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The changes in classical and nonlinear parameters after a maximal bout to elicit fatigue in competitive swimming

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A R T I C L E I N F O

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A B S T R A C T

The aim was to assess the effect of fatigue on linear and nonlinear parameters in swimming. Twenty-four fitness-oriented swimmers performed a maximal bout of 100 m at front-crawl to elicit fatigue. Before (pre-) and immediately after (post-test) the bout, participants swam an all-out 25 m to derive the speed fluctuation (dv), approximate entropy (ApEn) and fractal dimension (FD) from the speed-time series collected by a speedo-meter. Swim speed was 10.85% slower in the post-test than in the pre-test ($p < .001$, $\eta^2 = 0.72$). There was an effect of the fatigue on the dv with a moderate effect size. The dv increased shifting the 95CI band from 0.116–0.134 to 0.140–0.161. The ApEn showed non-significant variations between the pre- and post-test having the 95CI of pre- and post-test overlapped (pre: 0.659–0.700; post: 0.641–0.682). The FD showed as well a significant variation (the 95CI moved from 1.954–1.965 to 1.933–1.951). It can be concluded that in swimming there are changes in classical and nonlinear parameters under fatigue.

1. Introduction

In some sports settings, high-level performers (the athlete) are no longer able to elicit significant improvements of the performance determinants. The margins to improve the performance and/or its determinants are rather small (Allen, Vandenbogaerde, & Hopkins, 2014). In such event, an extra challenge is that the mainstream variables selected to monitor the athletes are not sensitive enough to trivial variations of the motor behaviour. For instance, it was reported that the performance of elite swimmers improved less than 1% by season (Costa et al., 2012). Therefore, the assessment of the sports performance as a linear system may not be insightful enough. A linear system is characterised by proportionality between inputs (in this case, the performance determinants) and the output (the sports performance). The alternative is to consider the relationship between sports performance and its determinants as a nonlinear and complex system (Komar, Seifert, & Thouvarecq, 2015).

A nonlinear and complex system features several components. These components interact among each other's direct and/or indirectly, having an effect ultimately on the output (Abarbanel, Rabinovich, & Sushchik, 1993). In sports settings one may argue that different determinants will interact among them, having an effect on the sports performance. A nonlinear complex system is

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characterized by interaction-dominant dynamics. Another main feature of these systems is that there is no proportionality between the changes in inputs and output (Bravi, Longtin, & Seely, 2011; Komar et al., 2015; Preatoni, Ferrario, Donà, Hamill, & Rodano, 2010). Trivial changes in one input can have a meaningful effect on the output. So, an alternative to tackle the concern reported early on about the lack of sensitivity of classical variables might be monitoring nonlinear parameters. Nonlinear parameters can be more sensitive to trivial changes in the performance and the motor behaviour of the performer than classical parameters (Bravi et al., 2011). However, there is scarce research in sports performance underpinned by nonlinear dynamics. In time-based sports, such as competitive swimming, the performance is measured with a 0.01 s of accuracy. Therefore, the follow-up question is how insightful nonlinear parameters can be in assessing the athletes' motor behaviour. On top of that, it has also been noted that in competitive swimming there are several interplaying factors that ultimately affect performance (Barbosa et al., 2010). Altogether, for such narrow margin of improvement, nonlinear parameters might be very insightful of the performance delivered.

On land walking, the magnitude of the stride-to-stride fluctuations and their changes over time helps to understand the motor control of gait (Hausdorff, 2007). The assessment of the fluctuations within the stride cycle by nonlinear parameters can provide insight into the organization, regulation, interactions and stability of the entire locomotor system. If on land it is assessed the stride-to-stride fluctuations, in water it is monitored the arm-stroke to arm-stroke fluctuations, being this known as speed fluctuation (dv). The dv quantifies the amount of variation of the time-series in reference to its mean value (Barbosa et al., 2005). This is a dimensionless measure that ranges between 0 (no fluctuation) and 1 (high fluctuation). There are several parameters that can be selected under complex science as well. The approximate entropy (ApEn) and fractal dimension (FD) are the most common ones. The ApEn describes the degree of irregularity and complexity over the time-series (Bravi et al., 2011). The ApEn ranges between 0 (repeatability over the time-series) and 2 (randomness over the time-series) (Pincus, 1991). The FD provides insight on the level of complexity of a time-series (Higuchi, 1988). The FD ranges between 0 (the motor behaviour is less complex) and 3 (the motor behaviour is more complex).

It was reported evidence of fractal-like fluctuations in human gait on land (Hausdorff, 2007). Over a 120-min load carriage March by servicemen, the FD decreased from 1.43 to 1.12 (Schiffman, Chelidze, Adams, Segala, & Hasselquist, 2009). Conversely, there are mixed findings on its effect in ApEn (Arif, Ohtaki, Nagatomi, Ishihara, & Inooka, 2002; Preatoni et al., 2010). In human gait on land, it was reported that the ApEn would increase by 12% to 30% between a pre- and post-test after being under a protocol that elicited fatigue (Arif et al., 2002). However, race-walkers performing a set of 40 × 20 m did not show any significant difference in the entropy between the first 20 and the last 20 trials (Preatoni et al., 2010). Altogether, there seems that fatigue has an effect on the nonlinear proprieties of human gait on land. If the same phenomenon happens in human swimming, it might help performers to excel because more insightful and sensitive details are provided to them.

In time-based sports, such as competitive swimming, the delay of the onset of the fatigue is paramount to improve performances. In alignment with this understanding, a lot of research has been carried out to understand the mechanisms of fatigue. The manifestation of fatigue can be observed by the impairment in the ability of producing mechanical force or power (Green, 1997). The mechanical output produced by the contractile properties of the skeletal muscle diminishes (Ament & Verkerke, 2009). In swimming, the fatigue will affect as well the kinetics, coordination and kinematics. Swimmers show an impairment of the swim kinetics (Toussaint, Carol, Kranenborg, & Truijens, 2006) and neuromuscular activity (Stirn, Jarm, Kapus, & Strojnik, 2011; Wakayoshi, Moritani, Mutoh, & Miyashita, 1994) under fatigue. These are coupled with a decrease in the energy expenditure of swimming (Stirn et al., 2011). The main consequence is a change in the inter-limb coordination (Alberty, Sidney, Huot-Marchand, Hespel, & Pelayo, 2005) and swim kinematics (Stirn et al., 2011; Toussaint et al., 2006). Therefore, swim speed decreases under fatigue (Aujouannet, Bonifazi, Hintzy, Vuillerme, & Rouard, 2006). The intra-cyclic variations assessed by RMS also showed a change under fatigue at front-crawl (Tella et al., 2008). Over a 200 m swim trial, the decrease in speed was coupled with an increase in the dv (Figueiredo, Pendergast, Vilas-Boas, & Fernandes, 2013). Another paper noted that there is a relationship between speed and dv (Barbosa et al., 2013). A faster swim is related to lower dv. All these modifications may lead to changes in the level of predictability and complexity of the motor behaviour (in this case, the swimming technique). Nevertheless, there is no available report in the literature on the changes in nonlinear parameters due to fatigue in competitive swimming.

Recent papers reported that swimming exhibits nonlinear proprieties but its magnitude differs according to the swim stroke performed ($14.048 \le dv \le 39.722$; $0.682 \le ApEn \le 1.025$; $1.823 \le FD \le 1.919$) (Barbosa, Goh, Morais, Costa, & Pendergast, 2016). Of the four swim strokes, front-crawl showed the lowest dv, ApEn and FD (Barbosa et al., 2016). The complexity of the swimming technique also varies depending on the level of expertise. The dv, ApEn and FD decreases with increasing expertise (front-crawl: $15.11 \le dv \le 18.40$; $0.66 \le ApEn \le 0.73$; $1.84 \le FD \le 1.89$) (Barbosa, Goh, Morais, & Costa, 2017). These two papers only assessed the variations of nonlinear characteristics depending on the swim stroke performed (task constraint) and the competitive level (organismic constraint) of the performer. In both papers the participants performed all-out trials, not being under the effect of fatigue. Indeed, examining the effect of fatigue in the motor control is a popular aim for researchers in this field (Seifert & Chollet, 2008). However, it is yet to be compared in swimming (as well as, the vast majority of time-based sports) the variations of nonlinear parameters under the effect of fatigue (organismic constraint). This might provide new insights on the fatigue mechanisms in this sport and other time-based sports. Ultimately, it can also help in understanding how to delay as much as possible the onset of fatigue.

The aim was to assess the effect of an all-out bout of 100 m at front-crawl to elicit fatigue on linear and nonlinear parameters. It was hypothesized that there would be meaningful variations in classical and nonlinear parameters immediately after the maximal swim bout.

2. Methods

2.1. Participants

A convenience sample of twenty-four participants (12 males and 12 females; 22.38 ± 1.68 years-old) were recruited for this research. The subjects were fitness-oriented swimmers, healthy and non-pregnant, attending swim sessions twice a week for at least four years.

The participants provided informed written consent for participation in this study. All procedures were in accordance with the Helsinki Declaration regarding human research. The University IRB committee also approved the research design.

2.2. Procedures

The swimmers performed a self-selected warm-up with a volume and intensity adjusted to their expertise and fitness level. Warm-up included continuous swimming at low-moderate intensity, technical drills and sprints.

The subjects were invited to perform alone in one lane, with no one else in the swimming pool, a simulated 100 m freestyle race. They were advised to perform the trial at their maximal possible pace. Due to their fitness level, a 100 m distance at maximal pace can be assumed as sufficient to elicit the onset of fatigue.

Before (pre-test, i.e. rested) and immediately after (post-test, i.e. under fatigue) the maximal 100 m trial, they performed all-out 25 m swim at freestyle with push-off starts. At least 15 mins of rest was provided between the 25 m pre-test bout and the 100 m trial.

2.3. Data collection and data handling

A speedo-meter cord (Swim speedo-meter, Swimsportec, Hildesheim, Germany) was attached to the swimmer's hip (Barbosa et al., 2013b; Barbosa, Morais, Marques, Silva, Marinho, & Kee, 2015) in the two 25 m trials. The speedo-meter was set on the forehead-wall of the swimming pool. A software interface in LabVIEW® (v. 2015) was used to acquire (f = 50 Hz), display and process speed-time data. Data was transferred from the speedo-meter to the software by a 12-bit acquisition card (USB-6008, National Instruments, Austin, Texas, USA). Data was thereafter exported to a signal processing software (AcqKnowledge v. 3.9.1, Biopac Systems, Santa Barbara, USA). The signal was filtered with a 5 Hz cut-off low-pass 4th order Butterworth filter after plotting the residuals vs. cut-off frequency of the raw data. The push-off start and the finish were discarded for the follow-up analysis. To compute the nonlinear parameters, at least 500 speed-time pairs must be collected, making the speedo-meter the most convenient device to collect data (Yentes et al., 2013).

The speed fluctuation was computed as (Barbosa et al., 2010):

$$dv = \frac{\sqrt{\frac{\sum_i (v_i - \bar{v})^2 F_i}{n}}}{\frac{\sum_i v_i \cdot F_i}{n}} \cdot 100 \quad (1)$$

where dv is the intra-cyclic variation of the horizontal velocity of the hip (also known as speed fluctuation), v is the mean swimming velocity, v_i is the instant swimming velocity, F_i is the acquisition frequency, and n is the number speed-time pairs. The dv of three consecutive stroke cycles between the 11thm and 24thm marks from the starting wall were selected for further analysis (Barbosa et al., 2013a).

The $ApEn$ was computed as follows (Pincus, 1991):

$$ApEn(N,m,r) = \ln\left[\frac{C_m(r)}{C_{m+1}(r)}\right] \quad (2)$$

where $ApEn$ is the approximate entropy, N is the data length [N = 700 speed-time pairs, as suggested by Yentes et al., 2013], m is the embedding dimension (m = 2, because two consecutive cycles contributing to two data points were considered for each mobile window), r is the tolerance value or similarity criterion [r = 0.1, determined beforehand as the maximum $ApEn$ for a wide range of r values between 0.01 and 0.3 as suggested by Yentes et al. (2013)], and:

$$C_{im}(r) = \frac{n_{im}}{N - m + 1} \quad (3)$$

where C_{im} is the fraction of patterns (cycles) of length m that resemble the pattern of the same length that begins at interval i, n_{im} is the number of cycles that are similar between two sets (given the similarity criterion, r), N is the data length, and m is the embedding dimension.

The swim strokes' complexity was assessed by the Fractal dimension (FD) (Higuchi, 1988):

$$FD = \frac{d\log N(L(k))}{d\log(k)} \quad (4)$$

where FD is the fractal dimension and N is the number of points from the speed-time series, k is the integer and L the length of the time series. The Higuchi's algorithm, selected for this research, is the most suitable technique for the analysis of fractal characteristics of time-series (Castiglioni, Di Rienzo, Parati, & Faini, 2011).

2.4. Statistical procedures

Data normality was tested by the Shapiro-Wilk test, described as mean ± 1SD and 95% of the confidence interval.

Because this is a crossover study, in which each participant it is his own control, mixed-designed ANOVA were tested between conditions (within-subject comparison: pre-test vs. post-test; $p \leq 0.05$) in each selected variable. It was controlled the hypothetical effect of the sex (between-subject comparison) and the fatigue status (co-variable: the difference in the swim pace between pre- and post-test) in the event that subjects have elicited different levels of fatigue. All assumptions to run ANOVAs were checked. E.g., sphericity was monitored by Mauchly's Test.

It was also computed the eta-squared (η^2) as an effect size index. As rule of thumb, for qualitative report of the effect sizes, a value $0 < \eta^2 \leq 0.04$ was noted as "no effect", $0.04 < \eta^2 \leq 0.25$ as "minimum or trivial effect", $0.25 < \eta^2 \leq 0.64$ as "moderate effect" and $\eta^2 > 0.64$ as "strong effect" (Ferguson, 2009).

3. Results

For the pooled sample, the speed in the pre-test was 1.44 ± 0.24 m/s and 1.28 ± 0.23 m/s in the post-test. The female subjects showed a decrease in speed (from 1.26 ± 0.11 m/s in the pre-test to 1.18 ± 0.14 m/s in the post-test). Their male counterparts also showed a decrease in speed (from 1.62 ± 0.20 m/s to 1.43 ± 0.24 m/s). There was a significant and large variation in the swimming speed between the pre- and post-test ($F = 55.136$, $p < .001$, $\eta^2 = 0.72$) but no sex interaction ($F = 0.087$, $p = .77$, $\eta^2 = 0.01$) or effect ($F = 1.983$, $p = .17$, $\eta^2 = 0.08$) was confirmed. Therefore, one may argue that the speed slowdown was imposed by the fatigue.

There was an effect of the condition (pre- v post-test) on the dv with a moderate effect size ($F = 15.048$, $p < .001$, $\eta^2 = 0.41$) but not of the sex ($F = 0.11$, $p = .74$, $\eta^2 < 0.01$). On average, the dv increased from the pre- to post-test (Table 1). There was a non-significant interaction between condition and the sex ($F = 0.361$, $p = .55$, $\eta^2 = 0.01$), and the level of fatigue was not a confounding factor ($F = 0.328$, $p = .57$, $\eta^2 = 0.01$). The 95CI band shifted from 0.116–0.134 to 0.140–0.161.

The ApEn showed non-significant main effect of the condition ($F = 0.037$, $p = .85$, $\eta^2 < 0.01$) and sex ($F = 0.224$, $p = .64$, $\eta^2 < 0.01$) (Table 2). As such, there was no interaction between condition and sex ($F = 1.634$, $p = .22$, $\eta^2 = 0.08$), and level of fatigue had no influence ($F = 0.233$, $p = .63$, $\eta^2 = 0.02$). There was a very slight trend for a decrease, despite the 95CI of the pre- and post-test overlaps (pre: 0.659–0.700; post: 0.641–0.682).

Regarding the FD, this variable showed a significant condition effect ($F = 5.186$, $p = .03$, $\eta^2 = 0.20$) despite no sex effect ($F = 0.126$, $p = .73$, $\eta^2 < 0.01$) was noted. The interaction between the condition and subjects' sex ($F = 0.126$, $p = .73$, $\eta^2 = 0.01$), and fatigue level ($F = 0.103$, $p = .75$, $\eta^2 < 0.01$) were non-significant (Table 3). The 95CI band moved from 1.954–1.965 to 1.933–1.951.

To have a deeper insight on the individual variations, follow-up analysis encompassed the plot of the within-subject changes between evaluation moments (Fig. 1). All 24 subjects increased the dv from pre- to post-test. Twenty-one out of 24 swimmers decreased the FD from pre- to post-test and 16 out of 24 decreased the ApEn.

Table 1
Analysis of the variation of the speed fluctuation (dv) from pre- to post-test after a maximal 100 m freestyle bout.

Speed fluctuation (dv, dimensionless)				
	Pre-test Mean (1SD) [95CI]		Post-test Mean (1SD) [95CI]	
Males	0.131 (0.013) [0.111–0.140]		0.157 (0.019) [0.137–0.170]	
Females	0.119 (0.029) [0.101–0.139]		0.143 (0.029) [0.130–0.164]	
Pooled sample	0.125 (0.023) [0.116–0.134]		0.150 (0.025) [0.140–0.161]	
ANOVA				
	df	F	p	η^2
Condition (pre- vs. post-test) effect	1,21	15.048	< 0.001	0.41
Sex effect	1,21	0.111	0.74	0.01
Condition × sex interaction	1,21	0.361	0.55	0.01
Fatigue level	1,21	0.328	0.57	0.01

Table 2
Analysis of the variation of the approximate entropy (ApEn) from pre- to post-test after a maximal 100 m freestyle bout.

Approximate entropy (ApEn, dimensionless)				
	Pre-test Mean (1SD) [95CI]		Post-test Mean (1SD) [95CI]	
Males	0.693 (0.043) [0.662–0.726]		0.650 (0.051) [0.624–0.686]	
Females	0.665 (0.051) [0.633–0.698]		0.672 (0.041) [0.636–0.699]	
Pooled sample	0.679 (0.048) [0.659–0.700]		0.661 (0.047) [0.641–0.682]	
ANOVA				
	df	F	p	η^2
Condition (pre- vs. post-test) effect	1,21	0.037	0.85	< 0.01
Sex effect	1,21	0.224	0.64	< 0.01
Condition × sex interaction	1,21	1.634	0.22	0.08
Fatigue level	1,21	0.233	0.63	0.02

Table 3
Analysis of the variation of the fractal dimension (FD) from pre- to post-test after a maximal 100 m freestyle bout.

Fractal dimension (FD, dimensionless)				
	Pre-test Mean (1SD) [95CI]		Post-test Mean (1SD) [95CI]	
Males	1.959 (0.014) [1.951–1.969]		1.944 (0.022) [1.930–1.958]	
Females	1.959 (0.010) [1.951–1.968]		1.939 (0.018) [1.930–1.958]	
Pooled sample	1.959 (0.012) [1.954–1.965]		1.942 (0.020) [1.933–1.951]	
ANOVA				
	df	F	p	η^2
Condition (pre- vs. post-test) effect	1,21	5.186	0.03	0.20
Sex effect	1,21	0.112	0.74	< 0.01
Condition × sex interaction	1,21	0.126	0.73	0.01
Fatigue level	1,21	0.103	0.75	< 0.01

4. Discussion

The aim was to assess the effect of fatigue on linear and nonlinear parameters in swimming. In this research, changes were found in both classical and nonlinear parameters under fatigue.

Before the 100 m all-out bout (pre-test), the 95CI of the speed fluctuation was $0.116 \leq dv \leq 0.134$ for the pooled sample. This interval matches data reported in previous papers using the same technique to assess young competitive swimmers (Barbosa et al., 2013a; Morais, Marques, Marinho, Silva, & Barbosa, 2014); but slightly lower than non-experts adults ($0.154 \leq dv \leq 0.213$) (Barbosa et al., 2017). The 95CI of the entropy was $0.659 \leq ApEn \leq 0.700$. In a sample of 25 talented young swimmers, at the beginning of a season the ApEn was 0.61 ± 0.045 and a 95CI of $0.592 \leq ApEn \leq 0.629$ in rested condition (Barbosa et al., 2015). This parameter was reported as being $0.64 \leq ApEn \leq 0.71$ in elite swimmers also in rested condition (Barbosa et al., 2016). Non-expert adults were reported as having $0.67 \leq ApEn \leq 0.77$ (Barbosa et al., 2017). The 95CI of the fractal proprieties was $1.954 \leq FD \leq 1.965$. It was noted that elite swimmers showed a 95CI of $1.821 \leq FD \leq 1.860$ (Barbosa et al., 2016) and non-expert adults $1.86 \leq FD \leq 1.91$ (Barbosa et al., 2017), both monitored by the same methodology not being under fatigue. All in all, considering the effect of the competitive level, the swim trial condition (rested) and age (and hence, the expertise level) the data reported here is within what is noted in the literature.

The mainstream procedure to assess the effect of fatigue in the motor behaviour, biomechanics or physiological response is monitoring the subjects before and after an intense, exhaustive or unusual task (a crossover research design). The pre-test is the rested condition whereas the post-test is the condition under fatigue. Alternatively, it is possible to collect data in the first few trials or

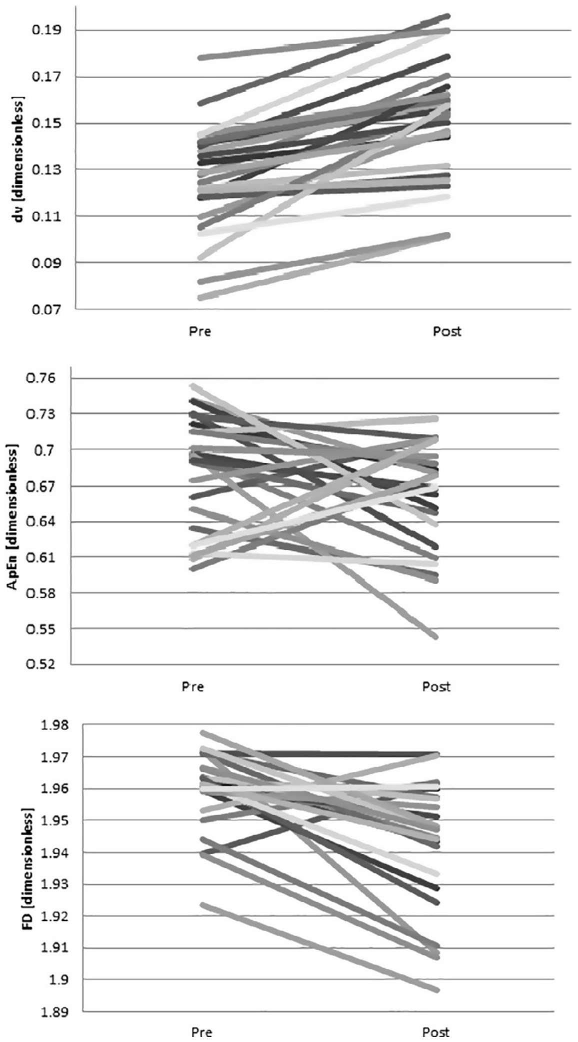

Fig. 1. Individual changes between pre- and post-test of the speed fluctuation (dv), approximate entropy (ApEn) and fractal dimension (FD) after a maximal 100 m freestyle bout.

repetitions or meters/minutes of the protocol and in the last ones. In our research the latter protocol was not feasible. Data was collected by a speedo-meter. This device was selected because enables to collect longer time-series of raw data in one single trial/bout than other systems. A cord or string is attached to the participant's hip to measure the instantaneous speed. Therefore, data can only be collected in one single lap, going out (in one direction). Hence, the former protocol (pre-test; task; post-test) was selected. In the literature it is possible to find a solid body of knowledge reporting the changes in linear parameters before and after intense, exhaustive or unusual tasks. E.g., it was assessed the swimming kinematics (trajectories, speed, stroke rate, stroke length, etc.) (Toussaint et al., 2006). There was a slowdown of the stroke rate and speed by 10% during an all-out 100 m bout of arms-only front-crawl. In addition, the power output decreased by 24% (Toussaint et al., 2006). Electromyography is also able to provide interesting details on this phenomenon (Wakayoshi et al., 1994). Both time- and spectral-domain variables can be selected. Over a 200 m time-trial in swimming, it was noted an increase in the integrated electromyography (20%–25%) and a decrease in spectral parameters (40%–60%) for all upper-limb muscles selected (Figueiredo, Rouard, Vilas-Boas, & Fernandes, 2013).

The dv is the response to increasing phases of acceleration and deceleration within the stroke cycle. As noted in Newtonian Mechanics, at a given pace, each time the body is under such acceleration-deceleration phases, it has to overcome inertia and as such, increase the energy expenditure. Therefore, theoretically, under fatigue, the performer should aim to keep the dv as low as possible. There was an effect of fatigue on the dv with a moderate effect size, increasing from 0.116–0.134 to 0.140-0.161. There is a strong and inverse relationship between swim speed and dv (Barbosa et al., 2013a). The onset of fatigue leads to a decrease in speed and an increase in the dv. For instance, over a 200 m time-trial at front-crawl, it was reported that the slowdown from one lap to the next was coupled with an increase in the dv (Figueiredo et al., 2013). The dv is also related to the energy cost of swimming. A high dv imposes a higher energy cost (Barbosa et al., 2005; 2010). Hence, one may assume that between pre- and post-test there was an increase in the energy cost of swimming. The dv is the balance between instantaneous thrust and drag acting upon the swimmer (Barbosa et al., 2010). Under fatigue, the swimmer may face a higher drag due to poor body alignment. For instance, the inter-limb coordination changes over a 100 m event due to the onset of fatigue (Seifert, Chollet, & Chatard, 2007). The change in inter-limb coordination affects the overall body alignment and therefore the magnitude of the drag force. The fatigue also impairs the output by the musculoskeletal system (Ament & Verkerke, 2009), preventing the performer to reach the same magnitude of mechanical power (Toussaint et al., 2006). All these factors are constraints that can affect the motor behaviour. As such, nonlinear variables can be considered as well rounded and holistic parameters to assess the predictability and complexity of the motor behaviour. If so, to have an overall understanding of the behaviour there is no need to select such a comprehensive number of variables. Being this assertion true, the predictability and complexity of the motor behaviour is monitored by nonlinear parameters because the latter ones are influenced by the constraints already reported in the literature.

If dv denotes the changes of acceleration-deceleration patters within the stroke cycle (intra-cyclic variations), the ApEn is a proxy of such acceleration-deceleration changes but between back-to-back stroke cycles (inter-cyclic variations). Again, in Newtonian Mechanics, a uniform motion (hence, at constant velocity and null acceleration) leads to a lower energy cost. In complex systems, an increase in the inter-cyclic fluctuations over the trial when inducing fatigue is due to a destabilization of the initially established integration by the system (Hristovski & Balagué, 2010). Altogether, under fatigue, one should aim to keep the same level of ApEn. The ApEn presented non-significant variations between the pre- and post-test. At least for land gait, the literature reports mixed findings on the effect of fatigue in the ApEn. Even though, a paper reported an increase in the ApEn from pre- to post-test after a protocol that elicited fatigue in walking (Arif et al., 2002); another noted non-significant variations in race-walkers (Preatoni et al., 2010). We found no changes in the inter-cyclic variations (i.e. ApEn) over the 25 m trials before and after the simulated race. The time-series kept the same level of predictability for the entire distance of the trial. It is unclear if the same phenomenon would happen for a trial longer than 25 m. Being the trial longer, the level of repeatability from cycle to cycle could have changed. If the distance of pre- and post-tests are longer, the effect of fatigue might be more pronounced and obvious to observe on ApEn. A longer trial means that the swimmer must do more stroke cycles. Under fatigue, the randomness over the trial, especially by the end of it, could have been more notorious. In other scientific domains, it was reported data in tandem to this reasoning and noting an increase of the entropy with fatigue (McGregor et al., 2011).

A higher FD can be interpreted as an increase of the inputs in the system and hence more solutions to reach a given level of performance. Therefore, in a complex system it is expected the FD to decrease under fatigue. The FD showed a significant decrease from the pre- to post-test, dropping from 1.954–1.965 to 1.933–1.951. Again, as far as our understanding goes, there is no research available in the literature that we can refer to. On land, over a 120-min load carriage March by servicemen the FD decreased from 1.43 to 1.12 (Schiffman et al., 2009). This finding is in agreement with what was reported in other scientific fields or using other assessment techniques. E.g., FD of surface EMG decreases with fatigue, even more so for tasks demanding higher intensities (Beretta-Piccoli et al., 2015). The decrease is a requirement to cope with fatigue by enhancing the level of synchronisation among motor units. It was reported an association between handgrip and FD of the EEG (Liu, Yang, Yao, Brown, & Yue, 2005). So, if under fatigue there is an impairment in the force and strength, likewise it is expected a decrease in the FD of the EEG. This may point out to a lower complexity of the brain activity under fatigue. FD of the heart rate and breath also decreases with exercise (West, Griffin, Frederick, & Moon, 2005). Therefore, the decrease of the swimming FD may be related to the decrease and lower level of complexity elicit by the neuromuscular system (EMG), brain (EEG) and, cardiovascular & respiratory systems (ECG & breathing). Follow-up studies testing the relationship between strength & power, neurophysiological response and FD in human swimming are advised.

In this research the focus was exclusively on kinematical adaptations to fatigue. Intensity, time and type of exercise are all variables that cause different effects within the systems of the body, which in turn create different types of "perceived-sensation" and ultimately fatigue (Ament & Verkerke, 2009). The type of exercise was the same for all subjects (front-crawl stroke) and they were briefed to perform at maximal intensity (all-out 25 m and 100 m trials). Therefore, we did our best to control these task constraints. Organismic constraints where also controlled because a crossover design was selected. Chronic fatigue and underperformance are typical signs and symptoms of overtraining (Budgett, 1998). Because these subjects are fitness-oriented swimmers, this is not a concern; even though, this should be considered in elite counterparts. Altogether, we have done our best to avoid the potential confounding factors reported by Ament and Verkerke (2009).

Fatigue is the result of the complex interaction by multiple components (Lambert, Gibson, & Noakes, 2005). A research assessed the partial contribution of different components to the performance in the 200 m freestyle event in swimming (Figueiredo et al., 2013). At 1.41 m/s, the main determinant was the biomechanics (58.1%) followed-up by the inter-limb coordination (18.9%), neuromuscular response (11.8%) and energetics (11.22%) (Figueiredo et al., 2013). The motor control (monitored by the inter-limb coordination) was the second main component explaining the swimming performance. The inter-limb coordination selected can be understood as an optimisation mechanist considering the constraints. Inter-limb coordination is a proxy of the motor behaviour's optimisation process. Facing a given set of constraints, the performer aims to select the coordination pattern that enable an optimization of the behaviour, for instance, to elicit the highest speed he is able to (Seifert & Chollet, 2008). Another study dedicated to inter-limb coordination in the 100 m freestyle event noted a shift in the coordination over the last lap that was explained by the onset of fatigue (Seifert et al., 2007). With the onset of fatigue, the inter-limb coordination shifts to superposition (Seifert et al., 2007). As reported in here, under fatigue there is a change in nonlinear (FD) and classical parameters (dv). Most of the mainstream variables selected to monitor the changes in the motor behaviour (kinematics, kinetics, energetics, etc.) are constraints affecting FD and dv. Therefore, a well-rounded set of classical and nonlinear parameters can be selected to monitor the effect of fatigue on motor behaviour.

It can be addressed as main limitations of this research that: (i) the study was conducted on fitness-oriented swimmers and one may argue that the motor behaviour of elite counterparts may vary; (ii) it was assessed the complexity of the front-crawl technique, remaining to be known if the same is verified in other swimming strokes; (iii) the concurrent assessment of physiological parameters could have provided a more holistic understanding of the results obtained. Future studies can address the question if there is an optimal level of complexity to deliver a given performance in sports; and if so, how can researchers and practitioners aid the performers to reach their goals.

5. Conclusions

The dv increased significantly under fatigue. There was a significant decrease in the FD and the ApEn showed non-significant variations. Altogether, there are variations in the classical and nonlinear parameters under fatigue in fitness-oriented swimmers.

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Conflict of interest

The authors have no professional relationships to disclose with companies or manufacturers who will benefit from the results of the present study.

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