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Full Length Article

Multiscale coordination between athletes: Complexity matching in ergometer rowing

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ABSTRACT

Complex systems applications in human movement sciences have increased our understanding of emergent coordination patterns between athletes. In the current study, we take a novel step and propose that movement coordination between athletes is a multiscale phenomenon. Specifically, we investigated so-called "complexity matching" of performance measured in the context of rowing. Sixteen rowers participated in two sessions on rowing ergometers: One individual session of 550 strokes and one dyadic session of 550 strokes side-by-side with a team member. We used evenly-spaced detrended fluctuation analysis (DFA) to calculate the complexity indices (DFA exponents) of the force-peak interval series for each rower in each session. The DFA exponents between team members were uncorrelated in the individual sessions ($r = 0.06$), but were strongly and significantly correlated when team members rowed together ($r = 0.87$). Furthermore, we found that complexity matching could not be attributed to the rowers mimicking or locally adapting to each other. These findings contribute to the current theoretical understanding of coordination dynamics in sports.

1. Introduction

In the past two decades, the research domain of sports has witnessed a rapid growth of complex systems applications, both in terms of theory and methodology (e.g., Davids et al., 2014; Den Hartigh, Cox, Gernigon, Van Yperen, & Van Geert, 2015; Grehaigne, Bouthier, & David, 1997; McGarry, Anderson, Wallace, Hughes, & Franks, 2002). These applications were inspired by research in human movement sciences, foundational works on coordination dynamics in particular (e.g., Haken, Kelso, & Bunz, 1985; Kugler, Kelso, & Turvey, 1982; Newell, 1986; Schmidt, Carello, & Turvey, 1990). Dynamical models of human movement coordination have been applied to study the formation of coordination patterns in sports when athletes cooperate (e.g., Cuijpers, Zaal, & de Poel, 2015; De Brouwer, de Poel, & Hofmijster, 2013; Den Hartigh, Gernigon, Van Yperen, Marin, & Van Geert, 2014), compete one-versus-one (e.g., McGarry et al., 2002; Passos et al., 2008; Varlet & Richardson, 2015), or compete team-versus-team (e.g., Bourbousson, Seve, & McGarry, 2010; Duarte et al., 2013; Frencken, Poel, Visscher, & Lemmink, 2012).

Previous studies on coordination dynamics in sports have primarily focused on global patterns as they emerge through the dynamic interactions between athletes. These global coordination patterns were typically captured by a macroscopic inter-athlete or inter-team variable at a local timescale, such as the relative phases (e.g., Bourbousson, Seve, & McGarry, 2010; De Brouwer et al., 2013; McGarry et al., 2002; Varlet & Richardson, 2015) or distances between athletes or teams at the same moments (e.g., Frencken, Poel, Visscher, & Lemmink, 2012; Passos et al., 2008). In the current article, we propose that athletes' movement coordination goes

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beyond behavioral matching or mimicry at local scales, and that athletes coordinate their movements across multiple time scales. This assumption means that the interpersonal coordination would be characterized by a correspondence between athletes' patterns of performance variability. Accordingly, the complexity indices (i.e., fractal scaling exponents) of the athletes' performance time series would align. We aim to test this "complexity matching" hypothesis (e.g., Marmelat & Delignières, 2012; West, Geneston, & Grigolini, 2008) by applying nonlinear time-series analyses to performance data in a cooperative sports task, namely team ergometer-rowing.

1.1. Capturing complexity in sport performance

At the level of the individual athlete, well-coordinated behavior self-organizes out of the ongoing coordination within and between components at multiple levels of the system (e.g., cell activity, muscle contractions, limb movements; see Beek, Peper, & Stegeman, 1995; Den Hartigh et al., 2015). This complexity can be detected when examining the fluctuations in time series of athletes' repeated movements, such as stride-to-stride intervals in running (Jordan, Challis, & Newell, 2006) or force peak intervals in rowing (Den Hartigh et al., 2015). Optimal complexity is reflected in a pattern of high-frequency and low-amplitude fluctuations that are nested within low-frequency and high-amplitude fluctuations (e.g., Wijnants, Cox, Hasselman, Bosman, & Van Orden, 2012). This particular pattern of fluctuations is called $1/f$ noise, or pink noise. Patterns of pink noise are assumed to be typical for healthy and well-trained behavior (e.g., Den Hartigh et al., 2015; Glass, 2001; Goldberger et al., 2002; Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009). In sports, an optimal level of complexity would allow athletes to be flexibly stable, a key property of sport expertise (Davids, Glazier, Araújo, & Bartlett, 2003; Den Hartigh et al., 2015). Indeed, studies with cyclists, long-distance runners, skiers, and rowers, have empirically demonstrated patterns close to pink noise in the athletes' performance time series (Den Hartigh et al., 2015; Hoos, Boeselt, Steiner, Hottenrott, & Beneke, 2014; Nourrit-Lucas, Tossa, Zélic, & Delignières, 2015; Tucker et al., 2006).

For stationary processes, the pattern of fluctuations can tend towards disorder or randomness, called white noise (Marmelat & Delignières, 2012). Originally, deviations from pink noise have been linked with suboptimal dynamics, and the presence of (physiological) pathology or less-trained behavior (e.g., Glass, 2001; Goldberger et al., 2002; Wijnants et al., 2009). However, some researchers also suggested that imposing additional constraints on movement coordination tasks results in a different organization of the motor system, thereby shifting the pattern of variation toward more randomness (e.g., Chen, Ding, & Kelso, 2001; Den Hartigh et al., 2015; Diniz et al., 2011; Kuznetsov & Wallot, 2011; Washburn, Coey, Romero, Malone, & Richardson, 2015). In particular when adding rigid constraints (e.g., specifying a movement rhythm to be followed), shifts toward white noise are expected to occur. For example, Washburn et al. (2015) let participants perform a rhythmic arm swinging task and manipulated the environmental constraints. When participants performed their task while being exposed to a visual metronome stimulus, a shift to white noise was observed compared to a condition in which the stimulus was absent. In addition, when participants explicitly intended to time their movements with the stimulus pattern, the shift toward random variation was even more prominent.

Taken together, although external constraints can significantly impact the pattern of variation in motor behavior, under low constraints one would expect a pink noise pattern in well-trained motor behavior (Den Hartigh et al., 2015; Washburn et al., 2015). In sports, this idea was recently supported by studies with rowers and skiers (Den Hartigh et al., 2015; Nourrit-Lucas et al., 2015). In the study by Den Hartigh et al. (2015), rowers with different levels of expertise were asked to just row at their preferred rhythm on a rowing ergometer (Den Hartigh et al., 2015), whereas Nourrit-Lucas et al. (2015) asked skiers with different expertise levels to make ample and frequent cyclical sideways movements on a ski simulator. Under these low constraints, higher-skilled rowers and skiers demonstrated more prominent patterns of pink noise in their performance than their less-skilled counterparts.

1.2. Complexity matching between athletes

So far, research has thus provided insights into interpersonal coordination in terms of macroscopic patterns of interaction (e.g., De Brouwer et al., 2013; Passos et al., 2008; Varlet & Richardson, 2015), and more recently into intrapersonal coordination across multiple time scales (e.g., Den Hartigh et al., 2015; Nourrit-Lucas et al., 2015). It is unclear whether athletes in team sports also coordinate their joint behavior across multiple time scales, although a fundamental study on interpersonal coordination outside the domain of sports hints that this might well be the case. Marmelat and Delignières (2012) demonstrated that two people oscillating a hand-held pendulum while sitting next to each other, match the complexity indices of their individual movement time series. They also showed that this complexity matching effect could not be attributed to just copying the movements of the partner, but that it reflected a pattern of *multiscale interpersonal coordination* (for more recent demonstrations of complexity matching in simple interpersonal tasks, see also Coey, Washburn, Hassebrock, & Richardson, 2016; Delignières & Marmelat, 2014; Fine, Likens, Amazeen, & Amazeen, 2015).

Based on the study by Marmelat and Delignières (2012), it is a plausible hypothesis that athletes demonstrate complexity matching in types of sports that require absolute coordination (i.e., synchronizing movements). A typical sport in this regard is rowing, in which athletes need to synchronize their movements for optimal performance (e.g., Den Hartigh et al., 2014; Hill, 2002; Wing & Woodburn, 1995). The aim of the current research is therefore to test whether complexity matching can be detected in rowing, more specifically, in rowers performing a relatively unconstrained and steady workout together on rowing ergometers. In line with recent research on individual ergometer rowing (Den Hartigh et al., 2015), our first hypothesis was that rowers show complex intra-system coordination, reflected by patterns of performance variation that are close to pink noise. Following previous research studying the complexity matching hypothesis outside sports (Delignières & Marmelat, 2014; Marmelat & Delignières, 2012), our second hypothesis was that interpersonal coordination occurs across multiple time scales, reflected by complexity indices between rowing team members that are highly, significantly correlated when they row together. Finally, in accordance with the notion of

Fig. 1. Illustration of the research setup.

complexity matching, our third hypothesis was that the coordination between rowers cannot be attributed to only short-term, local correction processes of the rowers to each other's rowing strokes. This would be reflected by an absence of significant local cross-correlations between rowers' performance variations when they row together, and by the absence of a significant correlation between the complexity matching outcomes and a collective variable reflecting global coordination patterns (i.e., temporal asynchrony). If all three hypotheses are supported, we can conclude that interpersonal coordination in ergometer rowing is likely a multiscale phenomenon, in which rowers engage in a global and mutual adaptation to each other's complexity structure.

2. Method

2.1. Participants

Sixteen competitive male rowers ($M_{\text{age}} = 20.13$, SD = 1.67) were contacted by the board of their rowing club to participate in our study. They were part of three teams, one men's eight and two men's fours. The average height of the rowers was 185.75 cm ($SD = 7.55$), and their average weight was 82.78 kg ($SD = 10.14$). The rowers in all three boats practiced together around three times a week for at least two months. Before the start of the study, participants signed an informed consent and a medical health form.

2.2. Materials and procedure

The protocol of the study was approved by the local ethical review board of the university where the experiment was conducted. The research setup included two rowing ergometers that were placed next to each other (see Fig. 1), a typical setup also used by the rowers during club training. A force sensor (Measurement Specialties, Inc.) was attached between the handle and the chain of each ergometer, which was connected to a data acquisition (DAQ) device (NI USB-6009). The DAQ device transferred the raw signals to a computer via USB, and these signals were collected in Volts at a frequency of 100 Hz. This setup allowed us to obtain densely sampled time series in a controlled setting.

The participants were involved in two ergometer rowing sessions: One individual rowing session in which the participant rowed alone, and one dyadic rowing session in which the participant rowed together with a team member, with whom he was randomly paired. Before each of the sessions, participants did a short warming-up on the rowing ergometers. In the individual rowing session, we instructed the participant to perform 550 strokes at a rhythm that he preferred, and in the dyadic rowing session we asked the rowers to perform 550 strokes at a joint rhythm that they preferred. The number of strokes (550) was based on the fact that we had to obtain a sufficiently long time series to conduct our nonlinear analysis (Delignières et al., 2006), while avoiding the effect of fatigue on performance. Performing 550 strokes took between 20 and 30 min for the rowers, which they were used to in regular workouts. However, a coach of the rowers' club indicated that rowing for more than 30 min would lead to fatigue effects. The drag factor was set

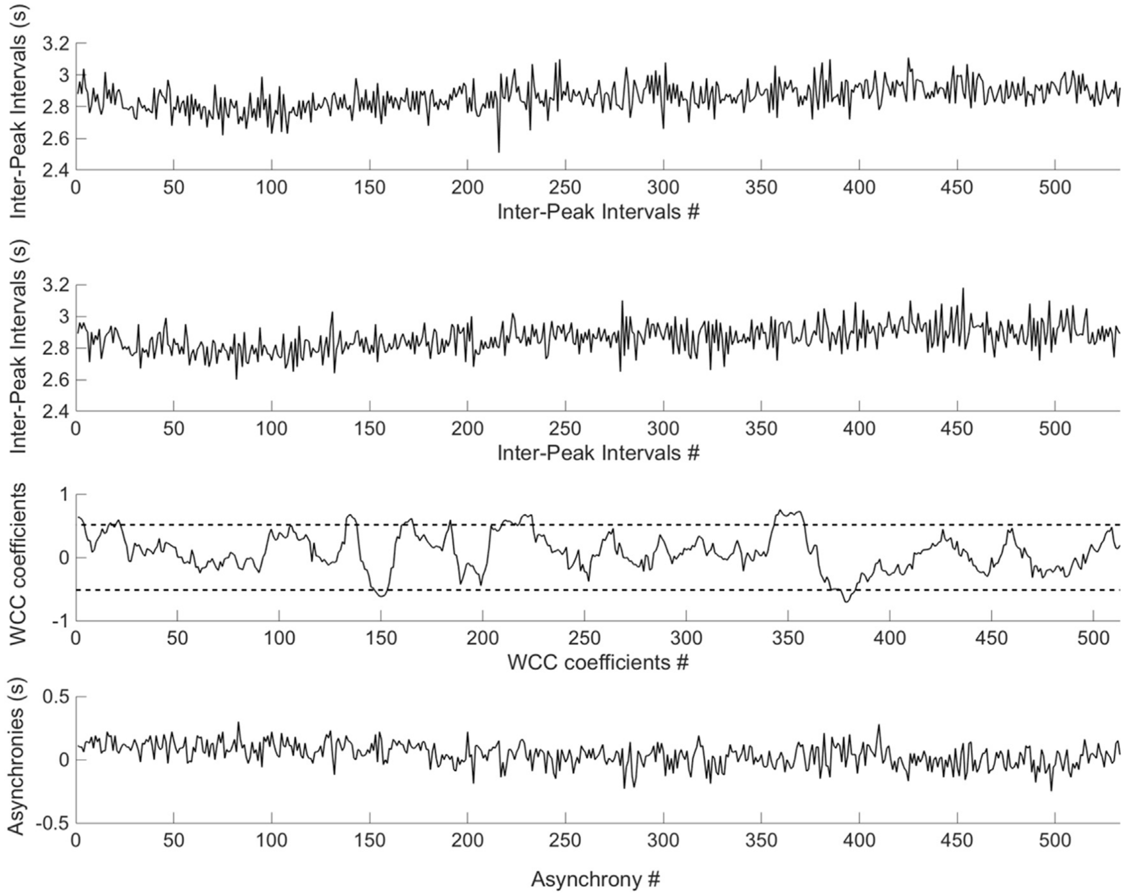

Fig. 2. Time series of two rowers (Team 1) in their dyadic session. For rower 1 (Panel a), the average duration of the IPI was 2.86 s ($SD = 0.09$), and his DFA was 0.72. For rower 2 (Panel b), the average duration of the IPI was 2.86 s, (SD = 0.09), and his DFA was 0.74. The percentage of significant WCC coefficients at lag 0 (Panel c) was 4.29%, and the average temporal asynchrony (Panel d) was 0.04 s (SD = 0.09). The dashed lines in Panel c highlight significance thresholds for the correlation ($r_{13} = 0.51$, $p < .05$).

at 120, which corresponds to the resistance set by the participants for their usual workouts.

During each session, the rowers' progress was tracked, and after each set of 80 strokes the completed number (and the preceding and following number, e.g., 79-80-81…159-160-161) was shown on a 27″ HD screen in front of the ergometers. This way, we interfered as little as possible, while the rowers still had some idea of their progression. In line with our intention to minimize the imposed constraints, we did not provide any additional instructions or feedback on the rowers' performance (e.g., speed, stroke frequency, or quality of coordination). Moreover, neither we nor the participants talked during the sessions.

2.3. Analysis

The raw force data were first low-pass filtered with the Butterworth filter (cut-off frequency 8 Hz). The unit of further analysis was the inter-peak interval (IPI) of the force curves in seconds, that is, the time interval between the moments at which maximal force was exerted (see Fig. 2a and b for representative examples). This measure was chosen because the coordination of force exertion is crucial for both individual and team rowing performance (Den Hartigh et al., 2015; Hill, 2002; Wing & Woodburn, 1995).

The first two hypotheses pertained to the complexity of rowing performance, as revealed by the temporal structure of the time series. For each IPI series we therefore determined a complexity index using the evenly-spaced detrended fluctuation analysis (DFA). This is a relatively new nonlinear time series analysis that has been found to reveal more reliable and consistent results than the traditional DFA (Almurad & Delignières, 2016). In brief, the DFA algorithm divides the time series into non-overlapping windows of size n, and within each window the series is detrended and the standard deviation of residuals is computed. The average (detrended) standard deviation, $F(n)$, is then calculated for all windows of size n, ranging from 10 to $N/4$, where N is the length of the entire time series. The complexity index α is traditionally given by the slope of $F(n)$ vs n on a log-log scale. However, the logarithmic transformation increases the density of points along the abscissa axis as the window size increases, thus increasing the influence of large windows in the estimation of the DFA exponent α. Almurad and Delignières (2016) therefore proposed to divide the range of $\log(n)$ into a series of 18 intervals of equal length, to then average the $F(n)$ values that fall within each interval (hence the term evenly-spaced DFA). When the DFA exponent (α) equals 1, this corresponds to pink noise, whereas deviations toward 0.5 or 1.5 correspond to white noise or Brownian motion (i.e., integrated white noise), respectively.

For our first statistical analysis we determined the 95% confidence interval around the DFA exponents of the participants, to assess whether or not the theoretical value of pink noise ($\alpha = 1$) falls within the interval (*hypothesis 1*). Second, we calculated the Pearson correlation between the DFA exponents of the two team members in the individual session (control condition) and in the dyadic session, in order to examine the degree to which these exponents matched while participants rowed together (*hypothesis 2*).

Finally, we examined the local dependencies between the team members' IPI series, and the correlation between the series of asynchronies and the (absolute) difference between DFA exponents of team members of the same dyad. This was done in order to determine whether their coordination patterns could be attributed to a short timescale, that is, to local adaptation processes (*hypothesis 3*). These tests are important, because one rower 'copying' the other on a stroke-by-stroke basis could also lead to similar DFA values of the team members' IPI series.

First, we conducted a windowed cross-correlation (WCC) analysis (e.g., Boker, Xu, Rotondo, & King, 2002; Marmelat & Delignières, 2012). Pearson correlations were calculated between the series of the team members in the dyadic session, in windows of 15 data points (i.e., IPI intervals). After the first correlation was computed, the window shifted one data point forward and a second correlation was computed. This shifting and correlating continued until the window had covered the entire IPI series (Fig. 2c). To determine whether participants copied each other's movements or whether one tended to mimic the pattern of the other, we examined both the zero-lagged windowed correlations and the -5 to $+5$ lagged windowed correlations. If the two rowers' IPIs were perfectly synchronized for 15 consecutive strokes, the WCC at lag 0 would be 1 and the percentage of significant correlations would equal 100. The same perfect WCC and percentage would be observed at lag n in case rower A would have a similar 15-strokes IPI series as rower B n strokes ahead, and at lag $-n$ if he would have a similar 15-stroke IPI series n strokes behind (where n ranges from 1 to 5 in these cases). Second, we determined the asynchronies by computing the difference in timing between team members' force peaks for each movement cycle (Fig. 2d). Next, we calculated the Pearson correlation between the average temporal asynchrony of the dyads, and the difference in DFA exponents of the dyads (i.e., the degree of matching of the complexity indices).

3. Results

On average, the DFA exponent of the participants' IPI series in the individual session was 1.00 ($SD = 0.10$; 95% CI = 0.95–1.05). In line with our first hypothesis, the 95% CI clearly includes the value 1.00, indicating that the patterns of fluctuation in the individual session were close to pink noise.

Fig. 3 displays the DFA exponents of all participants in the individual session and in the dyadic session. In line with the results in the individual session, the average DFA exponent was close to 1 in the dyadic session ($M = 1.03$, $SD = 0.15$; 95% CI = 0.96–1.11). As could be expected, the team members' complexity indices in the individual session did not correlate significantly ($r_6 = 0.06$, $p = .89$). However, in line with our second hypothesis, the complexity indices of the rowing team members were strongly correlated in the dyadic session ($r_6 = 0.87$, $p < .01$). Fig. 3 shows that the complexity matching effect occurs for all dyads except one. Excluding this dyad from the analysis would lead to an almost maximal correlation between the team members' DFA exponents ($r_5 = 0.99$, $p < .01$).

Fig. 4 displays the distribution of the WCC coefficients across the different lags for the individual and dyadic sessions, including all participants. We determined the percentage of significant correlations ($p < .05$), in this case correlations that were higher than 0.51. On average, the percentage of significant 0-lag correlations in the dyadic session was low ($r_{13} = 0.15$), and this value decreased with increasing lags. Notably, the percentage of significant WCC coefficients in the dyadic session was hardly higher than could be expected based on chance (i.e., the grey bars in Fig. 4, representing the WCCs based on the IPI series in the individual sessions). This indicates that the IPIs are largely locally *in*dependent.

With regard to the asynchronies, these have very low values for the dyads in our sample ($M = 0.02$, $SD = 0.04$), which means that team members' peak forces were highly synchronized. There was a significant negative correlation between temporal asynchrony and the difference in DFA values within dyads ($r = -0.76$, $p = .03$). However, this was due to the presence of an outlier, namely the dyad that did not show complexity matching. Excluding this dyad from the analysis revealed an almost neutral, non- significant correlation ($r = -0.041$, $p = .93$) between global coordination patterns and complexity matching outcomes. This result, and the outcomes of the WCC analysis, provide support for the third hypothesis that the coordination between rowers cannot be attributed to only short-term,

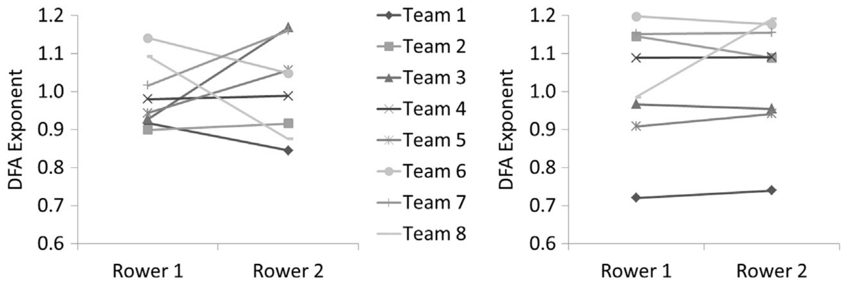

Fig. 3. DFA exponents of rowers in the individual session (left panel) and dyadic session (right panel).

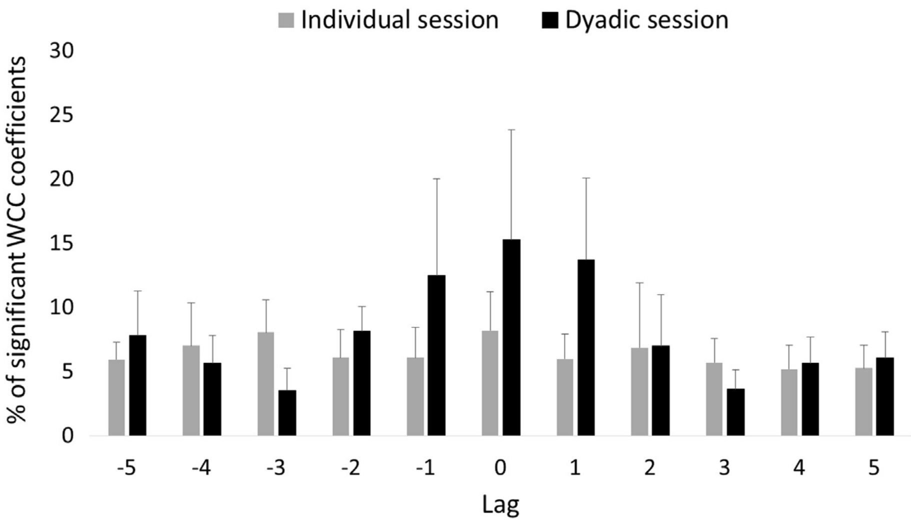

Fig. 4. Means and standard deviations of the percentage of significant windowed correlations between the (lagged) IPI series in the individual (grey) and dyadic (black) session.

local correction processes.

4. Discussion

In the current study, we took a novel step in studying coordination dynamics in sports. Our major aim was to test whether complexity matching occurs between rowers during an ergometer workout, suggesting multiscale coordination between the athletes. At the intrapersonal level we found prominent patterns of pink noise, which is in line with our first hypothesis. This finding replicates recent demonstrations of pink-noise performance fluctuations among skilled rowers (Den Hartigh et al., 2015), and skilled skiers (Nourrit-Lucas et al., 2015), while performing under low constraints. At the interpersonal level, previous research has already consistently demonstrated that patterns of coordination emerge between (dynamically coupled) athletes at a local time scale (e.g., De Brouwer et al., 2013; McGarry et al., 2002; Passos et al., 2008). In the current study we extend this line of research, by providing evidence that interpersonal coordination between athletes is a multiscale phenomenon. The complexity indices of the rowers in the dyadic session correlated very strongly, and almost perfectly when one of the dyads was not taken into account. This result is in accordance with the findings of Marmelat and Delignières (2012), who found a correlation between complexity indices of 0.99 when individuals performed synchronized oscillations with hand-held pendulums.

The observation that one of the dyads in our study did not align their complexity indices suggests that certain preconditions should be in place for complexity matching to occur. Remarkably, contrary to the other dyads, the two rowers in the "deviating" dyad differed considerably in height. The average height difference between team members in our sample was 6.75 cm, whereas the members of the deviating dyad had a height difference of 13 cm, corresponding to more than two standard deviations above the average. Possibly, in sports where athletes need to synchronize their movements, physical characteristics of the athletes, such as height, may determine whether or not complexity matching between the athletes occurs. However, this remains to be investigated in future research.

Our complexity matching hypothesis was further supported by the WCC analyses, which showed that the matching could *not* be accounted for by the rowers mimicking each other, or merely adjusting to a previous IPI of the team member after each stroke. In addition, although team members highly synchronized their peak forces, we found no systematic association between this collective variable of coordination (temporal asynchrony) and complexity matching. This suggests that local synchronization and global matching are rather independent. Together, these results provide evidence for the idea that the rowers coordinated their stroke patterns across multiple timescales and, more generally, that complexity matching takes the form of a global, multiscale pattern of coordination.

4.1. Limitations and future directions

The current study replicates the presence of pink noise in trained athletes' motor behavior, and is the first to demonstrate complexity matching during a sports task. However, some important questions remain to be answered in future research. First, as researchers have suggested, additional constraints may lead to a different organization of the motor system (e.g., Chen et al., 2001; Den Hartigh et al., 2015; Diniz et al., 2011; Kuznetsov & Wallot, 2011; Washburn et al., 2015). This raises the question: What are the effects of imposing external constraints on the noise patterns of individual athletes, and on the noise patterns around which athletes demonstrate complexity matching? Relatedly, complexity matching is typically expected to occur around pink noise, a hypothesis called “1/f resonance” (Aquino, Bologna, West, & Grigolini, 2011). The degree to which 1/f noise and complexity matching prevail under additional constraints related to competition or practice, is thus an interesting issue for further research.

Second, the conclusions of our study pertain to a sports task in which the coupling between the athletes is fairly cooperative and symmetrical. In rowing ergometer practice, performing the task next to each other is a typical setup, but in on-water rowing the perceptual coupling is asymmetrical (rowers are sitting behind each other). Furthermore, apart from perceptual coupling, the mechanical coupling plays a role as well. Such a mechanical coupling is naturally present when rowing in the same boat on the water, but may also be added in a lab setting. Ergometers can be mechanically connected by placing them on slides (e.g., Cuijpers et al., 2015; De Brouwer et al., 2013). Due to this additional coupling, rowers also have information about the coupled-ergometers' movements, and the stability of their coordination is expected to increase. Indeed, according to the literature on coordination dynamics, the stability of coordination is inherently connected to coupling forces (e.g., Haken et al., 1985; see Cuijpers et al., 2015 for a rowing-case). However, the consequences of different forms of perceptual and mechanical coupling for complexity matching remain to be explored. It could be, for instance, that an asymmetrical perceptual coupling results in a unilateral adaptation of one rower to the complexity of the other. Furthermore, when rowers are mechanically coupled, there are more rigid constraints on their movements, which may shift the patterns of variation toward white noise (cf. Washburn et al., 2015).

Finally, studying complexity matching in other types of sports, involving a competitive coupling between athletes and/or more relative coordination patterns (e.g., in squash, soccer and basketball), is an interesting avenue for future research (cf., Davids, Button, Araújo, Renshaw, & Hristovski, 2006; Duarte et al., 2013; McGarry et al., 2002).

4.2. Conclusion and implications

In this study, we provided evidence for complexity matching during sports (ergometer rowing) performance. Our results strongly suggest that athletes coordinate their behavior across multiple time scales, instead of merely locally adjusting to each other's movements. This contributes to the current theoretical understanding of coordination dynamics in sports, which so far is primarily based on research capturing coordination patterns in terms of macroscopic variables at a local time scale, such as relative phase measures between athletes' movements (e.g., De Brouwer et al., 2013; McGarry et al., 2002; Varlet & Richardson, 2015). Finally, in terms of practical implications, an important next step is to discover whether, and how, pink noise fluctuations of individual rowers' movements and complexity matching between rowers relate to performance in team sports, and how they can be improved through training.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.humov.2017.10.006.

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