscillator 66

(Delignières & Torre (2011); Lemoine (2007); Delignières et al. (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 et al. (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, 78 the present study added a cognitive challenge to normal cycling. It has 79 been shown for years that simultaneously performing a motor task and a 80 mental task deteriorates performance in one or both tasks (Kang et al. (2009); 81 Szturm et al. (2013)). It has been expected that fractal properties could also 82 be impacted by simultaneously performing a cognitive task (Gilden et al. 83 (1995); Gilden (2001)). Yet, such impact is neither trivial nor consistent. 84 Previous works on walking while performing a cognitive task reported either 85 a decrease in fractal scaling exponent (Hausdorff (2009); Lamoth et al. (2011); 86 Tanimoto et al. (2016)) or no change at all (Bollens et al. (2014); Grubaugh & 87 Rhea (2014); Hausdorff (2009); Kiefer et al. (2009)). More work is still needed 88 to fully understand the impact of dual-tasking on the temporal structure of 89 motor control output. As such, exploring cycling while adding a cognitive 90 challenge may improve our understanding of neurophysiological control in 91 human locomotion. 92

In the present work, we analyze short- and long-range fluctuations in cy-93 cling with and without a simultaneous cognitive task to better understand 94 control distribution and identify the functional role of cognitive resources. We 95 hypothesized that: i) like in other locomotor systems, the temporal struc-96 ture of cycling is fractal (Warlop et al. (2013)), ii) given the biomechanical 97 constraints and the smoothness of the movement, cycling is characterized by 98 positive short range correlations, iii) a cognitive challenge affects the longgc range fractal properties. 100

#### <sup>101</sup> 2. Material and Methods

#### 102 2.1. Protocol

19 subjects (15 men and 4 women) aged  $24.4 \pm 2.7$  years participated 103 in the study and gave informed consent. They were asked to cycle on a 104 friction-loaded cycle ergometer with light charge (50W), for a total of 20 105 minutes: 10 minutes without performing any task (reference situation), and 106 10 minutes while performing a cognitive task (dual-task situation), in a ran-107 domized order. Each time, they first had to synchronize their pedaling with a 108 metronome at 1Hz during 1 minute (not recorded) and were asked to continue 109 at the same cadence after the metronome was turned off. 110

The "cognitive task" situation was a Paced Auditory Serial Addition Test 111 (PASAT; Gronwall (1977)). PASAT recruits executive functions and requires 112 attentional functioning, working memory and information processing speed. 113 It has been suggested that the discrepancy in results obtained in fractal 114 modification during dual-tasking in walking may be due to a poor choice 115 of cognitive tasks; in order to avoid this problem here we selected PASAT 116 because it is known to recruit prefrontal cortical networks (Lambourne et al. 117 (2010)), and hence to be able to interfere with the motor area (also frontal; 118 Dietrich & Sparling (2004)). 119

In the PASAT, a list of numbers is given (one every 3 seconds 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 1kHz 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 Figure 1.

#### 133 2.2. Data analysis

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



Figure 1: Example of inter-cycle time series of one subject in normal (reference) and dual-task cycling.

The data analysis techniques used here will be described below, and an 136 overview is provided in Table 1. 137

138	Table 1: Overview of the data analysis methods used and their				
139	Focus	Method	Detects	Quantifies	
	Long range	Autocorrelation decay	yes	no	
	correlations	DFA	yes	yes	
	Short range	Lag-one Autocorrelation	yes	no	
	correlations	DWA	yes	no	
		$^{high}PSD_{we}$	yes	yes	

The time intervals between pedal strokes, generally fluctuating around 1s 140 (as the metronome heard during the first minute encouraged) were resampled 141 at 1Hz using a cubic spline for the DFA and PSD-based methods that will 142 be developed below, so that the periods and frequencies could be properly 143 expressed in s and Hz rather than respectively trial and inverse-trial numbers. 144

#### 2.2.1. Long-range correlations 145

First, to robustly confirm the fact that in normal situation cycling con-146 tains fractal properties (Warlop et al. (2013)), we visually controlled for the 147 slow decay of the autocorrelation function, and the scaling exponent  $\alpha$  was 148 computed with DFA and checked to be close to 1. 149

Once the presence of long-range correlations is validated, the subtle varia-150 tions of  $\alpha$  can be properly used as a marker of variations in fractal properties. 151

Autocorrelation decay. The decay of the time series autocorrelation function 152 was qualitatively observed up to lag 30 on the linearly-detrended signal (sub-153 straction of a linear fit of the whole signal). 154

Detrended Fluctuation Analysis. Detrended Fluctuation Analysis (DFA) is a 155 method to analyze the fractal properties in a signal (Peng et al. (1994)). It 156 relies on the monofractal framework, which describes a continuum between 157 white noise and brownian motion (Mandelbrot & Van Ness (1968)). This 158 class of signals is said to exhibit "scaling" properties; a specific power law 159 relation between a characteristic scale and the power in said scale. The power 160 spectral density in such a signal then follows the relation:  $P(f) \sim \frac{1}{f^{\beta}}$  (hence, 161  $log(P(f)) \sim \beta \times log(f)$ ). DFA has been designed specifically to analyze 162 this type of signals, it computes a scaling exponent  $\alpha$ , which in the limit of 163 perfect monofractals of infinite length, is linked to  $\beta$  by the relation  $\alpha = \frac{\beta+1}{2}$ . 164 Signals described by  $\alpha$  close to 1 ( $\alpha \in [0.75, 1.25]$ ), are called 1/f noise, while 165  $\alpha = 0.5$  describes white noise, and  $\alpha = 1.5$  describes Brownian motion. 166 DFA has been shown to give identical results as PSD analysis in long signals 167 (Heneghan & McDarby (2000)), but has been preferred for shorter signals, 168 or signals closer to 1/f noise (Delignières et al. (2005, 2006)), that is why it 160 has been preferred here for computing long-range correlations. 170

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

173 1. The cumulated sum of the signal x is computed (without its mean to 174 avoid a linear drift):

175 
$$y(k) = \sum_{i=1}^{k} (x(i) - \bar{x})$$

- 176 2. The time-series y is then divided into non-overlapping boxes of length 177 n and in each box a straight line is fit to the data using least square 178 approximation (representing the trend in each box). The signal con-179 structed with these lines is called  $y_n$ .
- After subtraction of the approximated signal, the root-mean-square
   fluctuation of the detrended time-series obtained is calculated by:

182  $F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2}$ 

- Steps 2 and 3 are repeated for a range of n (usually for n = 4 to  $n = \frac{184}{N/4}$ ).
- 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  $\alpha$  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 192 time-series representing successive pedal-stroke durations, an irregular series 193 by nature, was resampled in the present study at 1Hz using a cubic spline 194 interpolation. First DFA was computed on all box sizes and the shape of the 195 residuals was studied after the linear fit of  $\log(F(n))$  vs.  $\log(n)$ . The shape 196 of the residuals allows to check for statistical independence of the residuals, 197 in order to decide on which scales a proper linear fit can be done (Figure 3). 198 DFA is then applied a second time only on the chosen box size range and the 199 residuals of the linear fit are observed in order to check for the correctness of 200 a linear model (Figure 4). 201

It has been remarked that if all the integer values of n in a certain range 202 are selected, a high concentration of data points will be regrouped in the 203 large box sizes (due to the log plot), giving this zone excessive weight for 204 the linear fit. To cope with that problem, box sizes were selected to be a 205 geometric sequence, so that their log is an arithmetic sequence. This choice 206 was made to follow recommendations of "evenly-spaced" DFA (Almurad & 207 Delignières (2016)). The sequence was defined as follows: 208

• 
$$n(1)$$
 is the minimum timescale

• 
$$n(2) = n(1) + 1$$

211

• 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) 212

#### 2.2.2. Short-range correlations 213

Most methods to analyze short-range correlations in motor timing (Table 214 1) rely on the theoretical models event-based and emergent timing. It is use-215 ful to understand them to better understand the subsequent computational 216 methods. 217

Event-based timing is mostly represented through the model of Wing and 218 Kristofferson, or WK model, (Wing & Kristofferson (1973); Wing (1980)), 219 wherein each cycle duration is considered to depend on two factors: an in-220 ternal central explicit timer, and a motor delay so that j-th interval,  $I_j$ , is: 221

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

Where  $C_j$  is the j-th timekeeper's interval and  $M_j$  is the j-th motor delay. 222

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 timeseries.

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 tim-248 ing, describing the whole signal as a blend of short-range and long-range 249 behavior, reveal that the short-range scaling behavior can persist on sev-250 eral small scales, so that observing the scaling on the small scales can be 251 an interesting complementary information to lag-one autocorrelation anal-252 ysis (Delignières et al. (2004); Lemoine (2007); Torre et al. (2010)). This 253 way, a  $\beta$  value calculated in the high frequencies with a value above 0 (nega-254 tive slope) signs emergent timing (persistence) while a value below 0 (positive 255

slope) reveals an event-based timing (antipersistence) as illustrated in Figure8.

The  $\beta$  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 265 short range and long range processes, and the works of Eke et al. (Eke 266 et al. (2000)) on improving long range correlation analysis, but has then been 267 used by confusing  $f_N$  and  $f_s$  (Delignières et al. (2005, 2008)): we think that 268 this limit should rather be considered has having a physiological meaning at 260 the frontier between two different systems working on different frequencies, 270 so as for DFA long range analysis, the PSD was visually examined before 271 determining a frequency-range for short-range analysis (Figure 6). 272

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.

#### 280 3. Results

#### 281 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  $85.5 \pm 9.8\%$ .



Figure 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).

#### 289 3.2. Long-range correlations

#### 290 3.2.1. Autocorrelation decay

Qualitatively, Figure 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.

#### <sup>294</sup> 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 (Figure 3). We inferred that the linear fits could be done in the low frequencies on boxes of size  $\geq 10$ . The residuals of the linear fit on box sizes  $\geq 10$  indicate the adequacy of a linear fit in those scales (Figure 4).

Finally, with long-range scaling exponents  $\alpha$  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



Figure 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.



Figure 4: Detrended Fluctuation Analysis on the time series on box sizes  $\geq 10$  (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).



Figure 5: Long-range scaling exponent  $\alpha$  computed with DFA on box sizes  $\geq 10$ , for all subjects in reference and dual-task situations. Individual values as well as mean±standard deviation are given. In 14 subjects out of 19,  $\alpha$  increased in dual-task.

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 Figure 5), with a small effect size (Cohen's d = 0.14).

We should remind that the choice of the minimal box size for the quan-308 tification of this scaling using DFA is not trivial, especially since the smallest 309 boxes (high frequencies) are mostly influenced by the nature of the motor 310 timing (event-based or emergent) and should be ignored when analyzing 311 long-range 1/f noise. Here this choice was guided by a prior analysis of 312 the residuals of a linear fit on all box sizes. Some authors, using PSD, ad-313 vised to look at frequencies lower than  $\frac{f_s}{8}$  where  $f_s$  is the sampling frequency 314 (Delignières et al. (2005, 2008)), this is rather close to our result as it matches 315

- $_{316}$  box sizes higher than 8 (Gilfriche et al. (2018)).
- 317 3.3. Short-range correlations
- 318 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).

#### 323 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  $\geq 0.2Hz$ . The residuals of the individual linear fits on these frequency ranges indicate the adequacy of such linear fit (Figure 6). There is however a visible peak in spectral power around 0.34Hz in the dual task condition in all subjects (Figure 6), which still stands out in the residuals of the linear fit.

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

#### 335 4. Discussion

The present quantitative study of temporal fluctuations in ergometer cy-336 cling reveals several interesting findings using an exhaustive analysis of the 337 blend of long-range and short-range behaviors. 1) Cycling undoubtedly con-338 tains long-range fractal correlations as observed in other locomotor activities 339 in humans. 2) The addition of a cognitive task modifies the properties of 340 long-range correlations, which has not been clearly established in other loco-341 motor tasks. 3) A specific behavior emerges in the short-range fluctuations 342 (strong persistence) that has not been observed to date. Taken together, 343 these results may improve our understanding of control strategies and of the 344 associated neurophysiological system coordination engaged in a cycling task. 345

#### 346 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



Figure 6: Top: Power Spectral Density analysis of the time series on frequencies  $\geq 0.2$ 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).

DFA, we show strong evidence that a fractal temporal structure is definitively 349 a hallmark of motor timing in cycling (Warlop et al. (2013)). The emergence 350 of a fractal signal (1/f noise) as output of complex physiological systems is 351 understood as a multilevel process implying coordinated interactions between 352 many elements of the system. Such systems are especially interesting by the 353 way the coordination between sensory, cognitive and motor components takes 354 place across multiple levels, which allows a strong adaptability and flexible 355 stability (Wijnants (2014)). This way of considering control strategy, called 356 interaction-dominant dynamics, is in opposition with more conventional re-357 ductionist approaches that attempt to find a key critical structure (Eke et al. 358 (2002)), a view called component-dominant dynamics (Wijnants (2014)). 359

An original finding of the present study is a typical reference value of 360 scaling exponent for cycling based on DFA method ( $\alpha = 1.01 \pm 0.10$ ), which 361 allows to place cycling in the framework of fractal fluctuations that char-362 acterize the neurophysiological control of human locomotion. A classical 363 interpretation is that 1/f noise with  $\alpha$  closest to 1.0 indicates an optimal co-364 ordination within and between interacting components, that constraints like 365 pathology or aging can alter. This way, in response to constraints or pertur-366 bations, the scaling exponent moves away from 1.0, as remarked in physiology 367 (Goldberger et al. (2002)) and in cognitive science (Wijnants (2014)). How-368 ever, it has been shown in some studies that things may be more subtle. 369 Particularly, in locomotor tasks like walking and running, the typical uncon-370 strained scaling exponent is rather centered around 0.7-0.8 (Hausdorff et al. 371 (1995); Jordan et al. (2007); Terrier et al. (2005)). More than the distance 372 from  $\alpha = 1.0$ , the relevant information linked to control strategies seems to 373 be the way the signal becomes more persistent or more random when facing 374 constraints (Marmelat & Delignières (2012); Jordan et al. (2007)). Here in 375 the studied population we evidence a significant increase in signal persistence 376 with dual-task situation compared to reference situation (Figure 5). 377

#### 378 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 freerunning system as quantified by a higher scaling exponent  $\alpha$ , which signifies a more persistent signal (Figure 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, War-386 lop et al. (Warlop et al. (2013)) showed a breakdown in long-range fractal 387 fluctuations in cycling and inferred an active central control of locomotion 388 on the generation of long-range autocorrelations. This result was consistent 389 with the previously observed breakdown of fractal features in metronomic 390 walking (Hausdorff et al. (1996)). As well, a cognitive task has the potential 391 to alter long-range fractal dynamics in walking (Hausdorff (2009); Lamoth 392 et al. (2011); Tanimoto et al. (2016)). Unfortunately, the effect of a cogni-393 tive task reported by different groups can hardly allow a definitive synthetic 394 view of control strategy in dual-task locomotion, because of some discrepan-395 cies. Here  $\alpha$  slightly increased with dual-tasking in cycling, while precedent 396 studies on walking reported either a decrease in scaling exponent (Hausdorff 397 (2009); Lamoth et al. (2011); Tanimoto et al. (2016)) or no change at all 398 (Bollens et al. (2014); Grubaugh & Rhea (2014); Hausdorff (2009); Kiefer 390 et al. (2009)). The theories of interaction-dominant dynamics support the 400 idea that adding an external constraint to a system increases its random-401 ness (Wijnants (2014); Diniz et al. (2011); Kello et al.), which would mean 402 a decrease in  $\alpha$  and is once again contrary to our observations. 403

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

First, methodological issues, associated with the range over which long-406 range correlations are assessed (Wijnants (2014)) and the sensitivity of DFA 407 to box sizes distribution (Almurad & Delignières (2016); Gilfriche et al. 408 (2018)) can alter the reliability of the computed scaling markers in exper-409 imental works. In the present study, these issues were taken into account 410 by careful examination of DFA characteristics (Figures 4), and use of robust 411 methods (evenly-spaced DFA), which certainly improved the reliability of 412 scaling exponent computation by better distinguishing short- and long-range 413 behaviors. 414

A second, more probable, cause of discrepancy may be that fractal prop-415 erties variations in dual-task conditions are inherently dependent on the 416 cognitive task, so that the alterations to long-range correlations under ex-417 ternal constraints may depend on the type of constraints. Here in the 418 PASAT/cycling dual-task, the observed increase in long-range persistence 419 is not in line with interaction-dominance, which predicts that external con-420 straints reduce long-range persistence (Wijnants (2014)). This opens the 421 door to a deeper investigation about the interaction between constraints 422 typology and complex control network remodeling. To this end, more ex-423

perimental works may be needed to map changes in fractal behavior with different mental constraints. In this context, the increased 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 431 scaling exponent) lies in the peculiarity of the motor task. Indeed, in such 432 complex system wherein control is inherently distributed (as evidenced by 433 long-range fractal correlations), relying on the inertia of the pedaling move-434 ment could allow the subjects to reduce the cognitive demand of the motor 435 task by unloading central control towards more peripheral dominance (as 436 will be seen in the following section). This way, the complex control, partly 437 centrally-mediated, would slightly untighten and stabilize around a looser 438 form of control reflected in a higher long-range persistence. Simply put, the 439 mental task distracts the subjects from their primary task (cycling), decreas-440 ing their focus on their internal timing, hence drifting more and increasing 441 their long-range persistence. Once again more work is needed to explore this 442 hypothesis. 443

It is rather clear from Figure 5 that although the increase in long-range 444 scaling exponent  $\alpha$  with dual-tasking is significant, it is not systematic in all 445 subjects. In a few subjects, long-range persistence does not increase or even 446 decreases. One can suppose that this originates in a difference in engagement 447 in the task: less engaged subjects would focus more on their motor timing 448 by cutting on their focus on the PASAT. This hypothesis is rejected here 449 as shown by the absence of correlation between the variation of  $\alpha$  and the 450 PASAT score (Figure 7); at least, the effect is not directly reflected in the 451 PASAT score. Another possibility is that only individuals with a greater 452 capacity to manage dual-tasking increased their focus on the motor task, 453 without decreasing their efficiency in the PASAT. Unfortunately the design 454 of the study does not allow to conclude on that matter. 455

<sup>456</sup> Much less is known about another fundamental aspect of control, the <sup>457</sup> putative interference of a cognitive task with the behavior of a dynamic <sup>458</sup> oscillator supposed to be a key factor in motor timing of continuous motor <sup>459</sup> tasks. As cycling exhibit clearly such a characteristic, here we paid attention <sup>460</sup> to short-range correlations in order to shed some light on this particular <sup>461</sup> issue and be able to have a more comprehensive view of control strategies in



Figure 7: Correlation between the percentage of variation of  $\alpha$  with dual tasking and the score in the 17 subjects with exploitable PASAT results.

462 dual-task cycling.

#### 463 4.3. An unprecedented short-term correlation behavior

Some studies focusing on the temporal structure of variability pointed 464 to a blend of short-term and long-term serial correlations. In the present 465 study, a crossover was similarly observed in cycling time series (Figures 3). 466 Further explorations using classical lag-one autocorrelation and DWA showed 467 the presence of positive short-range autocorrelations, which are generally 468 associated with emergent timing, expected here due to the smoothness in 469 the rotating movement. A relevant supplementary information came in an 470 original high short-range persistence ( $\beta = 3.38 \pm 1.32$  in reference situation; 471 Figure 6) in our conditions demonstrated by the short-range PSD analysis, 472 which does not match currently used models of emergent timing (wherein 473  $\beta \leq 1$ ; Figure 8). Thus, this result uncovers a new short-term correlation 474 behavior which has not been reported before to our knowledge, and therefore 475 deserves further comments. 476

<sup>477</sup> Short-range characteristics have been a matter of interest to assess the <sup>478</sup> contribution of the motor subsystems in control strategies. It is understood



Figure 8: Example of the high frequency  $(\geq 0.2Hz)$  PSD of one typical subjects in reference situation, placed beside the classical zones associated with event-based and emergent timing.

that cycling exhibits a singular timing. We expect that this unusual behavior 479 typical of cycling signs a motor characteristic not engaged in other human 480 movements studied to date. In our conditions of cycling on a friction loaded 481 cycle ergometer, the heavy rotating flywheel likely plays a critical role in a 482 motor subsystem composed of a generator (skeletal muscles) and heavy parts 483 with large inertia: legs and flywheel, linked via the feet on the pedals. It 484 allows the subjects to rely on the large inertia of this bio-mechanical oscilla-485 tor, which does not require any quick adjustment by the neurophysiological 486 system to maintain the desired rhythm. Under this hypothesis, high short-487 range autocorrelations are the natural consequence of the persistence of the 488 rotating flywheel. 489

Although the theory behind the emergent timing / event-based timing 490 distinction lies in cognitive considerations (Delignières & Torre (2011)), the 491 association of such mechanisms with the short-range correlations in the out-492 put time-series has been a post-hoc task-specific models. This way, the use 493 of previous domain-specific models to any motor task is not straightforward. 494 Our observations of a highly persistent signal in the short timescales ( $\leq 5$ 495 pedal strokes), inconsistent with the usual event-based and emergent mod-496 els of short-range correlations, can feed new task-specific models (putatively 497 covering the field of human locomotion) and promote the development of a 498 more general framework in motor control theory. 499

As an additional piece of knowledge, our study shows the absence of effect 500 of a cognitive challenge on timing control in the short-range. This component 501 has generally been associated with a dominance of motor components of the 502 whole system for which we show here great persistence associated with high 503 inertia. It is therefore not surprising that a cognitive challenge, mobilizing 504 central resources, would not be reflected in this component of the temporal 505 structure of variability. In a more general way, this could point to a global 506 strategy to allocate a great part of the distributed control towards the mo-507 tor component when supported by the environment, in order to minimize 508 cognitive resource recruitment for timing generation and ensure cognitive 509 availability for dual-task. 510

#### 511 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, <sup>516</sup> typically behaving like 1/f noise, could spontaneously couple with a periodic <sup>517</sup> driver through a process called entrainment, while keeping an underlying <sup>518</sup> fractal scaling (Amon et al. (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 0.34Hz during dual-tasking, corresponding to the 3s period between two successive instructions (Figure 6). Thus, we observe a process similar to previous works (Amon et al. (2018)), but in the short- rather than 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.

#### 531 5. Conclusion and perspectives

The present study aimed at exploring neurophysiological control strate-532 gies in cycling by exploring concomitantly short- and long-range timing be-533 haviors. The presence of fractal fluctuations in the long range during cycling 534 was evidenced and could be definitively considered as a hallmark of tempo-535 ral fluctuations in cycling. This property reveals that a complex distributed 536 and coordinated system underlies control, which is considered to be an asset 537 to face perturbations thanks to many degrees of freedom for system respon-538 siveness (flexibility). Contrary to previous works, our study evidenced that 539 dual-tasking could increase long-range persistence, which may reveal a special 540 characteristics of the cognitive task (PASAT), of the motor task (continuity 541 and great inertia), or of the combination of both. A peculiar short-term 542 process was observed here in cycling, revealing that the interface between 543 the locomotor system and an external oscillator with great inertia can lead 544 to an original control distributions across central and peripheral instances. 545 Collectively, these results invite to explore more thoroughly both short- and 546 long-range persistence in different motor and cognitive situations to better 547 understand the neurophysiology of human locomotor control. For example, 548 future works may find it interesting to explore more thoroughly the effect of 549 inertia by testing a similar motor tasks with different loads. Other endeav-550 ors may aim at upgrading the current models of timing generation for them 551

to include such peculiar short-range inertia phenomenon (Delignières et al.(2008))

Such explorations may be interesting in applied contexts. The population 554 here was young and healthy and might represent a reference from which 555 elderly or diseased populations could be compared. The response to dual-556 tasking helps discriminating frailty in such populations (Kang et al. (2009)), 557 and the fact that cycling on an ergometer is safe for fallers offers new ways 558 of exploring neurophysiological functions in relation with psychological or 559 physiological defects. The fractal approach of physiological complexity also 560 has the potential to reveal the effect of training and motor learning (Nourrit-561 Lucas et al. (2015)), a domain in which the cycle ergometer is now obviously 562 relevant for fractal analysis. 563

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