

Pedaling time variability is increased in dropped riding position

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Received: 15 September 2011 / Accepted: 9 December 2011
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Abstract Variability of cycle-to-cycle duration during a pedaling task is probably related to the rhythmic control of the lower limb muscles as in gait. Although walking variability has been extensively studied for its clinical and physiological implications, pedaling variability has received little attention. The present contribution determines the variability of the cycling time during a 10-min exercise as a function of upper body position. Nine healthy males were required to pedal on cycle-ergometer at a self-selected speed for 10 min in two different upper body positions [hands on upper handlebars (UP) or lower handlebars (DP)]. Time domain measures of cycling variability [total standard deviation (SDtot), mean standard deviation cycle-to-cycle intervals over

100 cycles (SD100), standard deviation of the average cycle-to-cycle intervals over 100 cycles (SDA100)] were measured. Moreover, the same time domain measures were also calculated for heart rate in order to discriminate possible involvements of autonomic regulation. Finally, the structure of the cycle variations has been analyzed in the framework of deterministic chaos calculating the maximum Lyapunov exponents. Significant increases in cycle-to-cycle variability were found for SDtot, SD100 in DP compared to UP, whereas cardiac parameters and other cycling parameters were not changed in the two positions.

Moreover, the maximum Lyapunov exponent was significantly more negative in DP. The results suggest that small perturbations of upper body position can influence the control of cycling rhythmicity by increasing the variability in a dissipative deterministic regimen.

Keywords Long-range correlations · Variability · Fatigue · Motor control · Maximum Lyapunov exponent

Introduction

Cycling is a complex task involving the coordination of lower limbs, and requiring the organization of physiological muscle responses to the environment during races. To this aim, subjects need to adequately explore the immediate environment, and correct the cycling time to appropriate target values. It is taught that, in other movement types such as walking, stride-to-stride variability emerges as a consequence of system's need to continuously correct movement errors (Jordan et al. 2007; Meardon et al. 2011). The study of walking variability has received great attention because it is interesting parameter for pathological conditions such as aging, neuropsychiatric diseases, Parkinson's disease, cruciate ligament deficit (Hausdorff 2009). Therefore, stride time variability during walking and running has been widely studied (Hausdorff et al. 1995a, b; Hausdorff 2009). Unfortunately, pedal cycling variability has received little attention. Cycling at a specific, self-selected, pacing requires the subject to continuously adjust the force produced and its timing relative to the pedal position. When the timing or the module of the force is not applied appropriately, an unwanted acceleration or deceleration of the pedal occurs, inducing a fluctuation in cycle duration. It is possible that unusual riding

Communicated by David C. Poole.

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64	positions change cycling variability both due to fatigue/	displacement of the pedal. Moreover, a previous observa-	111
65	discomfort or to mechanical factors (Corbeil et al. 2003;	tion showed that cycling modulates the cardiac chrono-	112
66	Gates and Dingwell 2008; Jordan et al. 2007). Therefore,	tropic response to exercise, inducing a new component in	113
67	an increase in the number of corrections of the pedal	heart rate variability (Blain et al. 2009). Therefore, we	114
68	velocity through timing activation of lower leg muscles is	evaluated a possible connection between cycling variability	115
69	expected to increase cycling variability, possibly as a	and heart rate variability. To this aim heart function was	116
70	function of cycling speed.	monitored by measuring heart rate and the duration of each	117
71	The present study has been designed to test the	heart beat throughout the experiment, using a PE 3000	118
72	hypothesis that, in comparison with standard postures (UP),	Sport Tester (Polar Electro, Kempele, Finland).	119
73	drop position (DP) would modify the coordination of lower		
74	limb muscles during pedaling and consequently would	Cycling variability analysis	120
75	influence the motor control during pedaling, thus changing		
76	the pedaling variability.	To analyze the variability of the cycle duration, two	121
		approaches have been used: the classical calculation of the	122
77	Methods	variability around the average cycle, and the maximum	123
78	Subjects	Lyapunov exponent (LyE) within the framework of the	124
79	Nine voluntary male subjects (age 41.0 ± 8.1 years, height	dynamical system theory. The latter has the advantage to	125
80	171 ± 7.5 cm, weight 66.0 ± 7.5 kg; mean \pm SD) par-	further characterize the origin of the variability.	126
81	ticipated to this study. The subjects were healthy without	The standard deviation of cycle-to-cycle intervals	127
82	any muscular, neurological and tendineous injuries and did	(SDtot), the average standard deviation cycle-to-cycle	128
83	not report any consumption of drugs. After being informed	intervals over 100 cycles (SD100), the standard deviation	129
84	of the procedures, methods, benefits and possible risks	of the average cycle-to-cycle intervals over 100 cycles	130
85	involved in the study, each subject reviewed and signed an	(SDA100) and the average cycle duration were obtained as	131
86	informed consent to participate in the study. The experi-	time domain measures. Similarly, the same time domain	132
87	mental protocol was performed in accordance with the	measures were also applied for R-R interval variability	133
88	ethical standards laid down in the Declaration of Helsinki	analysis.	134
89	for human experimentation.	The mathematical approach of LyE is based on an	135
		infinite amount of data, whereas our time series derives	136
90	Procedures	from 10-min observation (about 600 cycles). Moreover, the	137
91	Each subject performed a standardized 5-min warm up,	noise within the dataset also represents a challenge for LyE	138
92	consisting of free pedaling on a spinning bike (Schwinn,	calculation from limited dataset (for a revision of the	139
93	Johnny G Pro Spin Bike; crank length: 17 cm), wearing	application of LyE for human movement see e.g. Sterigou	140
94	low-heeled athletic shoes. All subjects were then invited to	and Decker 2011). Details of the calculation of the LyE can	141
95	pedal, in seated position, at a freely chosen cadence. They	be found in Rosenstein et al. (1992). Briefly, after repre-	142
96	were required to pedal in two different positions of the	sentation of the data into State Space visualization, False	143
97	upper body: with hands on top of the upper handlebars,	Nearest Neighbors Statistic was used to estimate the	144
98	near the stem and elbow angle between 160° and 180° (UP)	number of embedding dimensions. The maximum Lyapu-	145
99	or the traditional racing position with the torso partially to	nov exponent was then calculated using custom software	146
100	fully bent-over, hands on the drops portion of the handle-	for each subject in each position.	147
101	bars and elbows partially flexed (DP; elbow angle less than		
102	160°) in according to (Dorel et al. 2009).	Statistical analysis	148
103	Each session lasted 10 min. Between the two sequences	The results are expressed as mean \pm standard error. <i>t</i> stu-	149
104	subjects could recover for 5 min. The order of the body	dent tests for paired data were used to compare the two	150
105	position was randomized across subjects. To study cycling	body positions. The rejection level was set at $p \leq 0.05$.	151
106	variability, the crank angular position was measured with a		
107	sampling frequency of 100 Hz using a linear encoder	Results	152
108	connected to the pedal (MuscleLabTM 4020e, Bosco	All subjects completed the exercise test without any clinical	153
109	System, Ergotest Technology, Langensund, Norway; spa-	abnormality. However, some subject reported subjective	154
110	tial resolution of 0.1 mm), which recorded the vertical	discomfort when pedaling for 10 min in dropped (DP)	155
		posture.	156

157 An exemplificative plot of cycle-to-cycle duration over
 158 several pedaling cycles for UP and DP position is shown in
 159 Fig. 1a, and the frequency histogram of different cycling
 160 durations is shown in the inset: it is evident that in DP posture
 161 the frequency histogram shows a larger distribution of ped-
 162 aling durations. Average cycle duration is reported in Fig. 1b
 163 and was not significantly different between the two upper body
 164 positions. The analysis of pedaling variability in the two body
 165 positions (Fig. 1c–e) showed that the position with the hands
 166 on dropped handlebars (DP) increased pedaling variability
 167 compared to UP position: the standard deviation of cycle-to-

cycle intervals (SDtot) and the average standard deviation
 cycle-to-cycle intervals over 100 cycles (SD100) were sig-
 nificantly greater in DP position compared to UP position as
 assessed by two tails *t* test for paired data ($p < 0.05$; Fig. 1c,
 d). Conversely, the standard deviation of the average cycle-to-
 cycle intervals over 100 cycles (SDA100) did not significantly
 change in two positions (Fig. 1e).

The heart rate at the end exercise was not affected by the
 upper body position during 10-min cycling, as reported in
 Fig. 2a. Moreover, riding position did not significantly
 affect heart rate variability (HRV) (Fig. 2).

Fig. 1 Analysis of pedaling variability in two upper body positions during a 10-min cycling exercise.
a Representative plot of cycle-to-cycle duration over several pedaling cycles in two riding positions (UP upper handlebars, DP lower handlebars); the inset show the frequency histogram of different pedaling durations.
b Average cycle duration.
c–e Pedaling variability in two upper body positions; **c** standard deviation of cycle-to-cycle intervals (SDtot), **d** average standard deviation cycle-to-cycle intervals over 100 cycles (SD100), **e** standard deviation of the average cycle-to-cycle intervals over 100 cycles (SDA100). **f,g** Calculation of Lyapunov exponents; **f** typical plot of the average log of divergence versus time for the two upper body positions. The lines represent the slopes of the log(divergence) before a plateau was reached; **g** maximum Lyapunov exponent of the dynamic system for the two upper body position. * $p < 0.05$ ($n = 9$; *t* test for paired samples)

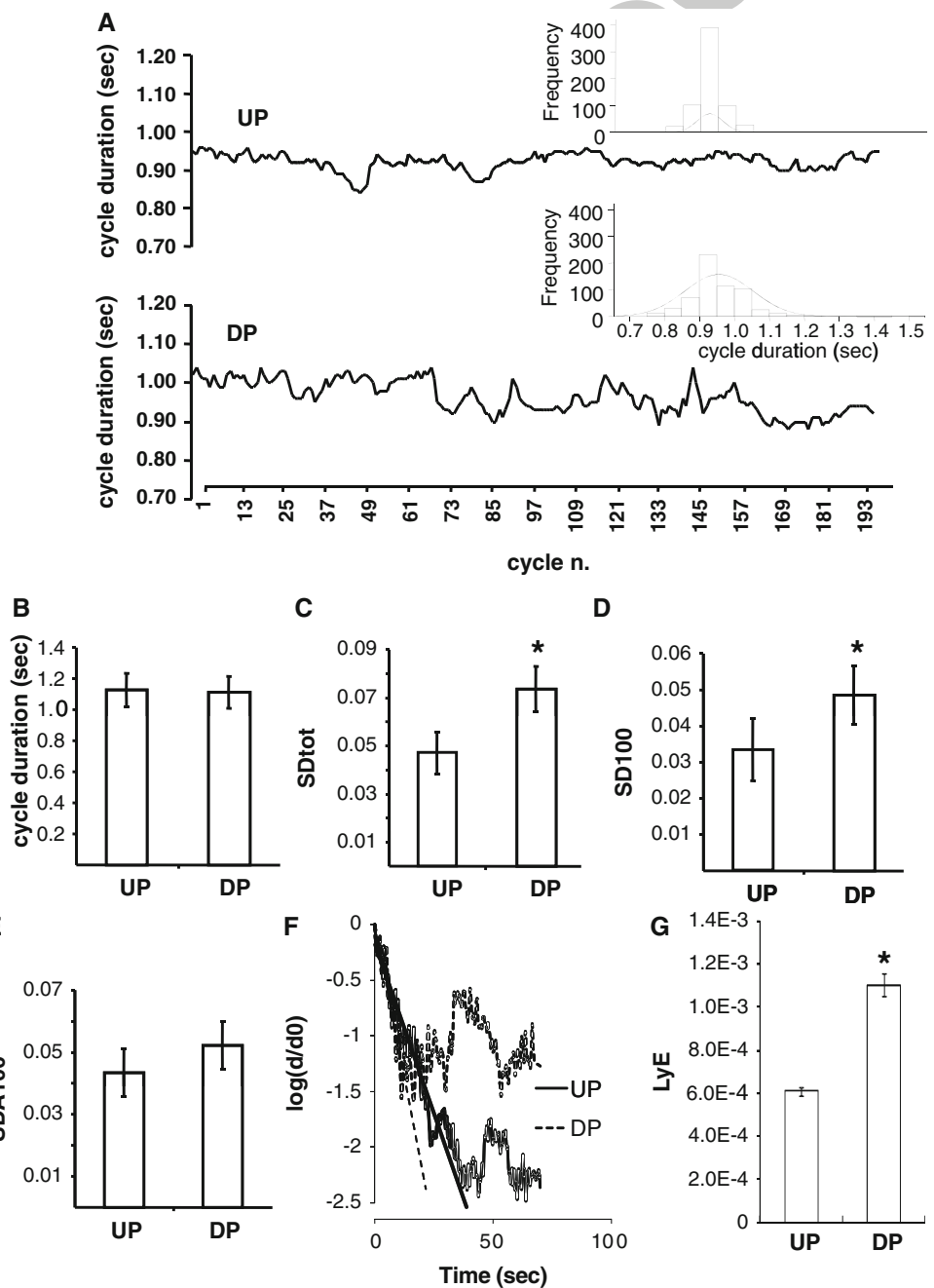
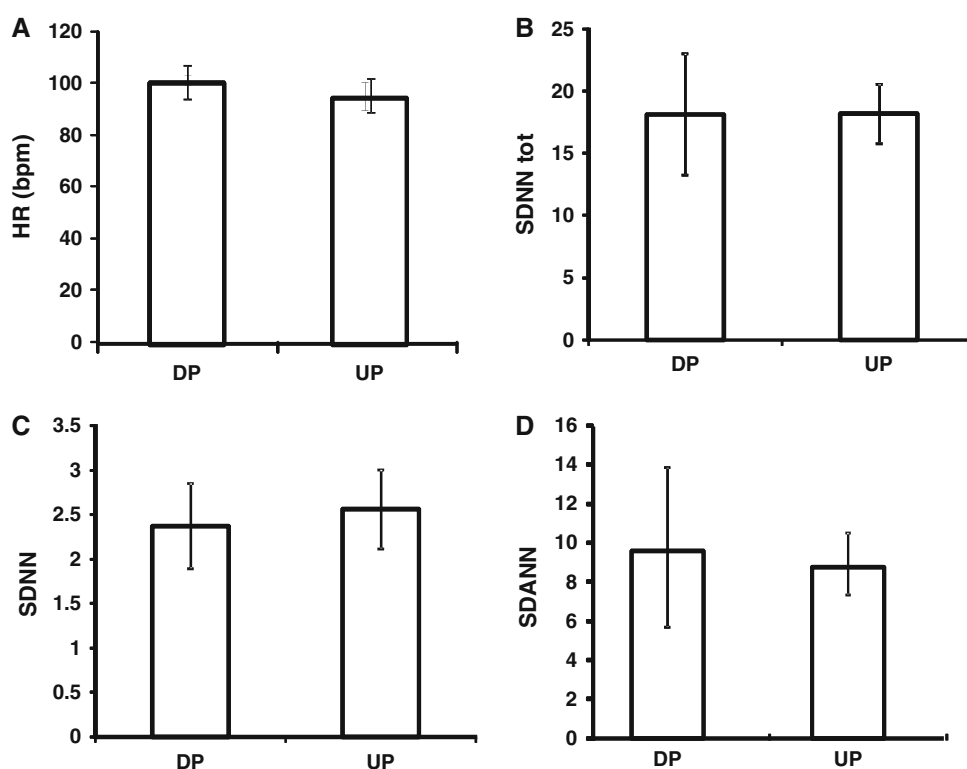


Fig. 2 Heart rate variability during 10-min cycling in two different upper body position (*DP* hands on lower handlebars, *UP* upper handlebars).

a Average heart rate during the exercise. **b–d** Heart rate variability in two upper body positions; **b** standard deviation of normal to normal (N–N) intervals (SDNNtot), **c** average standard deviation of N–N intervals over 100 heart beats (SDNN), **d** standard deviation of the average N–N intervals over 100 heart beats (SDANN) ($n = 9$)



179 For maximum Lyapunov exponent (LyE) calculation, a
180 5D embedding space was used after False Nearest Neighbors
181 Statistic. For each data point the minimum distance
182 between orbits (d_0) and the distance after a specific time
183 delay were then calculated (d). The ratio d/d_0 represented
184 the divergence. In Fig. 1f, a typical plot of the average log
185 of the divergence (d/d_0) versus time for the two upper body
186 positions is represented. To calculate the maximum LyE,
187 the slopes of such $\log(\text{divergence})$ before reaching the
188 plateau have been calculated. Figure 1g shows a significant
189 difference of the maximum Lyapunov exponent of the
190 dynamic system for the two upper body positions.

191 Discussion

192 The principal result of the present study is that upper body
193 position influences pedaling time variability during
194 cycling. Previous reports on walking variability demon-
195 strated that several factors such as aging, neuropsychiatric
196 diseases, Parkinson's disease, cruciate ligament deficit
197 (Hausdorff 2009), may influence step duration variability.
198 Therefore, this parameter is of interest to evaluate the
199 integrity of motor systems. However, although pedaling
200 involves cyclic movement of legs there are no data con-
201 cerning cycling variability. This report demonstrates that
202 the correction of the cycle period can be easily modulated
203 by small changes in the position of upper body, thereby

204 resulting in a greater number of corrections of pedaling
205 time. It was previously shown that, during cycling, the
206 electromyographic (EMG) pattern of lower limb muscles
207 (and particularly of the biceps femoris and tibialis anterior)
208 varies among different individuals and may even change in
209 the same individual during a test (Dorel et al. 2008). This
210 may result in a change of the cycling period.

211 The analysis of LyE also supports this hypothesis. In
212 fact, in our conditions the LyE is negative, which indicates
213 a deterministic system with an attractor. In other terms,
214 when the system is subject to a perturbation, it tends to
215 return to a stable steady state. In our case, if the rider stops
216 pedaling the resulting evolution of the system converges
217 toward the same state, being dictated by the friction: in
218 general, this is an example of a dissipative system. When
219 comparing the LyE of cycling and walking, the two sys-
220 tems appear quite different: LyE for walking has been
221 estimated to be about 0.14 (Smith et al. 2010), that is a
222 more chaotic regimen, whereas our data show a deter-
223 ministic system. This strong regularity of cycling behavior
224 is likely due to the fixed circular trajectory of the foot,
225 compared to the inverted pendulum dynamic of walking.

226 Intriguingly, the dropped posture induces the LyE to
227 become more negative in cycling. It is presently unclear
228 how the change in posture influences pedaling variability,
229 whether this derives from discomfort or from mechanical
230 factors or other physiological/neurophysiological contri-
231 butions, and carefully designed experiments are needed to

232 disentangle this question. As suggested by a referee, it
 233 seems unlikely that the changes in variability are due to
 234 fatigue, because we did not observe changes in heart rate
 235 and in heart rate variability. Moreover, the experiments
 236 were designed in order to reduce at minimum possible
 237 biases in the interpretation of the data deriving from dif-
 238 ferent workloads in the two riding conditions.

239 The variability of step time is taught to reflect the need
 240 of central pattern generators (CPG) to correct timing acti-
 241 vation of different muscles across the step cycle. Therefore,
 242 it is possible that the increase of the variability in DP is due
 243 to an increased number of corrections during the cycle due
 244 to the position (Jung et al. 1997; Norris et al. 2011). This is
 245 also suggested by the observation that restriction of arm
 246 movements changes hip movement variability during
 247 walking (Marks 1997).

248 Conclusion

249 Although cycling may be taught as a uniform phenomenon,
 250 there is actually some variability in cycle-to-cycle period,
 251 probably due to error corrections of cycle timing. We
 252 report that cycling variability is increased with a dropped
 253 posture, suggesting that in this position a larger number of
 254 errors occur. Therefore, cycling variability may be a simple
 255 index which could be studied and other physiological and
 256 pathological conditions.

257 **Conflict of interest** The authors declare that they have no conflict
 258 of interest.

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