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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. 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 et al. (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 et al. (2010); Stergiou & Decker (2011); Warlop et al. (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 et al. (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 et al. (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 et al. (2002); Nicolini et al. (2012); Whitacre (2010); Gilfriche et al. (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 fluc-

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

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

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

67 (Delignières & Torre (2011); Lemoine (2007); Delignières et al. (2008)). Pre-
68 vious studies have shown that the short-range correlation behavior can in
69 some tasks mark a difference between both modes. As the short-range be-
70 havior have been explained by the reliance (or non-reliance) on the dynamical
71 properties of the effector, movement continuity and inertia play a critical role
72 in this range.

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

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

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

101 2. Material and Methods

102 2.1. Protocol

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

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

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

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

133 2.2. Data analysis

134 All the data were processed using Matlab 2018a (Mathworks), using func-
135 tions we specifically designed to this end.

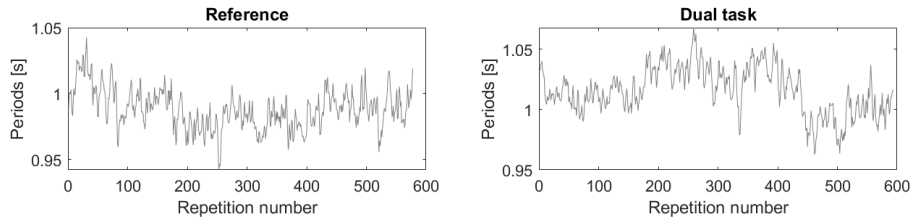


Figure 1: Example of inter-cycle time series of one subject in normal (reference) and dual-task cycling.

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

138 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

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

145 2.2.1. Long-range correlations

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

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

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

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

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

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

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

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 .

180 3. After subtraction of the approximated signal, the root-mean-square
181 fluctuation of the detrended time-series obtained is calculated by:

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

183 Steps 2 and 3 are repeated for a range of n (usually for $n = 4$ to $n =$
184 $N/4$).

185 4. In the case of a scaling phenomenon, $F(n)$ increases with n as a power
186 law:

$$187 \quad F(n) \sim n^\alpha \Rightarrow \log(F(n)) \sim \alpha \times \log(n)$$

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

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

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

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

213 2.2.2. Short-range correlations

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

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

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

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

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

$$I_j = D_j + M_j$$

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

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

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

237 *Detrended Windowed lag-one Autocorrelation.* When using lag-one autocor-
238 relation method, the presence of long-range correlations has been shown to
239 corrupt the results by artificially inducing persistence. To tackle this prob-
240 lem, it has been recently proposed to compute lag-one autocorrelations on a
241 detrended moving window, a method called detrended windowed lag-one au-
242 tocorrelation (DWA), giving an evaluation of the type of timing less impacted
243 by slow trends (Lemoine & Delignières (2009)).

244 DWA was computed using a 30 data points moving window and a linear
245 detrending (Delignières & Torre (2011); Lemoine & Delignières (2009)). From
246 the instantaneous value of DWA obtained, noted $w\gamma(1)$, the mean value of
247 $w\gamma(1)$, and the percentage of positive $w\gamma(1)$ were calculated.

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

256 slope) reveals an event-based timing (antipersistence) as illustrated in Figure
257 8.

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

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

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

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

280 3. Results

281 3.1. Cognitive task

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

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

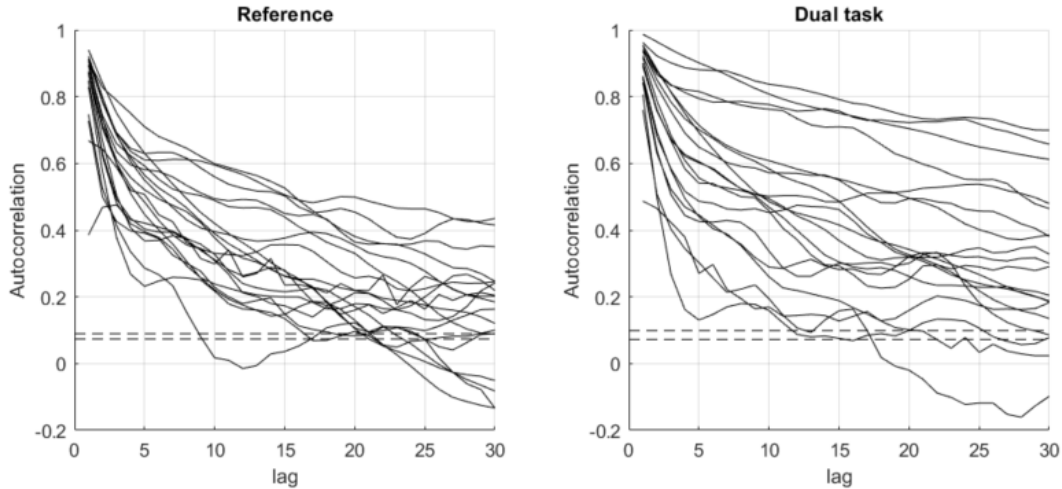


Figure 2: Autocorrelation function of the detrended time intervals for all subjects in the reference and dual-task situation (full lines, where each line represents a subject), and the 95% confidence intervals associated (dashed lines). Note that the 2 confidence intervals lines define the minimum and 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*

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

294 *3.2.2. Detrended Fluctuation Analysis*

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

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

303 Though the long-range scaling exponent of periods stays close to 1 for
 304 both reference and dual-task condition, a major result of this study is that

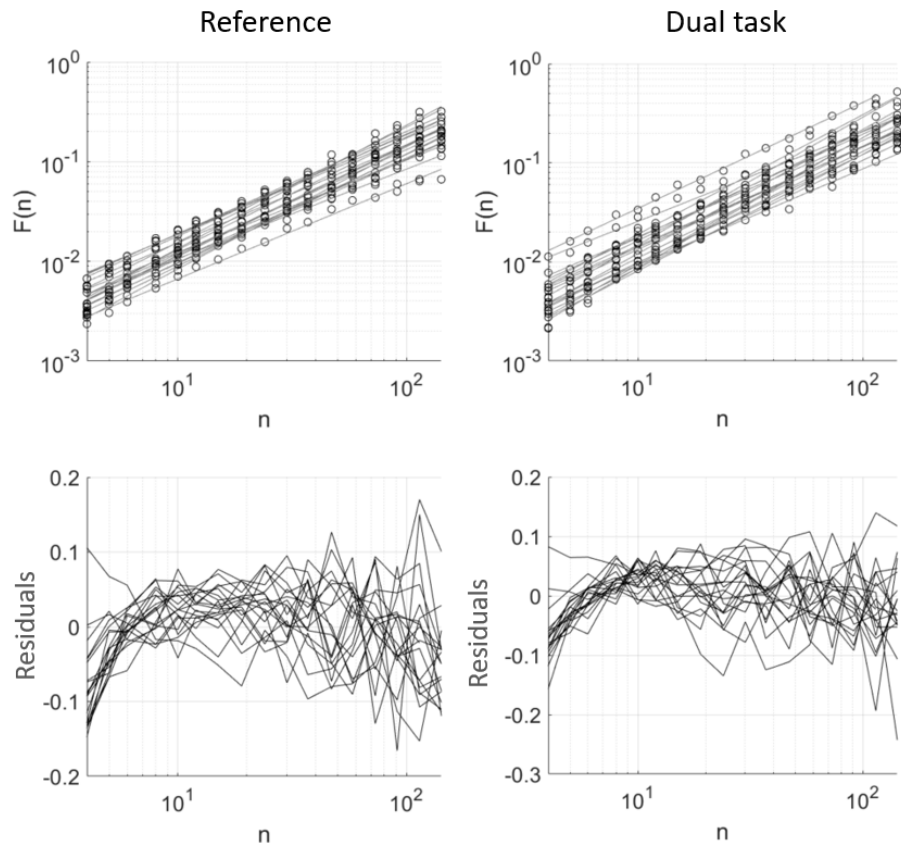


Figure 3: Detrended Fluctuation Analysis on the time series on all box sizes for all 19 subjects (each line represents a subject) in each experimental situation. The profile of the residuals (no statistical independence) indicates that a linear fit over the entire range of scales is poorly adapted.

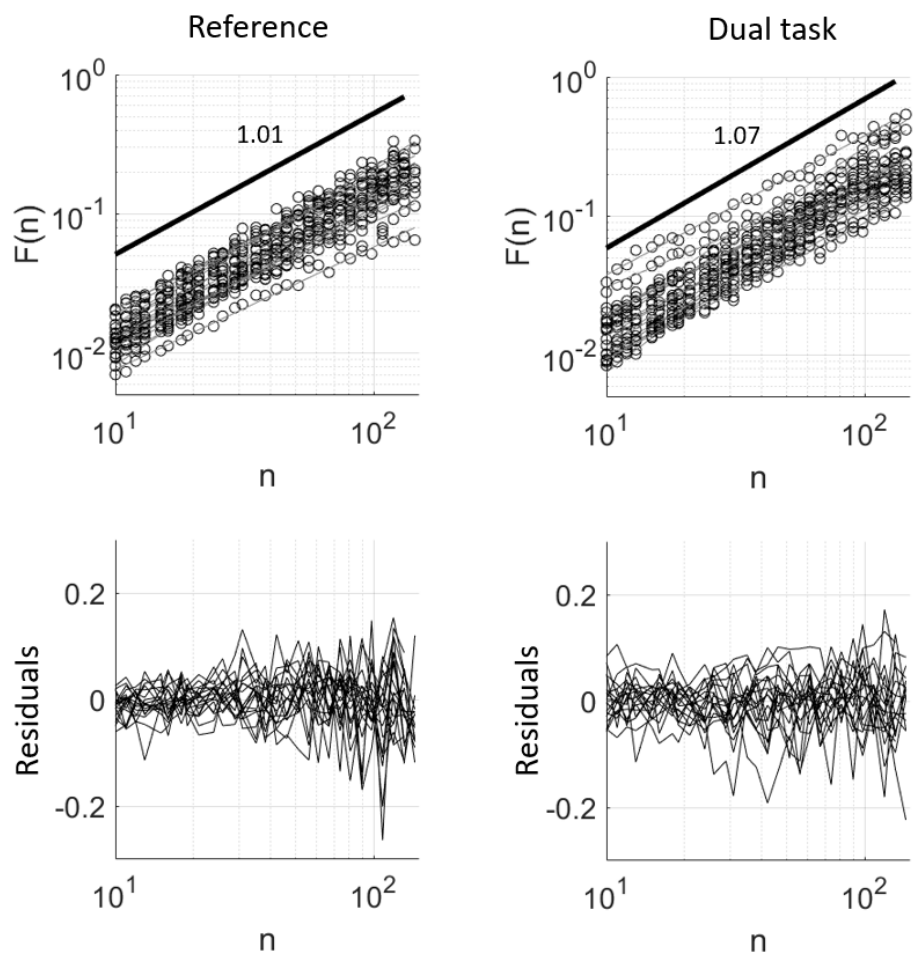


Figure 4: Detrended Fluctuation Analysis on the time series on box sizes ≥ 10 (long range) for all 19 subjects (each line represents a subject) in each experimental situation. The profile of the residuals (statistical independence) indicates that the linear fit computed on this box size range is adapted. The thick black lines represent the mean slope across all subjects (offset for clarity).

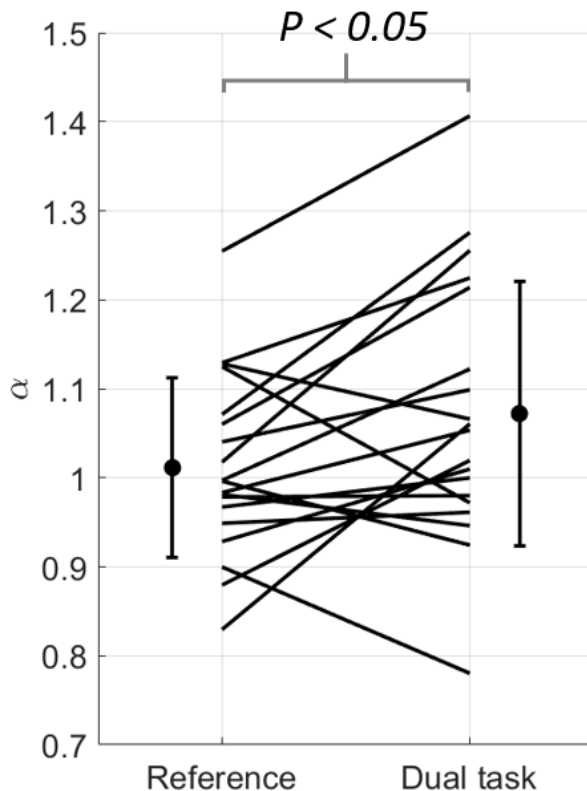


Figure 5: Long-range scaling exponent α computed with DFA on box sizes ≥ 10 , for all subjects in reference and dual-task situations. Individual values as well as mean \pm standard deviation are given. In 14 subjects out of 19, α increased in dual-task.

305 its value slightly but significantly increases from $\alpha = 1.01 \pm 0.10$ in reference
 306 to $\alpha = 1.07 \pm 0.15$ during cognitive task ($P < 0.05$; see Figure 5), with a
 307 small effect size (Cohen's $d = 0.14$).

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

316 box sizes higher than 8 (Gilfriche et al. (2018)).

317 3.3. Short-range correlations

318 3.3.1. Short-range autocorrelation analysis

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

323 3.3.2. Power spectral density

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

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

335 4. Discussion

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

346 4.1. Significance of fractal fluctuations in cycling

347 In the present study, using methods to assess the presence of long-range
348 fractal fluctuations in physiological signals, namely autocorrelation decay and

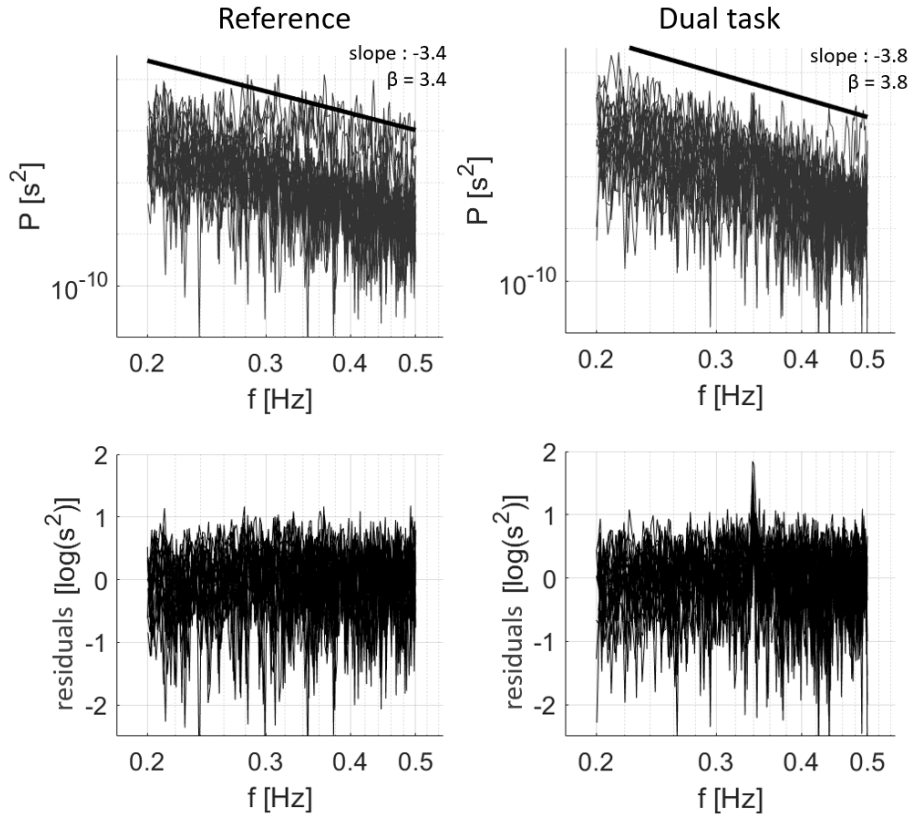


Figure 6: Top: Power Spectral Density analysis of the time series on frequencies ≥ 0.2 Hz (short range) for all 19 subjects (each line represents a subject) in each experimental situation. Bottom: residuals of the linear fit. The profile of the residuals (statistical independence) indicates that a linear fit on this frequency range is adapted. Thick black lines represent the mean slope (offset for clarity).

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

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

378 *4.2. Evidence for a cognitive contribution in fractal fluctuations*

379 By showing the impact of dual-tasking on long-range fractal properties
380 of scaling, we deduced a non-negligible role of a central integration in the
381 control strategy during cycling. The cognitive task presently used, PASAT,
382 recruiting executive functions, disrupted the ordinary behavior of the free-
383 running system as quantified by a higher scaling exponent α , which signifies
384 a more persistent signal (Figure 5). As cycling is a continuous task, which
385 are believed to rely even less on cognitive control (Lewis & Miall (2003)), this

386 result is not straightforward. By imposing the rhythm of a metronome, War-
387 lop et al. (Warlop et al. (2013)) showed a breakdown in long-range fractal
388 fluctuations in cycling and inferred an active central control of locomotion
389 on the generation of long-range autocorrelations. This result was consistent
390 with the previously observed breakdown of fractal features in metronomic
391 walking (Hausdorff et al. (1996)). As well, a cognitive task has the potential
392 to alter long-range fractal dynamics in walking (Hausdorff (2009); Lamothe
393 et al. (2011); Tanimoto et al. (2016)). Unfortunately, the effect of a cogni-
394 tive task reported by different groups can hardly allow a definitive synthetic
395 view of control strategy in dual-task locomotion, because of some discrepan-
396 cies. Here α slightly increased with dual-tasking in cycling, while precedent
397 studies on walking reported either a decrease in scaling exponent (Hausdorff
398 (2009); Lamothe et al. (2011); Tanimoto et al. (2016)) or no change at all
399 (Bollens et al. (2014); Grubaugh & Rhea (2014); Hausdorff (2009); Kiefer
400 et al. (2009)). The theories of interaction-dominant dynamics support the
401 idea that adding an external constraint to a system increases its random-
402 ness (Wijnants (2014); Diniz et al. (2011); Kello et al.), which would mean
403 a decrease in α and is once again contrary to our observations.

404 Three possible reasons, not mutually exclusive, may explain these dis-
405 crepancies.

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

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

424 perimental works may be needed to map changes in fractal behavior with
425 different mental constraints. In this context, the increased scaling exponent
426 during dual-tasking observed for the first time in the present study may be
427 specifically associated with the PASAT. This task recruits executive func-
428 tions and requires attentional functioning, working memory and information
429 processing speed, and this result cannot trivially be extended to any cognitive
430 task.

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

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

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

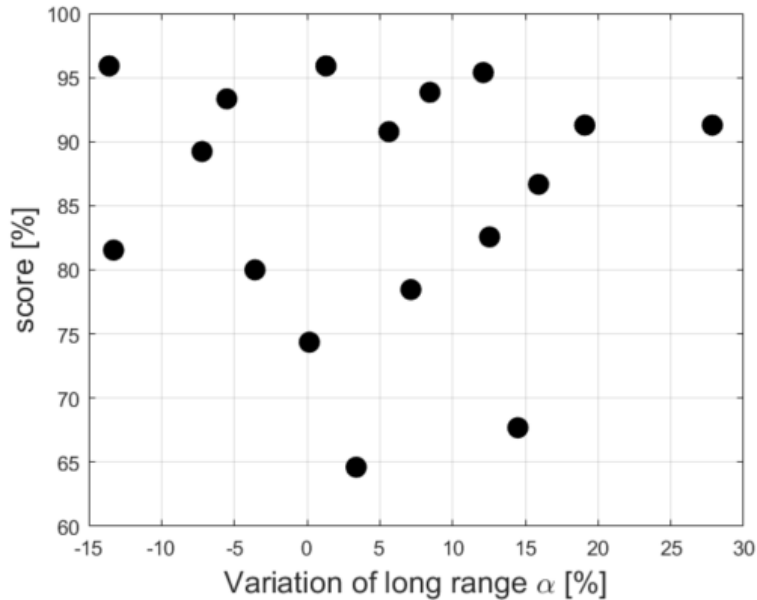


Figure 7: Correlation between the percentage of variation of α with dual tasking and the score in the 17 subjects with exploitable PASAT results.

462 dual-task cycling.

463 4.3. An unprecedented short-term correlation behavior

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

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

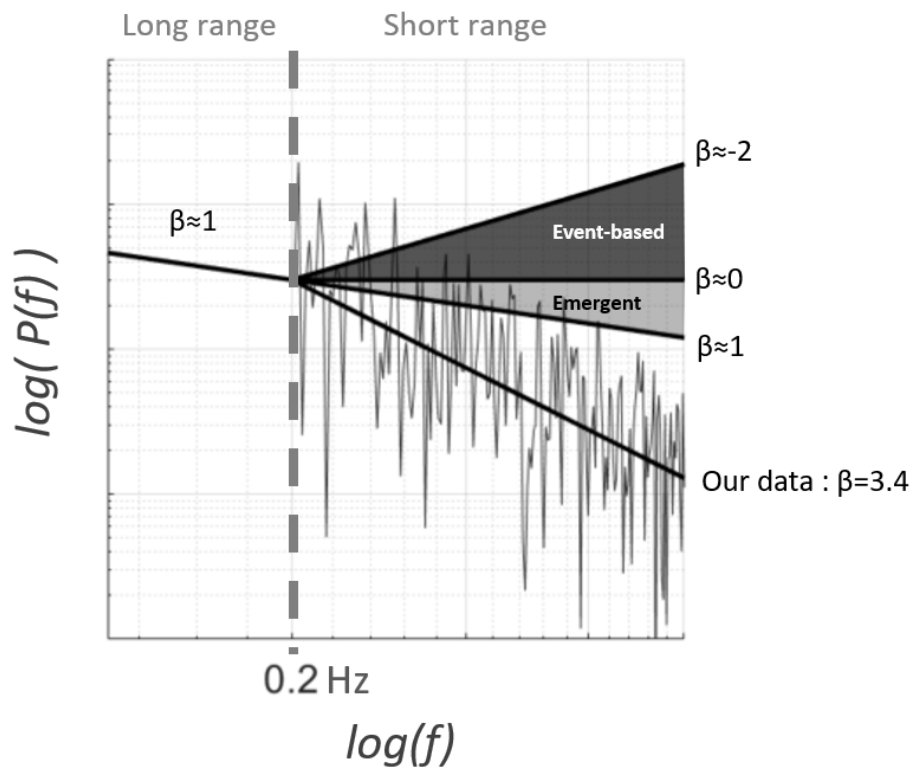


Figure 8: Example of the high frequency ($\geq 0.2 \text{ Hz}$) PSD of one typical subjects in reference situation, placed beside the classical zones associated with event-based and emergent timing.

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

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

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

511 *4.4. Impact of the periodicity in the cognitive task*

512 Interestingly enough, the cognitive task used here is repetitive at a con-
513 stant period (3s cycle of the delivered numbers during the PASAT), which
514 could alter the periodicity of cycling variability through a cyclic stimula-
515 tion. Indeed, it has been shown that cognitive time duration assessments,

516 typically behaving like $1/f$ noise, could spontaneously couple with a periodic
517 driver through a process called entrainment, while keeping an underlying
518 fractal scaling (Amon et al. (2018)).

519 Such a phenomenon, driven by the PASAT process, appears in our con-
520 ditions in the short-range, as revealed by a peak in the PSD graph around
521 0.34Hz during dual-tasking, corresponding to the 3s period between two suc-
522 cessive instructions (Figure 6). Thus, we observe a process similar to previous
523 works (Amon et al. (2018)), but in the short- rather than long-range localized
524 control.

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

531 5. Conclusion and perspectives

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

552 to include such peculiar short-range inertia phenomenon (Delignières et al.
553 (2008))

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

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