TEMPORAL STRUCTURE OF PEDALING CADENCE VARIABILITY DURING ROAD-BASED CYCLING

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The purpose of this study was to analyse the temporal structure of pedalling cadence variability for two groups of subjects (i.e. experienced cyclists and non-experienced cyclists). Pedalling cadence was measured for different parts of the pedalling cycle (i.e. transition and stroke phases) during a road-based ride. Mean ±standard deviation (SD) was calculated and detrended fluctuation analysis (DFA) was applied to the cadence time-series. Smaller standard deviation was calculated in experienced cyclists compared to the non-experienced cyclists during the transition phases (p=0.02) and stroke phases (p=0.03). DFA values were lower in the group of experienced cyclists compared to the group of non experienced cyclists, for both transition phases (p=0.02) and stroke phases (p=0.02). Differences in cadence regulation were observed between experienced and non-experienced cyclists.

KEY WORDS: persistence, detrended fluctuation analysis, pedalling technique.

INTRODUCTION: Irrespective of the level of expertise, when a human performs a task repetitively, movement variations between trials are non-repetitive (Bernstein, 1967). In sport, movement variability could reflect the ability of athletes to flexibly adapt to external perturbations (Stergiou & Decker, 2011). Cycling is an interesting sport to consider for analyzing movement variability, as cyclists repeat the pedaling movement a large number of times. Quantifying the nature of serial correlations of cycle-to-cycle repetitions from the pedaling movement time-series could provide new insights into the control and coordination of the movement system (Dingwell, John & Cusumano, 2010). There have been many proposed theories and models to explain the emergence of complex variations of cyclic motor actions (Ashkenazy, M. Hausdorff, Ch. Ivanov & Eugene Stanley, 2002; Schoner, 2002; Delignieres, Torre & Lemoine, 2009; Dingwell, John & Cusumano, 2010). A signature of a system's inherent deterministic and stochastic control processes is proposed to be expressed in the dynamic fluctuations of the movement output parameter (Goldberger, Amaral, Hausdorff, Ivanov, Peng & Stanley, 2002; Schoner, 2002; Wagenmakers, Grünwald & Steyvers, 2006). When external control is applied to a system's preferred intrinsic dynamics, there is evidence of reduced persistence likelihood in the serial correlations (Hausdorff, Purdon, Peng, Ladin, Wei & Goldberger, 1996; Dingwell, John & Cusumano, 2010; Torre, Balasubramaniam & Delignieres, 2010). In subjects with reduced performance of endpoint control, increased persistence likelihood has been observed (Khandoker, Taylor, Karmakar, Begg & Palaniswami, 2008). The context of this work has practical appeal to gain understanding the underlying motor system processes of mechanical parameters deemed important for cyclists.

To the best of our knowledge, the above mentioned approaches haven't been applied to cycling. In road cycling, experienced cyclists may regulate the consistency of the effective forces applied to the pedal within a pedal cycle (Korff, Romer, Mayhew & Martin, 2007). Indeed, limiting the variations of the effective force applied to the pedals is expected to provide a benefit in terms of performance (Lafortune & Cavanagh, 1983; Zameziati, Mornieux, Rouffet & Belli, 2006). Van Ingen Schenau (1989) suggested that pedalling movement variability is affected by the pedalling skill of the individuals, with a finer control of the pedalling movement being operated by bi-articular muscles of experienced cyclists. Despite the expected impact of pedalling movement variability and control interventions on

cycling performance, little attention has been directed towards the complex variations of pedal forces and/or cadence during road cycling.
In this study, a novel approach was adopted to extract a time-series of pedalling cadence from road-based cycling to evaluate cadence regulation in experienced and non experienced cyclists. The magnitude of variation of the pedalling cadence was also evaluated using linear statistical measures while the persistence likelihood of pedalling cadence was evaluated using the detrended fluctuation analysis (DFA) method. It was assumed that a higher persistence likelihood of cadence could be observed in experienced cyclists compared to non experienced cyclists, for both transition and stroke phases.

METHODS: Nine subjects volunteered to participate in the study. A group of non experienced cyclists (n=5) and a group of experienced cyclists and triathletes (n=4) were considered. All subjects were asked to ride a road bike on a cycle path for a period of 40 minutes. The experiment was approved by the Ethics Committee of Victoria University for Human Research. The bike was instrumented with sensors allowing crank angles to be measured. Crank angles were calculated considering that 0/360 degrees indicates that the left crank arm is oriented vertically with the pedal at its highest point. Data were sampled at 100 Hz and stored on a data logger that was fitted in a saddle bag. The first derivative of the crank displacement was calculated to obtain cadence. A minimum of pedalling cycles was analysed for each subject. Average cadence vs. crank angle profiles was calculated. Average cadence values were calculated for four functional sectors (330 to 30 degrees, 30 to 150 degrees, 150 to 210 degrees and 210 to 330 degrees) and each pedalling cycle. Data from pedalling cycles at non steady state (e.g. waiting at the red light, accelerating after a stop) were excluded from the subsequent analysis. This resulted in a piecewise time-series composed of extended steady-state periods.
Detrended fluctuation analysis (Hausdorff, Peng, Ladin, Wei & Goldberger, 1995; Peng, Havlin, Hausdorff, Mietus, Stanley & Goldberger, 1995) was selected to describe persistence likelihood in the pedal cadence time-series, $\mathrm{x_i}$. The DFA method is based upon a root mean square analysis of a random walk (Hausdorff, Purdon, Peng, Ladin, Wei & Goldberger, 1996). A benefit of the DFA method is that it performs well when there are non-stationary points in a time-series. Briefly, the DFA procedure to obtain a scaling exponent is outlined in the following general steps. Step one, the original time series is integrated $\mathrm{Y(n)} = \sum_{\mathrm{i=1}}^{\mathrm{n}}[\mathrm{x_i} - \langle \mathrm{x} \rangle]$, where $\mathrm{x_i}$ is the i^{th} cycle and $\langle \mathrm{x} \rangle$ is the time series average. Step two, the integrated series $\{Y(n)\}_{i=1}^{N}$, is divided into equal segment lengths, l (e.g. l=9, 17, 33, 65, 129). Step three, the integrated time series is detrended to obtain a new time series $\{\tilde{Y}_l(n)\}_{n=1}^{N_l}$. This is done by fitting a least squares line in each segment of the time series, $y_l(n)$. The fluctuation of $\mathrm{Y(n)}$ about the best fit line $y_l(n)$ was computed for each segment length l, yeilding the detrended time series $\tilde{Y}_l(n) = [y(n) - y_l(n)]^2$. Step four, the average fluctuations were then determined for that segment length, where $F(n) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \tilde{Y}_l(n)}$. Step five, the average fluctuations are computed across set of all segment lengths, therefore forming a relationship between $F(n)$ and n. This relationship is plotted on a log-log scale and the least squares fitted slope of the relationship yeilds the DFA scaling exponent α (i.e. the persistence likelihood parameter). Larger scaling exponents indicates that the time series $\mathrm{x_n}$ contains an increase in persistence likelihood.

RESULTS: Variations of the pedalling cadence were observed within the pedalling cycle for both groups. For experienced cyclists, cadence varied between 92.2 ±2.6 rpm and 91.1 ±2.3 rpm. For non-experienced cyclists, cadence varied between 83.4 ±10.4 rpm and 81.7 ±10.3 rpm. Both maximal (p=0.01) and minimal (p=0.01) cadences were higher in the group of experienced cyclists. Cadence variations (i.e., maximal – minimal) were higher in the group of non experienced cyclists compared to the experienced cyclists group (1.7 ±0.5 rpm vs. 1.2 ±0.4 rpm, p=0.02). Using linear statistical measures, a higher standard deviation was observed in the non experienced cyclists compared to the experienced cyclists during the transition phases (6.2 ±1.7rpm vs. 4.7 ±0.4rpm, p=0.02) and stroke phases (6.0 ±1.7rpm vs. 4.7 ±0.4rpm, p=0.03). In the non experienced cyclists, standard deviation measured during the transitions phases was higher compared to the stroke phases (p=0.01). Analysis of the cadence time-series using the DFA showed that the persistence likelihood of cadence was lower in the group of experienced cyclists compared to the group of non experienced cyclists, for both transition phases (1.21 ±0.15 vs. 1.35 ±0.75 , p=0.02) and stroke phases (1.24 ±0.13vs. 1.36 ±0.06, p=0.02).

DISCUSSION: To the best of our knowledge, this is the first study to analyze the variability of pedalling cadence measured for different parts of the pedalling cycle while subjects are performing in real-world conditions. It has been considered that the ecological validity provided by this experimental situation overcompensated for the limitations associated with the lack of control of parameters usually considered in laboratory settings.
In support of our hypothesis, a higher likelihood of persistence in the pedalling cadence was observed in experienced cyclists compared to non experienced cyclists. These results also suggest that experienced cyclists naturally demonstrated an advanced circling technique (Korff, Romer, Mayhew & Martin, 2007), as evidenced by lower variations of the pedalling cadence within the pedalling cycle (i.e. maximal cadence – minimal cadence). Also, it seems that the natural variations of the neural and motor patterns selected by experienced cyclists resulted in lower variations of the performance variable (i.e. pedalling cadence) compared to non-experienced cyclists. This result can be explained by the fact that increasing cycle time (i.e. reducing cadence) usually results in increased cycle-to-cycle variance (Wing & Kristofferson, 1973), suggesting that natural variations of the motor patterns increase with the time duration of the cycle. One can wonder if lower variations in the recruitment of the bi-articular muscles in experienced cyclists could also explain this result (van Ingen Schenau, 1989). Interestingly, analysis of the variance revealed that the non-experienced group had more difficulty with controlling cadence during the transition phases (i.e. when the action of the bi-articular muscles is critical) of the pedalling cycle compared to the stroke phases, whereas the variance was similar for all phases in experienced cyclists. The analysis of the complex variations of cadence suggests that the control regulation of the pedalling cadence is tighter in experienced cyclists compared to non experienced cyclists. Based upon previous results of altered persistence in externally paced cyclical tasks (Torre, Balasubramaniam & Delignieres, 2010), and theories of cyclic tasks (Schoner, 2002), the results of this study may reflect the fact that experienced cyclists intervene more frequently to control pedalling cadence. This is also consistent with theories suggesting that cycling performance requires a good circling technique (Lafortune & Cavanagh, 1983; Zameziati, Mornieux, Rouffet & Belli, 2006). For non-experienced cyclists, there can be two possible explanations as to why they are less likely to intervene and effectively regulate cadence. First, from a dynamical systems perspective, once predicted future states are known to require correction, there could be delay in the self-organised coupling behaviour among the multiple sub-system components (Schoner, 2002). Second, from a perspective of hierarchical control, there can be uncertainty in the effectiveness that an intervening motor act will indeed be effective, therefore the choice not to intervene can incur minimal movement costs (Todorov, 2004; Nagengast, Braun & Wolpert, 2010).

CONCLUSION: Analysis of the serial correlations in the pedalling cadence implies differences in cadence regulation when comparing between experienced and non-experienced cyclists. These findings come from an ecologically valid cycling situation. A future approach can apply similar methods to investigate the control processes of other variables of the pedalling movement that can affect performance and risk of injury in cycling.

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