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Functional role of movement and performance variability: Adaptation of front crawl swimmers to competitive swimming constraints

David Simbaña-Escobar,^{1,2} Philippe Hellard,^{1,3} David B. Pyne,^{4,5} Ludovic Seifert²

¹Département Etudes, Recherche et Optimisation de la Performance, Fédération Française de Natation, Pantin, France; ²Centre d'Etudes des Transformations des Activités Physiques et

Sportives, EA-3832, Faculté des Sciences du Sport, Université de Rouen Normandie, France;

³Institut de Recherche Biomédicale et d'Epidémiologie du Sport, Insep, Paris, France;

⁴Australian Institute of Sport, Canberra, ACT, Australia, ⁵Research Institute for Sport and Exercise, University of Canberra Canberra, ACT, Australia

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Correspondance Adresse:

David Simbaña-Escobar, D.S-E.

Département Etudes, Recherche et Optimisation de la Performance, Fédération Française de Natation,

93508 Pantin Cedex, France

Phone: (33) 141 838 725

Email: david.simbana@ffnatation.fr

Abstract

To study the variability in stroking parameters between and within laps and individuals during competitions, we compared and modelled the changes of speed, stroke rate and stroke length in thirty-two top-level male and female swimmers over four laps (L1-L4) in 200-m freestyle events using video-derived 2-dimensional direct linear transformation. For the whole group, speed was greater in L1, with significant decreases across L2, L3 and L4 (1.80 ± 0.10 vs. 1.73 ± 0.08 ; 1.69 ± 0.09 ; 1.66 ± 0.09 m.s⁻¹, $p < .05$). This variability was attributed to a decrease in stroke length (L2: 2.43 ± 0.19 vs. L4: 2.20 ± 0.13 m, $p < .05$) and an increase in stroke rate (L2: 42.8 ± 2.6 vs. L4: 45.4 ± 2.3 stroke.min⁻¹, $p < .05$). The coefficient of variation and the biological coefficient of variation in speed were greater for male vs. female (3.9 ± 0.7 vs. 3.1 ± 0.7 ; 2.9 ± 1.0 vs. 2.6 ± 0.7 , $p < .05$) and higher in L1 vs. L2 (3.9 ± 1.3 vs. 3.1 ± 0.1 ; 2.9 ± 0.9 vs. 2.3 ± 0.7 , $p < .05$). Intra-lap speed values were best represented by a cubic ($n=38$), then linear ($n=37$) and quadratic model ($n=8$). The cubic fit was more frequent for male (43.8%) than female (15.6%) suggesting greater capacity to generate higher acceleration after the turn. The various stroking parameters managements within lap suggest that each swimmer adapts his/her behaviour to the race constraints.

Keywords: Performance, swimming, 200-m freestyle, variability, stroking parameters.

Word Count: 4205 words

Introduction

For 30 years, performance analysis has been conducted at international events to give swimmers immediate feedback on the stroking parameters (swimming speed, stroke rate, stroke length and stroke index) in relation to the resultant performance outcome (swimming time). Previous studies of athletes' technical and tactical race parameters have shed light on the various profiles of swimmers in relation to race distance, skill level, gender and the four swimming strokes.^{1,2,3} In 200-m freestyle events, the analysis of the stroking parameters variability between laps showed that a fast first lap (L1) after the dive start is generally followed by even pacing through the middle laps (L2, L3) and an evenly paced or slightly faster (0.1 s) final lap (L4).^{3,4} Given the high resistance of water, the race management is more critical in swimming than other sports.⁵ In swimming, propulsive efficiency is low because only 6–18% of metabolic energy is transformed into speed.^{6,7} Therefore, inappropriate speed variations and mismanagement of the SR and SL between laps, but also within laps, can increase energy expenditure and negatively affect performance, with rapid fatigue, faster power loss and less efficiency.^{5,8,9}

Few previous studies have focused on within lap variability of stroking parameters during competition. Hellard et al.³ measured SR cycle-by-cycle and reported lower variability in female Olympic 200-m freestyle swimmers than national swimmers (-2.3%), associated with longer SL and greater swimming speed stability. In elite male 100-m freestyle swimmers, Seifert et al.¹⁰ analyzed swimming speed, SR, SL and coordination over each 5-m segment in a 25-m swimming pool. The SL and SR were stable during stroking time and higher or lower during the starts, turns and finish. The effect of turns and starts on stroking parameters has also been observed during competitive swimming events.^{11,12,13} In particular, Veiga and Roig¹² compared the free swimming and underwater speed after the start and turns for the 200 m at the FINA 2013 World Swimming Championships. They showed that

free swimming speeds of elite swimmers decreased throughout the 200 m race laps, whereas underwater speeds, which were faster than free swimming, remained constant during the race. This finding confirms that the start and turns play an important role on the average swimming speed of athletes and strongly suggests for further research to investigate the stroking parameters variability within laps.

To address this question of the possible functional role of movement and performance variability, between and within (e.g. inter- and intra-lap variability during a 200 m free style) individuals, our study took roots in the complexity science paradigm. This paradigm has renewed conception of the status and role of movement and performance variability in motor tasks, suggesting that movement variability could have a functional role as it might reflect adaptive flexibility process when the performance outcome remained unchanged.¹⁴ For example, in ecological dynamics framework, it is postulated that behavior emerges from the interaction between the self-organizational capacity of the energetic neuro-musculoskeletal system (for which inter-individual variability comes from expertise level, individual skills, swimming specialty, gender or body composition) and a set of constraints (i.e., task, environment, organism) supporting that movement variability in complex perception-action systems could be functional.^{15,16} In swimming, it has been suggested that, more than simply ensuring stability against perturbations and adaptive flexibility to dynamic performance environments, functional movement variability could reflect the ability of experts to better exploit information about task-related constraints to organize their behavior.^{17,18}

As mentioned previously, in competitive swimming events, the main task constraints relate to the race segments (e.g. start, turn in-out, four laps and the finish) as the wall imposes to reverse and to transform the horizontal swimming speed into rotational speed for the flip turn. Additionally, environmental constraints such as adversity, waves and water turbulence (leading to additional drag) coming from other swimmers could also impact on the

97 stroking parameters variability between and within laps. From this perspective, variability of
98 the stroking parameters in swimming could be a key signature of adaptive behaviors, in
99 response to dynamical changes in the environment and task constraints^{19,20} In competitive
100 context, investigating the inter- and intra-individual variability of the stroking parameters
101 should provide useful information to assess the swimmer's adaptations to race constraints and
102 the potential impacts of these variations on swimming economy.^{21,22,23} Therefore, the aim of
103 this study was to investigate how elite swimmers adapt their patterns and variability in
104 swimming speed, SR and SL between and within the 50-m laps of the 200-m front crawl
105 event, using direct video-derived linear transformation. To reach that aim, the originality of
106 our study was to examine the inter- and intra-individual variability of the stroking parameters
107 management by modeling the changes of swimming speed, SR and SL between and within
108 lap in competition for each swimmer. We hypothesized that of four possible race
109 managements—inter- and intra-lap speed stability, inter- and intra-lap speed variability, inter-
110 lap speed stability but intra-lap speed variability, and inter-lap speed variability but intra-lap
111 speed stability—the fastest swimmers would show stable stroking parameters between laps as
112 much as possible and with greater variability within laps as they adapted to the various task
113 constraints.

114

115 **Methods**

116 Participants and Protocol

117 The performances of 32 top-level swimmers were video-analyzed during the 200-m
118 freestyle finals of the Fédération Internationale de Natation Amateur (FINA) World
119 Championships (Kazan, Russia 2015) (8 males, 8 females) and the French National
120 Championships (Montpellier 2016) (8 males, 8 females). Their main characteristics are
121 summarized in *Table 1*. The procedures (data collection and analysis) were approved by the

French Federation of Swimming, FINA and the local University ethics committee, and conformed to the declaration of Helsinki. The procedures were explained to the swimmers, who then gave their written informed consent to participate.

Insert Table 1

Data Collection and Analysis

The swim events were videoed with a Black Magic 4K camera (25 Hz, Ultra HD, 3840×2160 pixels ® Blackmagicdesign, Melbourne, Australia) equipped with a 10-mm focal lens (f/4.5-5.6 IS STM) (®Canon Inc, Ôta, Tokyo, Japan) to visualize the entire pool (50 x 25 m). The camera was focused on the middle of the pool (25 m) and located in the top row of spectator seats approximately 25 m above and 15 m away from the side of the pool.

Race analysis software compiled in Matlab 2012 (The MathWorks, Inc., Natick, MA, USA) was used for calibration and image processing to obtain SR, SL and swim speed (S) for every stroke cycle.

Four poolside marks in the swimming lane were chosen to calibrate the pool using 2D direct linear transformation algorithms.^{24,25} The operator for each event made this calibration and then manually digitalized the head position at the beginning of each stroke cycle (right hand entry). The stroking phase was defined as the first and last right hand entry after the start or underwater phase and before the turn in each lap.

To quantify the reproducibility of the tracking procedure, the same race and same swimmer was digitalized ten times by eight operators. The root mean square was calculated to estimate the tracking measure reproducibility and showed low value: 0.0121 ± 0.0084 m.

The total stroke cycle and the number of cycles in the 200-m are presented in *Table 1*.

The SL (in m) and SR (in stroke.min⁻¹) were calculated for each stroke using the

145 following equations:

$$146 \quad SL = Y_{i+1} - Y_i \quad (1)$$

$$147 \quad SR = \frac{60}{t_{i+1} - t_i} \quad (2)$$

148 where i is the number of strokes, t is the time and Y the projection of the head position of the
149 horizontal axis at the pool.

150 S was expressed in meters per second (m.s^{-1}) as:

$$151 \quad S = \frac{Y_{i+1} - Y_i}{t_{i+1} - t_i} \quad (3)$$

152 The stroke index (SI ; in $\text{m}^2.\text{s}^{-1}$) was computed as follows:

$$153 \quad SI = SL * S \quad (4)$$

154 The S , SR , SL and SI were calculated for each stroke and each lap. The coefficient of
155 variation (CV %) and the variability induced by technological error (SEM %) were calculated
156 for each individual and then used to compute the biological movement variability (BCV %).

$$157 \quad CV (\%) = \frac{M}{SD} * 100 \quad (5)$$

$$158 \quad SEM (\%) = \frac{SD / \sqrt{n}}{M} * 100 \quad (6)$$

$$159 \quad BCV (\%) = CV - SEM \quad (7)$$

160 M represents the mean, SD the standard deviation SEM the standard error of the mean
161 where n is the number of trials.²⁶

162

163 Statistical Analysis

164 The descriptive statistics of stroke parameters are expressed as mean (M) $\pm$ standard
165 deviation (SD). First, normality of the distribution (Shapiro-Wilk) and homogeneity of
166 variances (Levene test) were checked. The Mauchly test was then employed to check the
167 sphericity.²⁷ When the assumption of sphericity was not met, the significance levels of F -

ratios were adjusted according to the Greenhouse-Geisser or Huynh-Feldt procedure.²⁸ Where the Greenhouse-Geisser epsilon was >0.75 , the Huynh-Feldt corrected value was used for that parameter. Three-way repeated measure ANOVA was employed to assess differences in stroking parameters (S, SL, SR, SI, coefficient of variation [%CV] and biological coefficient of variation [%BCV] of these parameters) between laps (L1, L2, L3 L4), gender and skill level. Post-hoc tests were performed using the Bonferroni correction. The partial eta squared (η_p^2) statistic was used to characterize the effect size, with $\eta_p^2 = .01$ indicating a small effect, $\eta_p^2 = .06$ a medium effect, and $\eta_p^2 = .15$ a large effect.²⁹ For all tests, significance was fixed at $p < .05$. All tests were performed using SPSS Statistics 21.0 (® IBM, NY, USA).

To determine the best model fitting the changes in stroking parameters within each 50-m lap for all swimmers (male and female international, and male and female national), we explored 3 regression models: linear ($y = ax + d$), quadratic ($y = bx^2 + ax + d$) and cubic ($y = cx^3 + bx^2 + ax + d$) with $a, b, c \neq 0$. No higher polynomial degrees were examined because they have no biological meaning.³⁰ To attribute the right penalty to each regression model according to the number of parameters,^{31,32} for each model the adjusted coefficient of determination r_{adj}^2 :

$$r_{adj}^2 = 1 - (1 - r^2) \frac{n-1}{n-p-1} \quad (8)$$

with n the sample size and p the number of predictors and the sum of squared errors of prediction (SSE) and r^2 the coefficient of determination, then Akaike Information Criterion (AIC) was calculated for model selection³³. The fit between raw data and the regression models was tested by analysis of variance (F -ratio test). The accuracy of parameter estimations was assessed by calculating the absolute 95% confidence interval for each parameter of the three models, and only the significant model was retained. Last, the mean

model for each group and for each lap was computed. R© software (version 3.3.0 GUI 1.68 Mavericks, R Foundation for Statistical Computing, 2016) was used to fit the models to the data.

Results

For the entire population, S and SI decreased from L1 to L4 (Table 2 and Figure 1). Stroke rate decreased from L1 to L2 and then increased to L4 and stroke length decreased from L2 to L4 (Table 2 and Figure 1).

Insert Table 2 and Figure 1

Stroke rate was higher for international than national finalists ($45.1 \pm 2.5 \text{ cycle} \cdot \text{min}^{-1}$ vs. $43.1 \pm 2.4 \text{ cycle} \cdot \text{min}^{-1}$) and higher for females than males in L1 ($45.6 \pm 2.8 \text{ cycle} \cdot \text{min}^{-1}$ vs. $43.8 \pm 2.1 \text{ cycle} \cdot \text{min}^{-1}$) (Table 2 and Figure 2). Stroke length and SI were higher for males than females ($2.5 \pm 0.1 \text{ m}$ vs. $2.2 \pm 0.1 \text{ m}$; $4.5 \pm 0.4 \text{ m}$ vs. $3.7 \pm 0.4 \text{ m}$, respectively) (Table 2 and Figure 2).

Insert Figure 2

The coefficient of variability (CV) and the biological variability (BCV) of the speed decreased for the entire population from L1 to L2 (3.9 ± 1.3 vs. 3.0 ± 0.1 , 2.9 ± 0.9 vs. 2.3 ± 0.7 , respectively, $p < .05$) and increased in L4 in comparison to L2 (3.5 ± 1.0 vs. 3.0 ± 0.1 , 2.7 ± 0.8 vs. 2.3 ± 0.7 , respectively, $p < .05$). In other hand CV and BCV of speed were higher for male than the female (3.9 ± 0.7 vs. 3.1 ± 0.7 , 2.9 ± 1.0 vs. 2.6 ± 0.7 , $p < .05$).

The mean linear, quadratic and cubic models are presented in Figures 3, 4 and 5. In supplementary data an example of a swimmer with the different speed fitting models and their confidence interval and the Table 3 with the adjustment parameters of fitting to the four groups and four laps.

Insert Figure 3

Out of 128 datasets (32 participants $\times$ 4 laps), 83 significant models for speed were found (Table 3), with 25 fits for L1, 20 fits for L2, 19 fits for L3 and 19 fits for L4 (out of 32 for each lap) whilst 45 data cannot be modelled due to high variation of instantaneous swimming speed (i.e. high dispersion the data). The cubic polynomial fitted the data best in 38 cases, with 8 datasets fitting the quadratic polynomial model and 37 for the linear regression. Forty-seven datasets fit were significant for one of the three models for men and 36 for women. The cubic polynomial fit was better for men in 28 of 48 cases (16 participants $\times$ 3 models), and for women in 10 cases. Forty datasets fit were significant for international swimmers *versus* 43 for national swimmers. For the male and female national swimmers, the linear model provided the best fit in 23 cases, 5 cases in quadratic and for cubic models the best fit in 15 cases. For the male and female international swimmers, the cubic model was best in 23 cases, the linear model in 14 cases, and the quadratic model in 3 cases.

Insert Figure 4

The SL data were significantly fit by one of the 3 models in 68 cases out of 128 (32 participants $\times$ 4 laps): 17 for L1, 15 for L2, 16 for L3 and 20 for L4. The goodness of fit was higher for the cubic model in 37 cases, for the quadratic model in 20 cases, and for the linear model in 11 cases. Out of 128 datasets, 45 were significant for men *versus* 23 for women. Out of 48 datasets, the cubic model showed a better fit in 26 cases for men *versus* 11 cases for women. The quadratic model showed a better fit in 12 cases for men *versus* 8 cases for women. The linear model showed a better fit in 7 cases for men *versus* 4 cases for women. Thirty-six fits were significant in international swimmers *versus* 32 in national swimmers. The cubic model was predominant in 22 cases for international swimmers *versus* 15 for national swimmers. The quadratic model predominated in 13 cases for international swimmers *versus* 7 for national swimmers. The linear model was predominant in 4 cases for international swimmers *versus* 7 for national swimmers.

Insert Figure 5

For SR, out of 128 datasets (32 participants $\times$ 4 laps), 79 of the fits were significant. The best fit in 33 cases was the cubic model, with 18 for the quadratic model and 28 for the linear model. For L1, the data were significantly adjusted in 26 cases against 16 cases in each of L2 and L3 and 21 cases in L4. Out of 128 datasets, fits were significant in 45 cases for men *versus* 34 cases for women. Out of 48 datasets, the cubic model showed a better fit in 25 cases for men *versus* 8 cases for women. The quadratic model showed a better fit in 9 cases for men and women. Last, the linear model showed a better fit in 11 cases for men *versus* 17 cases for women. Of 128 datasets, 36 fits were significant in international swimmers *versus* 43 in national swimmers. The cubic model predominated in 14 cases for international swimmers *versus* 19 for national swimmers. The quadratic model predominated in 5 cases in international swimmers *versus* 13 in national swimmers; and the linear model in 17 cases for international swimmers *versus* 11 for national swimmers.

Discussion

The originality of our study was to investigate the variability of stroking parameters within laps using a video-derived direct linear transformation method. Our main aim was to examine how swimmers adapt race management of the stroking parameters to task constraints (e.g., start, turn and finish) to achieve optimal performance. The coefficient of variation and the biological coefficient of variation in speed were greater for male *vs.* female and for international *vs.* national swimmers. For the 128 datasets (32 swimmers $\times$ 4 laps) intra-lap speed values were fitted mostly by a cubic model (38), followed by linear regression (37) and quadratic polynomial (8) models, suggesting various profiles of adaptation to constraints.

Our analysis of national and international 200m freestyle events indicated that speed decreased between laps over the race. The male international swimmers showed larger decreases in speed between L1 and L2 than the other swimmers. As already observed by Chollet et al.^{22,23}, for all groups, the inter-lap speed decrease was characterized by the well-established decrease in SL and a compensatory increase in SR. The swimmers exhibited race management in three phases: a rapid first lap, then two middle laps are swum slightly slower, and a final lap at the same speed or slightly slower than middle laps (as observed in previous studies).^{4,34,35} As previously observed, the mean stroke length per lap decreased,^{3,34,36} and the mean stroke rate per lap evolved in U-shaped fashion.³⁷ This technical change can be interpreted as an adaptation to maintain relative speed despite increasing fatigue during the first lap. Figueiredo et al.³⁸ reported a constant decline in alactic anaerobic metabolism from L1 to L4 (41, 22, 12 and 5%) and an inverted U- and U-shaped change in both aerobic (45, 73, 83 and 67%) and anaerobic (14, 5, 4, 28%) metabolism. The high speed in the first 50-m can be attributed to powerful alactic anaerobic processes,^{38,39} and the speed following the dive start and glide can reach up to $2.5 \text{ m}\cdot\text{s}^{-1}$ ^{40,12,41} which is about 20% higher than the mean race speed. To maintain this speed over the first 50-m, swimmers must achieve an optimal SR/SL ratio.^{10,37}

In our study, the L2 and L3 swim speeds did not differ significantly, yet stroke length decreased across L2 to L4, while SR increased. Several studies showed that, for the same speed, an increase in SR decreases propulsive efficiency⁴² and increases anaerobic metabolism, in contrast to an increase in SL, which is an index of motor efficiency.²³ Therefore, excessively high speed or SR in the third lap might increase lactic anaerobic contribution, thereby increasing acidosis, inhibiting oxidative processes and decreasing the total available metabolic power.⁴³ Despite high fatigue in the last lap, the swimmers swam as fast as possible by increasing SR, which increased the energy cost.^{44,45} The inter-lap analysis

confirmed our hypothesis of energy-dependent race management only for the difference between L1 and L2, which was more marked in male international swimmers than other groups. This result complements the work of Robertson et al.⁴, who studied the 16 semi-finalists and finalists in 9 international competitions over seven years and found no swimmer level-dependent difference in the general pattern of race management. The striking speed decline between L1 and L2 for the male swimmers may have been the consequence of their start phase, much faster than that female,^{34,36} which in turn reflects the large difference in muscular power between men and women.^{46,47}

The swimmers displayed three typical patterns of speed variation within laps; linear, inverted U-shape, or a cubic pattern. Most often, the cubic pattern showed three phases: turn-out (speed increases or decreases), then stability, and speed decreases at the approach of turn-in. The linear pattern refers to uniform motion, which could mean constant speed (i.e. no acceleration) or constant acceleration such as a linear increase or decrease of speed within each lap. In our case, a linear decrease of speed within each lap was mainly observed. The quadratic pattern showed an inverted U-shape, with speed increasing from the first stroke cycle after turn-out to a maximal value in the middle of the lap, and then gradually decreasing until the next turn. These three models could be understood according to the first law of Newton (law of inertia) where an object continue in a state of rest or uniform motion (i.e., linear pattern) unless acted upon by external forces that are not in equilibrium (for reviews, see Hay, 1993; Bartlett, 2007). In cyclical locomotor activities such as swimming, drag forces act in a direction opposite to the object's motion and, therefore, limit swimming speed. To maintain a constant speed, propulsive forces that equal the total drag force, but in opposite direction, must be exerted. According to Barbosa et al.⁴⁸, the aim of swimmers was to minimize intra-lap speed variations to maintain a constant high speed.

314 The best fit for the L1 data was the linear model (16 cases). At L1, the linear pattern was
315 more frequent than the quadratic and cubic models, showing a decrease in speed probably
316 due to the dive start. However, the cubic models might reflect the capacity of the swimmers
317 to adapt their race management to maintain the high speed after the dive start. Fischer et al.⁴¹
318 and Tor et al.⁴⁰ showed differences between men and women for the mean speed of the dive
319 start, with a decrease in the mean glide speed, and then an increase in the speed during the
320 glide and undulation phase. Conversely, the underwater speed following turns was lower than
321 after starts.⁴⁹ However, the turn disrupts the continuity of the swim and constrains the
322 maintaining of a constant high speed, explaining why cubic patterns occurred more
323 frequently at L2 for 12 cases and L3 with 13 cases. No modeling of the third lap was done for
324 international female swimmers because they exhibited high dispersion of their data, which
325 could be due to the fatigue effect and might lead inability to sustain constant swimming speed
326 within lap. At L4, the linear model was the best fit in 13 of the 32 datasets. In the linear and
327 cubic models, the speed of turn-out was higher than the mean 50-m speed. Conversely, the
328 quadratic model indicated that turn-out speed was lower than the mean speed. Our results of
329 the linear and cubic models confirm recent studies showing that glide speed after the dive and
330 turn is higher than the mean swimming speed for most high-level swimmers.^{50,51} However,
331 Puel et al.⁵² suggested that there is not only one profile of turn, but instead the swimmers
332 must find the best compromise to applied the highest force in the shortest turn time. This
333 necessary compromise led to inter-individual variability of the turn time and turn distance
334 during competition (e.g. Veiga & Roig¹³), and explained the three models of speed exhibited
335 by our study. In particular, different models distinguished fast swimmers in the underwater
336 glide and the swim start (cubic and linear patterns) from slower swimmers (quadratic
337 patterns), supporting that the start and turn correspond to important task constraints.

However, with our protocol, the modeling accounts for the speed of the first stroke cycles after the turn and not the speed of the underwater glide.

In the linear, quadratic and cubic patterns modeling the intra-lap speed variations, the speed always decreased before the turn, confirming that the turn is one of the major task-constraint, as already observed by Veiga et al.^{51,12,49}. Indeed, these authors showed that regardless of performance level or gender, the speed from the swimmer's last stroke to wall contact was lower than the mean 50-m speed. In that case, cubic modeling means that although swimmers increased speed after the turn, they also decreased speed when approaching the wall and turning, confirming the constraint of turn on the performance outcome (swimming time). This reduction may be due to triple constraint for the swimmer: estimating the remaining distance to the wall, adjusting the stroking parameters for an optimal turn, and reaching maximal swimming speed.¹⁰

In our study, speed was adjusted following starts and before and after turns by adapting SR and SL. Indeed, modeling the variations in these two parameters also revealed differences in the intra-lap variations that indicate the capacity of swimmers to adapt their race management to the race constraints. The predominance of a cubic fit in males compared with females reflected intra-lap speed variability tending toward an increase in the middle portion of L2 and L3. At the same time, this great speed production was associated with greater intra-lap variability in SR and SL. Coaches and swimmers should be informed that variation in the stroking parameters is associated with the highest speed in each part of the race.

Our results also show that the CV and BCV for speed and SI were higher in the male international swimmers, and the cubic fit was more frequent in international compared with national swimmers (23 significant fits in internationals vs. 15 in nationals). Most often, the

higher intra-lap variability in international and male swimmers was associated with a cubic fit for SR and SL. We hypothesize that the greater stroking parameters intra-lap variability in male international swimmers relates their capacity to generate higher speed after the turn.

In conclusion, our study highlighted the extent of variability in stroking parameters within- lap that could be mainly modelled by a linear pattern at L1 and L4, and cubic patterns for the other laps. The cubic pattern was associated with higher swimming speed and suggests better adaptation to the task constraints of the race (start, turns and fatigue), given the capacity of international swimmers to rapidly increase their speed after the turn. Globally, intra-lap variability of speed was associated with inter-lap stability in L2 and L3. Our study indicates that top-level performance in competition is a combination of variability within laps and stability between laps. The competitive conditions nevertheless restricted the measure of other metabolic and biomechanical parameters that might be complementary indicators (such as energy cost) of swimmers' resources. Additionally, the low capture frequency of the camera used for filming trials could potentially have resulted in inaccuracies defining precise start and end phases of cycles, however this is compensated by the high quality resolution of each frame.

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Tables

534

Table 1: Primary performance and anthropometric characteristics for the different groups

535

(Mean $\pm$ SD).

Group (N=2132 cycles)	Stroke cycle at 200-m	200-m race time (s)	(% of World Record)	Mass (kg)	Height (m)	Age (y)
Male N (N= 483)	59.8 $\pm$ 4.6	107.9 $\pm$ 1.2	94.6 $\pm$ 1.1	79.4 $\pm$ 7.1	1.90 $\pm$ 0.06	24.5 $\pm$ 3.9
Male I (N=498)	62.3 $\pm$ 3.6	106.0 $\pm$ 0.8	96.2 $\pm$ 0.7	84.9 $\pm$ 6.4	1.89 $\pm$ 0.06	24.9 $\pm$ 4.2
Fem N (N=564)	70.4 $\pm$ 4.9	119.5 $\pm$ 1.8	94.6 $\pm$ 1.5	60.4 $\pm$ 4.7	1.74 $\pm$ 0.04	22.4 $\pm$ 3.4
Fem I (N=587)	74.3 $\pm$ 4.2	116.0 $\pm$ 0.6	97.4 $\pm$ 0.5	66.7 $\pm$ 7.2	1.80 $\pm$ 0.05	23.3 $\pm$ 3.5

536

Note: The different groups: Male national (Male N), Male international (Male I), Female

537

national (Fem N) and Female international (Fem I).

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Table 2: Statistics of three-way analysis of variance for the stroking parameters and biological coefficient of variation.

	Gender	Level	Lap	Gender *Level	Gender *Lap	Level *Lap	Gender *Level *Lap
SR	N.S.	p=.010 $F_{1,28}=7.54$ $\eta^2=.21$	p<.001 $F_{2,91.84}=38.55$ $\eta^2=.58$	N.S.	p<.001 $F_{2,91.84}=9.74$ $\eta^2=.22$	N.S.	N.S.
S	p<.001 $F_{1,28}=544.21$ $\eta^2=.95$	p=.010 $F_{1,28}=7.65$ $\eta^2=.21$	p<.001 $F_{1,73,48.52}=160.25$ $\eta^2=.85$	N.S.	N.S.	N.S.	N.S.
SL	p<.001 $F_{1,28}=41.89$ $\eta^2=.60$	p=.050 $F_{1,28}=4.16$ $\eta^2=.13$	p<.001 $F_{2,24,62.69}=148.13$ $\eta^2=.84$	N.S.	p<.001 $F_{2,24,62.89}=15.45$ $\eta^2=.36$	N.S.	N.S.
SI	p<.001 $F_{1,28}=124.88$ $\eta^2=.82$	N.S.	p<.001 $F_{1,71,47.92}=251.67$ $\eta^2=.58$	N.S.	p<.001 $F_{1,71,47.92}=19.58$ $\eta^2=.41$	N.S.	N.S.
CV SR	N.S.	N.S.	p=.002 $F_{3,84}=5.58$ $\eta^2=.17$	N.S.	N.S.	N.S.	N.S.
CV S	p=.004 $F_{1,28}=9.69$ $\eta^2=.26$	N.S.	p=.002 $F_{3,84}=5.31$ $\eta^2=.17$	p=.032 $F_{1,28}=5.11$ $\eta^2=.15$	N.S.	N.S.	p=.036 $F_{3,84}=2.98$ $\eta^2=.01$
CV SL	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
CV SI	p=.005 $F_{1,28}=9.53$ $\eta^2=.25$	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
BCV SR	N.S.	N.S.	p=.006 $F_{3,84}=4.39$ $\eta^2=.13$	N.S.	N.S.	N.S.	N.S.
BCV S	p=.012 $F_{1,28}=7.18$ $\eta^2=.20$	N.S.	p=.007 $F_{3,84}=4.28$ $\eta^2=.13$	p=.037 $F_{1,28}=4.78$ $\eta^2=.15$	N.S.	N.S.	p=.044 $F_{3,84}=1.11$ $\eta^2=.01$
BCV SL	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.
BCV SI	p=.013 $F_{1,28}=7.07$ $\eta^2=.20$	N.S.	N.S.	N.S.	N.S.	N.S.	N.S.

Note: The different stroking parameters SR: Stroke rate (Stroke.min⁻¹); S: Speed (m.s⁻¹); SL: Stroke length (m); SI: Stroke index (m².s⁻¹); CV: Coefficient of variation (%); BCV: Biological Coefficient of variation (%). F= F-test. η^2 = effect size. Significant at p<.05 and N.S. non significant. N=2132 for all variables.

Figure Captions

Figure 1: Inter-lap distance effect through the 200-m for all the participants (N=32). In the top: a) the different technical parameters: Stroke rate (SR), Speed (S), Stroke length (SL) and Stroke index (SI) and in the bottom b) the Biological Coefficient of Variation (BCV %) of technical parameters. ** significant difference between each distance trial ($p<.01$). δ significant difference between male and female ($p<.05$).

Figure 2: Inter-lap distance effect through the 200-m for the different groups: male's national (Male N), male's international (Male I), female's national (Fem N) and female's international (Fem I). The evolution of different technical parameters: Stroke rate (SR), Speed (S), Stroke length (SL) and Stroke index (SI) and his Biological coefficient of variance (BCV). Level significant differences: σ international between 2 laps, β national difference between 2 laps ($p<.05$).

Figure 3: The evolution of different means model for each group was plotted for the Speed (S) through the 200-m. The male swimmers are in the top panel and the female swimmers in the bottom panel. The black dot corresponds to the international level and the white dot for national level. The 3 models regressions are represented by a different marker: linear (●), quadratic (▲) and cubic (■) model. N correspond to the number of swimmer fitted to a specifically model regression.

Figure 4: The evolution of different means model for each group was plotted for the Stroke Length (SL) through the 200-m. The male swimmers are in the top panel and the female swimmers in the bottom panel. The black dot corresponds to the international level and the white dot for national level. The 3 models regressions are represented by a different marker: linear (●), quadratic (▲) and cubic (■) model. N correspond to the number of swimmer fitted to a specifically model regression.

Figure 5: The evolution of different means model for each group was plotted for the Stroke Rate (SR) through the 200-m. The male swimmers are in the top panel and the female swimmers in the bottom panel. The black dot corresponds to the international level and the white dot for national level. The 3 models regressions are represented by a different marker: linear (●), quadratic (▲) and cubic (■) model. N correspond to the number of swimmer fitted to a specifically model regression

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Figure 1:Inter-lap distance effect through the 200-m for all the participants (N=32). In the top: a) the different technical parameters: Stroke rate (SR), Speed (S), Stroke length (SL) and Stroke index (SI) and in the bottom b) the Biological Coefficient of Variation (BCV %) of technical parameters. ** significant difference between each distance trial (p<.01).δ significant difference between male and female (p<.05).

150x228mm (300 x 300 DPI)

Figure 2: Inter-lap distance effect through the 200-m for the different groups: male's national (Male N), male's international (Male I), female's national (Fem N) and female's international (Fem I). The evolution of different technical parameters: Stroke rate (SR), Speed (S), Stroke length (SL) and Stroke index (SI) and his Biological coefficient of variance (BCV). Level significant differences: σ international between 2 laps, β national difference between 2 laps ($p < .05$).

221x326mm (300 x 300 DPI)

Figure 3: The evolution of different means model for each group was plotted for the Speed (S) through the 200-m. The male swimmers are in the top panel and the female swimmers in the bottom panel. The black dot corresponds to the international level and the white dot for national level. The 3 models regressions are represented by a different marker: linear ($\circ$), quadratic (Δ) and cubic ($\square$) model. N correspond to the number of swimmer fitted to a specifically model regression.

152x203mm (300 x 300 DPI)

Figure 4: The evolution of different means model for each group was plotted for the Stroke Length (SL) through the 200-m. The male swimmers are in the top panel and the female swimmers in the bottom panel. The black dot corresponds to the international level and the white dot for national level. The 3 models regressions are represented by a different marker: linear ($\circ$), quadratic (Δ) and cubic ($\square$) model. N correspond to the number of swimmer fitted to a specifically model regression.

152x203mm (300 x 300 DPI)

Figure 5: The evolution of different means model for each group was plotted for the Stroke Rate (SR) through the 200-m. The male swimmers are in the top panel and the female swimmers in the bottom panel. The black dot corresponds to the international level and the white dot for national level. The 3 models regressions are represented by a different marker: linear ($\circ$), quadratic (Δ) and cubic ($\square$) model. N correspond to the number of swimmer fitted to a specifically model regression.

152x203mm (300 x 300 DPI)

152x159mm (300 x 300 DPI)

Table 3: Regression mean modelling for each model equation (linear, poly 2 and poly 3). The number of swimmer (# s), the adjustment modeling parameters: Akaike weight (AIC w), coefficient of determination adjusted (r^2 ajust) and squared error of prediction (SSE) for each Lap (L1, L2, L3, L4) and each group.

Group	Model	L1				L2				L3				L4			
		# s	AIC w	SSE	R^2 ajust	# s	AIC w	SSE	R^2 ajust	# s	AIC w	SSE	R^2 ajust	# s	AIC w	SSE	R^2 ajust
Fem I S	Linear	4	0,69	0,02	0,48	3	0,60	0,02	0,27	0				2	0,86	0,02	0,36
	Poly 2	1	0,52	0,02	0,57	0				0				0			
	Poly 3	1	0,61	0,02	0,60	3	0,67	0,02	0,57	0				0			
Fem N S	Linear	5	0,60	0,02	0,71	0				4	0,53	0,02	0,48	4	0,58	0,02	0,37
	Poly 2	1	0,52	0,03	0,63	2	0,74	0,02	0,29	0				0			
	Poly 3	2	0,40	0,02	0,76	2	0,56	0,02	0,40	1	0,41	0,02	0,43	1	0,50	0,03	0,61
Male I S	Linear	2	0,49	0,04	0,66	0				0				3	0,74	0,03	0,60
	Poly 2	1	0,76	0,02	0,69	1	0,70	0,02	0,69	0				0			
	Poly 3	1	1,00	0,01	0,86	6	0,91	0,02	0,75	7	0,48	0,06	0,66	5	0,50	0,02	0,76
Male N S	Linear	5	0,57	0,02	0,60	1	0,51	0,03	0,25	2	0,61	0,03	0,70	2	0,89	0,04	0,24
	Poly 2	1	0,51	0,02	0,62	1	0,60	0,01	0,63	0				0			
	Poly 3	1	0,89	0,02	0,86	1	0,70	0,04	0,62	5	0,47	0,02	0,64	2	0,44	0,02	0,54
Fem I SR	Linear	5	0,17	1,46	0,60	2	0,18	1,36	0,56	0				4	0,29	1,34	0,20
	Poly 2	1	0,12	1,21	0,50	0				1	0,19	0,61	0,42	0			
	Poly 3	0				1	0,27	0,63	0,35	0				0			
Fem N SR	Linear	2	0,32	2,00	0,53	1	0,38	1,03	0,39	1	0,36	0,95	0,18	2	0,33	1,62	0,26
	Poly 2	3	0,62	2,37	0,66	0				1	0,65	0,92	0,30	3	0,45	1,04	0,51
	Poly 3	2	0,96	0,66	0,85	2	0,66	0,97	0,59	2	0,84	0,77	0,62	1	0,80	0,91	0,37
Male I SR	Linear	1	0,35	1,29	0,60	1	0,30	0,74	0,67	2	0,35	1,14	0,27	2	0,36	1,18	0,19
	Poly 2	1	0,37	0,77	0,36	0				2	0,59	2,00	0,33	0			
	Poly 3	4	0,75	0,75	0,86	3	0,85	0,85	0,68	2	0,80	1,03	0,49	4	0,73	1,51	0,46
Male N SR	Linear	2	0,38	0,88	0,60	1	0,37	0,64	0,52	2	0,32	0,67	0,34	0			
	Poly 2	3	0,54	1,02	0,73	2	0,65	1,07	0,74	0	0,00			1	0,54	0,85	0,27
	Poly 3	2	0,84	1,46	0,54	3	0,88	1,23	0,70	3	0,59	1,06	0,49	4	0,63	1,18	0,66
Fem I SL	Linear	2	0,39	0,06	0,43	0				0				1	0,30	0,04	0,20
	Poly 2	0				1	0,65	0,04	0,57	0				0			
	Poly 3	2	0,75	0,04	0,66	2	0,68	0,03	0,50	0				1	0,41	0,06	0,82
Fem N SL	Linear	0				0				1	0,36	0,05	0,34	0			
	Poly 2	1	0,53	0,05	0,66	1	0,51	0,10	0,26	1	0,47	0,06	0,31	4	0,56	0,06	0,38
	Poly 3	3	0,78	0,07	0,57	1	0,53	0,08	0,40	1	0,54	0,04	0,39	1	0,47	0,06	0,36
Male I SL	Linear	0				1	0,39	0,06	0,44	1	0,38	0,10	0,51	2	0,28	0,09	0,52
	Poly 2	3	0,56	0,09	0,45	1	0,67	0,05	0,64	2	0,63	0,11	0,39	0			
	Poly 3	2	0,95	0,06	0,59	4	0,85	0,09	0,57	5	0,69	0,08	0,45	6	0,90	0,07	0,52
Male N SL	Linear	1	0,37	0,06	0,37	0				2	0,32	0,09	0,36	0			
	Poly 2	1	0,58	0,05	0,77	1	0,61	0,10	0,79	3	0,63	0,10	0,46	1	0,72	0,05	0,67
	Poly 3	2	0,77	0,09	0,61	3	0,68	0,11	0,48	0				4	0,69	0,09	0,52

Note: The different stroking parameters SR: Stroke rate; S: Speed; SL: Stroke length. The different group: male national (Male N), male international (Male I), female's national (Fem N) and female's international (Fem I). S=0 means no regression model (p value >0.05 for individual fitting)

**Functional role of movement and performance variability:
Adaptation of front crawl swimmers to competitive
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