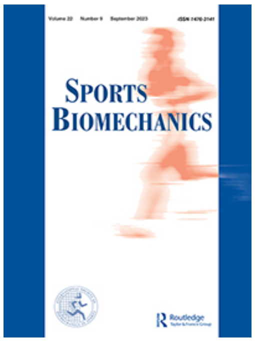

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Comparison of swimming velocity between age-group swimmers through discrete variables and continuous variables by Statistical Parametric Mapping

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ABSTRACT

The aim of this study was to compare the swimming velocity in front-crawl between age-group swimmers using discrete variables against Statistical Parametric Mapping (SPM). The sample consisted of 30 young male swimmers divided into three groups (each with 10 swimmers) based on their age (group #1: 13.60 ± 0.84 years; group #2: 15.40 ± 0.32 years; group 3: 16.39 ± 0.69 years). Swimmers performed three maximal trials in front-crawl. The best performance was used for analysis. Comparison of swimming velocity between groups was analysed using discrete variables and as a continuous variable (SPM). As a discrete variable, the mean swimming velocity showed a significant difference between groups ($p < 0.05$). Moreover, when analysed by SPM, swimming velocity showed a significant difference ($p = 0.021$) between the ~ 44% and ~ 51% of the stroke cycle (transition of the propulsion phases between sides). Post-hoc comparison revealed a significant difference between group #1 and group #3 only in SPM analysis. Researchers, coaches, and practitioners should know that both measurement approaches can be used simultaneously. However, SPM offers more sensitive and accurate results about the swimmers' stroke cycle.

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Swimming; biomechanics; technique; training; performance

Introduction

As a time-based sport, swimming is fundamentally dependent on swimming velocity (Craig & Pendergast, 1979; Seifert et al., 2010). Therefore, researchers and coaches are interested in identifying the main determinants responsible for improving swimming velocity (Morais et al., 2018; Narita et al., 2018; Sanders & Psycharakis, 2009). The front-crawl stroke receives a lot of attention from the swimming community because it is well established since the younger ages based on teaching and training perspectives (Costa et al., 2017; Stallman, 2014), and also the fastest technique (Kennedy et al., 1990).

Most research on front-crawl and other swimming strokes is based on straightforward discrete variables (with no time dimension – 0-D; Figueiredo et al., 2013; Silva et al.,

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2019), that is, for convenience of data handling or statistical constraints, researchers often use mean values during trials (i.e., including several consecutive stroke cycles; Silva et al., 2019) or independent stroke cycles (Morais et al., 2021). These discrete variables, such as mean swimming velocity, may not provide the details needed to better understand how swimmers differ from each other. For example, studies have observed that in age-group swimmers, expert swimmers have a faster mean swimming velocity than less experienced swimmers (Morais et al., 2013; Silva et al., 2019). The authors claimed that better stroke mechanics (higher stroke frequency, larger stroke length, and lower intra-cyclic variation of the swimming velocity) was the main factor for this phenomenon. However, when using discrete variables (namely based on the average), it is not possible to indicate precisely at which point in the stroke cycle these differences occur. As researchers generally refer to discrete variables, readers can only get the average value of the swimming velocity and related metrics.

Swimming velocity is characterised by a periodically accelerated/decelerated movement where intra-cyclic variations of the horizontal velocity occur (Barbosa et al., 2010). Researchers often use the 'velocity fluctuation' (dv) as a discrete variable to quantify these intra-cyclic variations of the swimming velocity (Barbosa et al., 2013; Morais et al., 2015; Silva et al., 2019). Notwithstanding, the dv is calculated as being the coefficient of variation (CV = one standard deviation/mean *100) (Barbosa et al., 2005). Consequently, the average value of the swimming velocity fluctuations over the entire stroke cycle may not provide insightful information about such a complex movement. The literature reports that the front-crawl stroke is characterised by five key moments (for the left cycle): (i) left hand catch; (ii) left limb insweep; (iii) left hand exit and right hand catch; (iv) right limb insweep, and; (v) right hand exit and left hand catch (Morais et al., 2020). Therefore, knowing at which key moment (or transitions between key moments) swimmers differ in swimming velocity can help researchers, coaches, and practitioners to better understand the swimming velocity pattern and develop training strategies to improve swimming velocity.

As opposed to discrete variables (0-D), there are statistical methods which allow statistical examination of entire time-series. Principal Component Analysis (PCA) or Statistical Parametric Modelling (SPM) have increased in popularity over the years in human movement research (Warmenhoven et al., 2018). These statistical methods have already shown significant advantages by providing more sensitive details in several sports (Bertozzi et al., 2022; Federolf et al., 2014). Regarding PCA, this is driven by Functional Data Analysis which expresses discrete observations arising from time-series in the form of a function, and then consider each measured function as a single observation for subsequent statistical analysis (Ramsay & Silverman, 2005). In the case of SPM, time-series variables are analysed as a single observation exploiting the use of random field theory (Adler & Taylor, 2007). However, in the context of swimming, only a few studies used SPM, and the main aim was to understand muscle kinematics and electromyographic pattern (Blache et al., 2018; Gaudet et al., 2018; Martens et al., 2016). In the specific context of swimming velocity, two studies analysed the breaststroke (Gonjo & Olstad, 2021; Gourgoulis & Nikodelis, 2022), and one study the underwater swimming velocity (Ruiz-Navarro et al., 2021).

The aim of this study was to compare swimming velocity in front-crawl between age-group swimmers using discrete variables against SPM. Based on discrete variables, both mean swimming velocity and dv were compared. Based on SPM, the swimming velocity was analysed as a continuous variable. Thus, all fluctuations within the stroke cycle were considered. It was hypothesised that, through discrete variables, a significant difference in mean swimming velocity and dv would be observed in age-group swimmers. The older ones would present better performances (i.e., faster mean swimming velocity and lower dv). Moreover, based on SPM, a significant difference would also be observed with the advantage of accurately indicating at what point it occurred within the stroke cycle.

Materials and methods

Participants

The sample consisted of 30 boys divided into three groups based on their competitive level categorised by their age (group #1: $N = 10$ with 13.60 ± 0.84 years, 61.55 ± 6.01 kg of body mass, 1.74 ± 0.04 m of height, 1.80 ± 0.08 m of arm span, and 358.50 ± 70.61 FINA points; group #2: $N = 10$ with 15.40 ± 0.32 years, 66.88 ± 8.14 kg of body mass, 1.76 ± 0.06 m of height, 1.83 ± 0.08 m of arm span, and 560.30 ± 43.72 FINA points; group #3: $N = 10$ with 16.39 ± 0.69 years, 70.38 ± 5.97 kg of body mass, 1.77 ± 0.06 m of height, 1.84 ± 0.10 m of arm span, and 581.80 ± 116.22 FINA points) and who participated on a regular basis at regional and national-level competitions. The sample included age-group national record holders, age-group national champions, and other swimmers who enrolled in a national talent-identification scheme (Tier 2 and 3 swimmers, McKay et al., 2021). They performed five to six training sessions per week (90 minutes each session). Parents or guardians and swimmers signed an informed consent form. All procedures were in accordance with the Declaration of Helsinki regarding human research, and the Polytechnic Ethics Board approved the research (N.º 72/2022).

Research design

Before the test, the swimmers underwent familiarisation sessions with the equipment they would use in a 25 m indoor swimming pool. Prior to in-water data collection, swimmers performed a standardised 1,000 m warm-up for sprinters (Neiva et al., 2014). All in-water data were collected during the all-out 25 m trials. Swimmers were requested to perform three all-out trials in front-crawl with a push-off start. Swimmers were instructed to minimise the underwater gliding and broke the water surface around the 5th metre mark. The first three consecutive stroke cycles after the 10th metre mark were analysed. This was done to disregard the advantage obtained with the push-off start and avoid the initial stroke cycle overspinning, and thus representing the ‘clean swim’ (Morais, Barbosa, et al., 2020). Swimmers were instructed to perform non-breathing strokes during this distance to avoid changes in coordination or technique. The best trial based on the mean swimming velocity during the 10th to 20th metre range was used for analysis. Subsequently, the average of three stroke cycles obtained from this range (which is representative of the swimmer’s clean swim) was used for analysis.

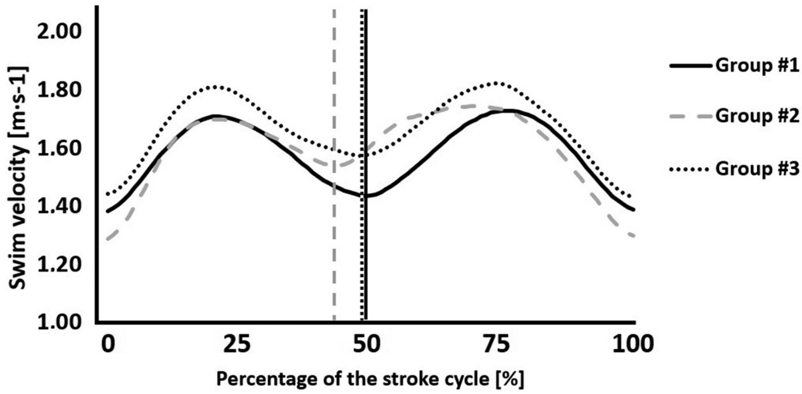

Figure 1. Average for 10 swimmers of the mean of three consecutive left stroke cycles per swimmer by group. Vertical lines correspond to the average right hand catch for each group.

Measurement of instantaneous swimming velocity

A video camera (Sony FDR-X3000, Japan) synchronised with the mechanical apparatus recorded the swimmers in the sagittal plane to identify the entry and exit of the hand in the water. The string of a mechanical speedometer (SpeedRT, ApLab, Rome, Italy) was attached to the swimmers' waist (Dadashi et al., 2012). The speedometer calculated the swimmer's displacement and velocity at a rate of 100 Hz and transferred data to a PC. Subsequently, the velocity-time series were imported into a signal processing software (AcqKnowledge v. 3.9.0, Biopac Systems, Santa Barbara, USA). Signal was handled with a Butterworth 4th order low-pass filter (cut-off: 5 Hz) upon residual analysis. Swimming velocity (in m·s^{-1}) was obtained from the software during three consecutive stroke cycles. Afterwards, the dv (in %) of each stroke cycle was computed as the CV, as previously mentioned (Barbosa et al., 2005). Figure 1 presents the filtered swimming velocity for the three groups. Specifically, for each group, it shows the average of the 10 swimmers, being each of them represented by the mean of three consecutive stroke cycles. The beginning and end of each stroke cycle was considered the consecutive entry of the left hand into the water.

Statistical analysis

The Kolmogorov–Smirnov and Levene tests were used to assess normality and homoscedasticity, respectively. The mean and standard deviation (SD) were computed as descriptive statistics.

One-way ANOVA was used to verify a group effect. The level of significance was set at $\alpha = 0.05$. The effect size index (eta square - η^2) was computed and interpreted as: (i) without effect if $0 < \eta^2 \leq 0.04$; (ii) minimum if $0.04 < \eta^2 \leq 0.25$; (iii) moderate if $0.25 < \eta^2 \leq 0.64$ and; (iv) strong if $\eta^2 > 0.64$ (Ferguson, 2009). If necessary, the Bonferroni correction was used to verify pairwise differences. For this, the level of significance was set at $\alpha = 0.017$. Cohen's d estimated the standardised effect sizes, and was deemed as: (i) trivial if $0 \leq d < 0.20$; (ii) small if $0.20 \leq d < 0.60$; (iii) moderate if $0.60 \leq d < 1.20$; (iv) large if $1.20 \leq d < 2.00$; (v) very large if $2.00 \leq d < 4.00$; (vi) nearly distinct if $d \geq 4.00$ (Hopkins, 2019).

The 95% confidence intervals (95 CI) were also calculated. These statistical analyses were performed with SPSS software (Version 26, IBM, Chicago, IL, USA).

Statistical analyses with SPM were performed within Matlab (v. 2019b, Mathworks Inc., Natwick, WY, United States). Statistical Parametric Mapping one-way ANOVA was used to verify the difference of the swimming velocity between groups (Pataky, 2010). The SPM Bonferroni correction was used to verify differences between pairs. The current method of ANOVA post-hoc analysis using the SPM T-test and Bonferroni correction is probably too simple (Pataky, 2018). Notwithstanding, whenever a significant difference is observed, post-hoc comparison is used to further explore the ability of the SPM analysis method to generate future hypothesis. For post-hoc comparisons, the alpha value was set at $\alpha = 0.017$. Scalar output statistics (SPM{F} – variance statistic) and (SPM{T} – post-hoc comparison) were calculated separately on each individual data point. When the scalar output statistic crossed the critical threshold, i.e., 95 CI of the {F} and {T} the null hypothesis was rejected. SPM analyses were implemented using the opensource spm1d code (v.M0.1, www.spm1d.org).

Prior to these analyses, each stroke cycle was normalised to its duration on R software (Team, 2017). As mentioned before, the beginning and end of each stroke cycle was considered the consecutive entry of the left hand in the water. Afterwards, for each swimmer, the average of these three time-normalised stroke cycles was used.

Results

Table 1 presents the descriptive statistics of the swimmers' age, mean swimming velocity, and dv by group. There was a significant difference in age ($F = 46.21$, $p < 0.001$, $\eta^2 = 0.77$), where all groups were significantly different from each other. Swimmers in group #3 presented the fastest mean swimming velocity, followed by group #2 and group #1. Through discrete values, mean swimming velocity revealed a significant difference with a small effect size ($F = 4.20$, $p = 0.026$, $\eta^2 = 0.24$). Post-hoc comparison revealed a non-significant difference but with a large effect size between group #1 and #3 (mean difference = −0.089, $p = 0.030$, 95 CI = −0.171 to −0.007, d = 1.27). The dv also revealed a non-significant difference ($p > 0.05$) between groups with a trivial effect size. The lowest values were observed in group #1, followed by group #3 and group #2.

Figure 2 presents the swimming velocity differences by SPM between the three groups, and the corresponding post-hoc comparison. There was a significant difference ($F = 7.441$, $p = 0.021$) between the ~ 44% and ~ 51% of the stroke cycle. This significant

Table 1. Descriptive statistics (mean ± standard deviation—SD) of the swimmers' age, swim velocity and velocity fluctuation (dv) by group. The results of a one-way ANOVA between groups are also shown.

	Mean ±1 SD				
	Group #1	Group #2	Group #3	F-ratio (p)	η^2
Age [years][a]	13.60 ± .84	15.40 ± .32	16.39 ± .69	46.21 (<0.001)	0.77
Swim velocity [$m \cdot s^{-1}$]	1.58 ± .06	1.60 ± .09	1.67 ± .08	4.20 (0.026)	0.24
dv [%]	7.26 ± 1.56	9.93 ± 5.62	8.29 ± 3.54	1.71 (0.200)	0.11

dv—intra-cyclic variation of the swim velocity; η^2 – effect size index; [a] – all groups are significantly different after the post-hoc correction.

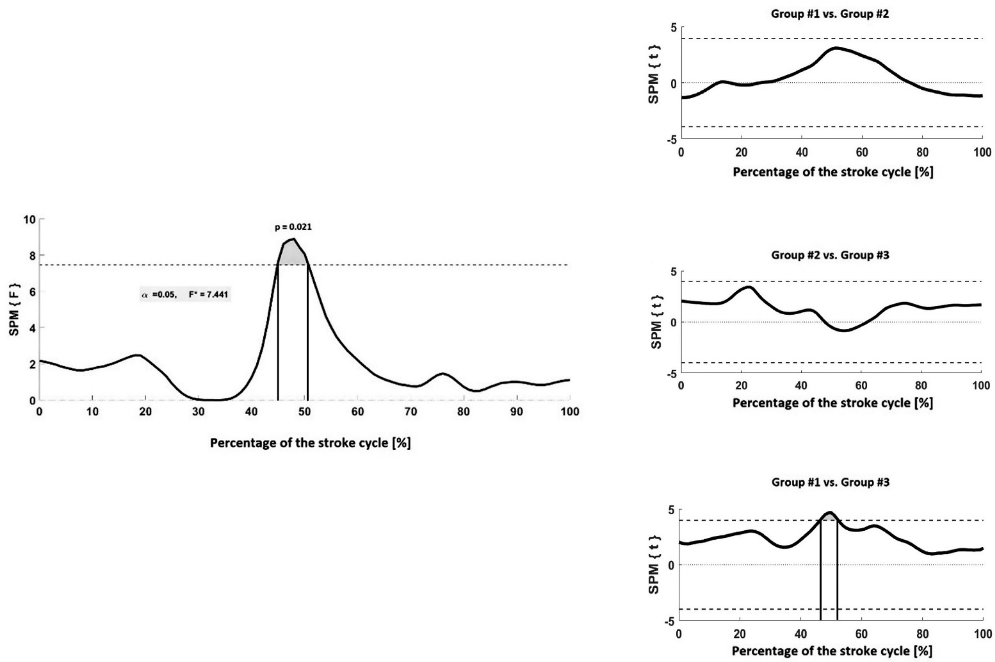

Figure 2. Variance analysis of swim velocity by SPM between the three groups, and the correspondent post-hoc comparison. SPM {F} – variance statistic for Statistical Parametric Mapping. SPM {t} – post-hoc comparison for Statistical Parametric Mapping. Grey areas with vertical lines represent the significant difference zone. Dash horizontal lines represent the 95% confidence intervals (95 CI).

difference occurred in the transition of the propulsion phases between sides. SPM post-hoc comparison revealed significant differences in this moment of the stroke cycle (~47% to ~51%) between group #1 and group #3.

Discussion and implications

The aim of this study was to compare the swimming velocity in front-crawl between age-group swimmers using discrete variables against SPM. The main findings indicate that, through discrete values, mean swimming velocity presented a significant difference between groups. However, post-hoc comparisons indicated a non-significant difference between groups #1 and #3. The dv also did not present a significant difference between groups. As for SPM, it is a more sensitive analysis of time-series data and also revealed a significant difference in swimming velocity between groups. This difference was observed between ~44% and ~51% of the stroke cycle. Furthermore, and contrarily to discrete values, post-hoc comparisons revealed a significant difference between swimmers in group #1 and #3. Based on SPM, it was possible to verify that this difference occurred between ~47% and ~51% of the stroke cycle.

The data from the present study revealed that swimmers included in group #3 presented a faster mean swimming velocity, followed by swimmers in group #2 and group #1, respectively (i.e., significant age effect). These findings were expected and are in line with what has already been reported in the literature (Barbosa et al., 2019; Figueiredo et al., 2013; Morais et al., 2013). Based on discrete variables, it can only be assumed that these groups presented a significant difference for the entire stroke cycle. However, post-hoc corrections did not yield significant differences between groups. But even if significant differences were verified, it would not be possible to identify at which point in the stroke cycle the differences occur. Moreover, the dv, which is an efficiency proxy that quantifies the intra-cyclic variations in swimming velocity, did not present a significant difference (even when mean swimming velocity did).

Swimming is considered a highly complex locomotion technique (Barbosa et al., 2017). Additionally, it has been claimed that beginners or lower level swimmers have lower motor skills than their trained or expert counterparts (Barbosa et al., 2017). Thus, using swimming velocity as a discrete variable (i.e., mean) may not always be the best approach to provide the expected results to help coaches. In such a complex movement, other approaches may be more useful to better understand the swimming velocity pattern, and at which point in the stroke cycle the fastest swimmers differentiate from the slowest ones.

The SPM, as a more sensitive analysis that specifically deals with time-series data, allowed identifying at which key moments within the stroke cycle the groups differed. The SPM revealed a significant difference in swimming velocity between the ~44% and ~51% of the stroke cycle. This moment corresponds to the transition of the propulsion phases between sides. Thus, it seems that the groups differed from each other specifically in the transition between propulsion phases. Swimmers are not always in the propulsive phase, there are moments when the swimming velocity decreases (Fernandes, Goethel, et al., 2022; Psycharakis et al., 2010). At least in age-group swimmers, it has been shown that the phase where it decreases meaningfully is in the transition between arm-pulls (Fernandes, Mezêncio, et al., 2022; Morais et al., 2020). Data from this study revealed similar findings.

In front-crawl, swimmers can use three strategies regarding their upper limbs' coordination (i.e., index of coordination—IdC): (i) 'opposition' (IdC = 0;); (ii) 'catch-up' (IdC <0), and; (iii) 'super-position' (IdC >0) (Chollet et al., 2000). The literature reports that swimmers are likely to switch from a 'catch-up' to an 'opposition' to a 'super-position' IdC to increase swimming velocity (by decreasing the lag between propulsive phases) (Seifert et al., 2004). However, younger swimmers tend to present an IdC lower than zero (i.e., 'catch-up' mode) (Figueiredo et al., 2016; Silva et al., 2019). Nonetheless, and despite being a 'catch-up' coordination, the fastest swimmers tend to have an IdC value closer to zero than their poorer performers counterparts (Figueiredo et al., 2016; Silva et al., 2019). Thus, it can be argued that swimmers included in group #3 (i.e., the fastest swimming velocity) were more likely to lose less time between propulsion phases and, consequently their performance, to present a faster swimming velocity.

The dv, computed as the CV, is a discrete variable that is considered to characterise the swimmer's pattern of displacement and efficiency, and consequently his performance (Barbosa et al., 2005, 2010). Overall, in age-group swimmers, a lower dv is related to faster swimming velocities (Morais et al., 2015; Silva et al., 2019). However, in the present study, the dv did not reveal a significant difference among groups. Additionally, group #1, which had the slowest mean swimming velocity, had also the lowest dv. The dv has the advantage of being able to standardise data variability across different datasets with different magnitudes. For this, these assumptions must be verified: (i) the dataset must be heteroscedastic (Atkinson & Nevill, 1998), and; (ii) the standard deviation must be directly proportional to the mean (Reed et al., 2002). However, the dv can be significantly biased by the mean when the dataset does not meet these assumptions. That is, when the mean increase/decrease rate is much greater than the standard deviation (i.e., the larger the mean, the smaller the CV), the dv will be affected by the mean (Atkinson & Nevill, 1998). Thus, although there is a general reasoning that faster swimming velocities are related to lower dv values, there are cases in which this may not occur. Recently, a study by Fernandes, Mezêncio et al., (2022) argued that studies using the dv (as the CV) provided several contradictory results in the literature (Barbosa et al., 2013; Psycharakis et al., 2010). Swimmers can achieve fast performances with more constant swimming velocities (i.e., less fluctuations) based on smoother motor patterns (Ganzevles et al., 2019). But they can also achieve fast swimming velocities by promoting propulsive forces more aggressively, and hence with greater dv's (Morouco et al., 2017). Thus, the dv (as the CV) may not be the cause of a given behaviour, but rather a consequence (Fernandes, Mezêncio, et al., 2022). At least in maximal trials (i.e., the fastest swimming velocity), the interpretation of the dv must be performed with caution. Discrete variables only provide an overview of the stroke cycle but are easily computable. On the other hand, SPM helps to identify at which key moment(s) within the stroke cycle differences occur. This happens because the entire curve (accelerations and decelerations) is analysed.

As main limitations, it can be considered that (i) our findings are valid only for maximal trials and in these age-group swimmers; (ii) only male swimmers were analysed, and (iii) the IdC was not measured. Therefore, researchers working on future studies on this topic are advised to calculate the IdC to gain deeper insight into the reasoning behind the difference in swimming velocity across age-group swimmers. Moreover, as a discrete variable, the literature has shown that mean swimming velocity denotes a stroke-by-stroke difference (repeated measures, i.e., within-subject effect) (Bideault et al., 2013). Thus, future studies should also analyse this phenomenon using SPM analysis to understand at which point in the stroke cycle a within-subject effect is observed. In addition to SPM, researchers should also be aware that there are other statistical procedures for 1-D analysis, such as PCA. Therefore, researchers must select the variables and outcomes they wish to study.

Conclusions

Older swimmers presented the fastest mean swimming velocity, followed by the intermediate and youngest groups, respectively. Swimming velocity analysed as a discrete variable (mean of the entire stroke cycle) revealed a non-significant difference between age-groups after the post-hoc correction. The dv also revealed non-significant differences. Conversely, swimming velocity analysed as time-series data through SPM, revealed a significant difference between groups. Analysing in more detail the entire stroke cycle, the SPM showed that age-groups were significantly different in the transition between arm-pulls propulsion. Researchers and coaches should be aware that swimming velocity analysed with discrete variables provide an overview of the stroke cycle. On the contrary, SPM allows for deeper and more sensitive insights indicating at which point in the stroke-cycle these differences may occur.

Disclosure statement

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References

Adler, R. J., & Taylor, J. E. (2007). *Random fields and geometry* (Vol. 80). Springer.

Atkinson, G., & Nevill, A. M. (1998). Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Medicine*, *26*(4), 217–238. https://doi.org/10.2165/00007256-199826040-00002

Barbosa, T. M., Bartolomeu, R., Morais, J. E., & Costa, M. J. (2019). Skillful swimming in age-groups is determined by anthropometrics, biomechanics and energetics. *Frontiers in Physiology*, *10*(FEB). https://doi.org/10.3389/fphys.2019.00073

Barbosa, T. M., Bragada, J. A., Reis, V. M., Marinho, D. A., Carvalho, C., & Silva, A. J. (2010). Energetics and biomechanics as determining factors of swimming performance: Updating the state of the art. *Journal of Science & Medicine in Sport*, *13*(2), 262–269. https://doi.org/10.1016/j.jsams.2009.01.003

Barbosa, T. M., Goh, W. X., Morais, J. E., & Costa, M. J. (2017). Variation of linear and nonlinear parameters in the swim strokes according to the level of expertise. *Motor Control*, *21*(3), 312–326. https://doi.org/10.1123/mc.2015-0097

Barbosa, T. M., Keskinen, K. L., Fernandes, R., Colaco, P., Lima, A. B., & Vilas-Boas, J. P. (2005). Energy cost and intracyclic variation of the velocity of the centre of mass in butterfly stroke. *European Journal of Applied Physiology*, *93*(5–6), 519–523. https://doi.org/10.1007/s00421-004-1251-x

Barbosa, T. M., Morouco, P. G., Jesus, S., Feitosa, W. G., Costa, M. J., Marinho, D. A., Silva, A. J., & Garrido, N. D. (2013). The interaction between intra-cyclic variation of the velocity and mean swimming velocity in young competitive swimmers. *International Journal of Sports Medicine*, *34*(2), 123–130. https://doi.org/10.1055/s-0032-1312582

Bertozzi, F., Porcelli, S., Marzorati, M., Pilotto, A. M., Galli, M., Sforza, C., & Zago, M. (2022). Whole-body kinematics during a simulated sprint in flat-water kayakers. *European Journal of Sport Science*, *22*(6), 817–825. Scopus. https://doi.org/10.1080/17461391.2021.1930190

Bideault, G., Herault, R., & Seifert, L. (2013). Data modelling reveals inter-individual variability of front crawl swimming. *Journal of Science & Medicine in Sport*, *16*(3), 281–285. https://doi.org/10.1016/j.jsams.2012.08.001

Blache, Y., Gillet, B., Selin, J., Sevrez, V., & Rogowski, I. (2018). Scapular kinematics during scaption in competitive swimmers. *European Journal of Sport Science*, *18*(5), 659–666. https://doi.org/10.1080/17461391.2018.1449893

Chollet, D., Chalies, S., & Chatard, J. (2000). A new index of coordination for the crawl: Description and usefulness. *International Journal of Sports Medicine*, *21*(1), 54–59. https://doi.org/10.1055/s-2000-8855

Costa, M. J., Barbosa, T. M., Morais, J. E., Miranda, S., & Marinho, D. A. (2017). Can concurrent teaching promote equal biomechanical adaptations at front crawl and backstroke swimming? *Acta of Bioengineering and Biomechanics*, *19*(1), 81–88. https://doi.org/10.5277/ABB-00511-2015-03

Craig, A. B., & Pendergast, D. R. (1979). Relationships of stroke rate, distance per stroke, and velocity in competitive swimming. *Medicine and Science in Sports*, *11*(3), 278–283. https://doi.org/10.1249/00005768-197901130-00011

Dadashi, F., Crettenand, F., Millet, G. P., & Aminian, K. (2012). Front-crawl instantaneous velocity estimation using a wearable inertial measurement unit. *Sensors*, *12*(10), 12927–12939. https://doi.org/10.3390/s121012927

Federolf, P., Reid, R., Gilgien, M., Haugen, P., & Smith, G. (2014). The application of principal component analysis to quantify technique in sports. *Scandinavian Journal of Medicine & Science in Sports*, *24*(3), 491–499. https://doi.org/10.1111/j.1600-0838.2012.01455.x

Ferguson, C. J. (2009). An effect size primer: A guide for clinicians and researchers. *Professional Psychology: Research and Practice*, *40*(5), 532–538. https://doi.org/10.1037/a0015808

Fernandes, A., Goethel, M., Marinho, D. A., Mezêncio, B., Vilas-Boas, J. P., & Fernandes, R. J. (2022). Velocity variability and performance in backstroke in elite and good-level swimmers. *International Journal of Environmental Research and Public Health*, *19*(11), 6744. https://doi.org/10.3390/ijerph19116744

Fernandes, A., Mezêncio, B., Soares, S., Duarte Carvalho, D., Silva, A., Vilas-Boas, J. P., & Fernandes, R. J. (2022). Intra-and inter-cycle velocity variations in sprint front crawl swimming. *Sports Biomechanics*, 1–14. https://doi.org/10.1080/14763141.2022.2077815

Figueiredo, P., Pendergast, D. R., Vilas-Boas, J. P., & Fernandes, R. J. (2013). Interplay of biomechanical, energetic, coordinative, and muscular factors in a 200 m front crawl swim. *BioMed Research International*, *2013*, 897232. https://doi.org/10.1155/2013/897232

Figueiredo, P., Silva, A., Sampaio, A., Vilas-Boas, J. P., & Fernandes, R. J. (2016). Front crawl sprint performance: a cluster analysis of biomechanics, energetics, coordinative, and anthropometric determinants in young swimmers. *Motor Control*, *20*(3), 209–221. https://doi.org/10.1123/mc.2014-0050

Ganzevles, S. P., Beek, P. J., Daanen, H. A., Coolen, B. M., & Truijens, M. J. (2019). Differences in swimming smoothness between elite and non-elite swimmers. *Sports Biomechanics*, *22*(5), 675–688. https://doi.org/10.1080/14763141.2019.1650102

Gaudet, S., Tremblay, J., & Begon, M. (2018). Muscle recruitment patterns of the subscapularis, serratus anterior and other shoulder girdle muscles during isokinetic internal and external rotations. *Journal of Sports Sciences*, *36*(9), 985–993. https://doi.org/10.1080/02640414.2017.1347697

Gonjo, T., & Olstad, B. H. (2021). Differences between elite and sub-elite swimmers in a - 100 m breaststroke: A new race analysis approach with time-series velocity data. *Sports Biomechanics*, 1–12. https://doi.org/10.1080/14763141.2021.1954238

Gourgoulis, V., & Nikodelis, T. (2022). Comparison of the arm-stroke kinematics between maximal and sub-maximal breaststroke swimming using discrete data and time series analysis. *Journal of Biomechanics*, *142*, 111255. https://doi.org/10.1016/j.jbiomech.2022.111255

Hopkins, W. (2019). A scale of magnitudes for effect statistics. A new view of statistics. 2002. *Internet.* Retrieved October 10, 2022, from http://sportsci.org/resource/stats/effectmag.html

Kennedy, P., Brown, P., Chengalur, S. N., & Nelson, R. C. (1990). Analysis of male and female Olympic swimmers in the 100-meter events. *Journal of Applied Biomechanics*, *6*(2), 187–197. https://doi.org/10.1123/ijsb.6.2.187

Martens, J., Daly, D., Deschamps, K., Staes, F., & Fernandes, R. J. (2016). Inter-individual variability and pattern recognition of surface electromyography in front crawl swimming. *Journal of Electromyography and Kinesiology*, *31*, 14–21. Scopus. https://doi.org/10.1016/j.jelekin.2016.08.016

McKay, A., Stellingwerff, T., Smith, E., Martin, D., Mujika, I., Goosey-Tolfrey, V., Sheppard, J., & Burke, L. (2021). Defining training and performance caliber: A participant classification framework. *International Journal of Sports Physiology and Performance*, *17*(2), 317–331. https://doi.org/10.1123/ijspp.2021-0451

Morais, J. E., Barbosa, T. M., Forte, P., Bragada, J. A., Castro, F. A. D. S., & Marinho, D. A. (2020). Stability analysis and prediction of pacing in elite 1500 m freestyle male swimmers. *Sports Biomechanics*, 1–18. https://doi.org/10.1080/14763141.2020.1810749

Morais, J., Barbosa, T. M., Lopes, V. P., Marques, M. C., & Marinho, D. A. (2021). Propulsive force of upper limbs and its relationship to swim velocity in the butterfly stroke. *International Journal of Sports Medicine*, *42*(12), 1105–1112. https://doi.org/10.1055/a-1386-4985

Morais, J. E., Garrido, N. D., Marques, M. C., Silva, A. J., Marinho, D. A., & Barbosa, T. M. (2013). The influence of anthropometric, kinematic and energetic variables and gender on swimming performance in youth athletes. *Journal of Human Kinetics*, *39*(1), 203–211. https://doi.org/10.2478/hukin-2013-0083

Morais, J. E., Sanders, R. H., Papic, C., Barbosa, T. M., & Marinho, D. A. (2020). The influence of the frontal surface area and swim velocity variation in front crawl active drag. *Medicine and Science in Sports and Exercise*, *52*(11), 2357–2364. https://doi.org/10.1249/MSS.0000000000002400

Morais, J. E., Silva, A. J., Garrido, N. D., Marinho, D. A., & Barbosa, T. M. (2018). The transfer of strength and power into the stroke biomechanics of young swimmers over a 34-week period. *European Journal of Sport Science*, *18*(6), 787–795. https://doi.org/10.1080/17461391.2018.1453869

Morais, J. E., Silva, A. J., Marinho, D. A., Seifert, L., & Barbosa, T. M. (2015). Cluster stability as a new method to assess changes in performance and its determinant factors over a season in young swimmers. *International Journal of Sports Physiology and Performance*, *10*(2), 261–268. https://doi.org/10.1123/ijspp.2013-0533

Morouco, P. G., Barbosa, T., Arellano, R., & Vilas-Boas, J. P. (2017). Intra-cyclic variation of force and swimming performance. *International Journal of Sports Physiol Perform*, 1–20. https://doi.org/10.1123/ijspp.2017-0223

Narita, K., Nakashima, M., & Takagi, H. (2018). Effect of leg kick on active drag in front-crawl swimming: Comparison of whole stroke and arms-only stroke during front-crawl and the streamlined position. *Journal of Biomechanics*, *76*, 197–203. https://doi.org/10.1016/j.jbiomech.2018.05.027

Neiva, H. P., Marques, M. C., Barbosa, T. M., Izquierdo, M., & Marinho, D. A. (2014). Warm-up and performance in competitive swimming. *Sports Medicine*, *44*(3), 319–330. https://doi.org/10.1007/s40279-013-0117-y

Pataky, T. (2010). Generalized n-dimensional biomechanical field analysis using statistical parametric mapping. *Journal of Biomechanics*, *43*(10), 1976–1982. https://doi.org/10.1016/j.jbiomech.2010.03.008

Pataky, T. (2018). *ANOVA post hoc analysis*. Retrieved January 10, 2023, fromhttp://spm1d.org/doc/PostHoc/anova.html

Psycharakis, S. G., Naemi, R., Connaboy, C., McCabe, C., & Sanders, R. H. (2010). Three-dimensional analysis of intracycle velocity fluctuations in frontcrawl swimming. *Scandinavian Journal of Medicine & Science in Sports*, *20*(1), 128–135. https://doi.org/10.1111/j.1600-0838.2009.00891.x

Ramsay, J., & Silverman, B. (2005). *Functional data analysis*. Wiley Online Library.

R Core Team. (2017). R: A language and environment for statistical computing. *R Foundation for Statistical Computing Vienna, Austria.*

Reed, G. F., Lynn, F., & Meade, B. D. (2002). Use of coefficient of variation in assessing variability of quantitative assays. *Clinical and Vaccine Immunology*, *9*(6), 1235–1239. https://doi.org/10.1128/CDLI.9.6.1235-1239.2002

Ruiz-Navarro, J. J., Cano-Adamuz, M., Andersen, J. T., Cuenca-Fernández, F., López-Contreras, G., Vanrenterghem, J., & Arellano, R. (2021). Understanding the effects of training on underwater undulatory swimming performance and kinematics. *Sports Biomechanics*, 1–16. https://doi.org/10.1080/14763141.2021.1891276

Sanders, R. H., & Psycharakis, S. G. (2009). Rolling rhythms in front crawl swimming with six-beat kick. *Journal of Biomechanics*, *42*(3), 273–279. https://doi.org/10.1016/j.jbiomech.2008.10.037

Seifert, L., Chollet, D., & Bardy, B. G. (2004). Effect of swimming velocity on arm coordination in the front crawl: A dynamic analysis. *Journal of Sports Sciences*, *22*(7), 651–660. https://doi.org/10.1080/02640410310001655787

Seifert, L., Leblanc, H., Chollet, D., & Delignieres, D. (2010). Inter-limb coordination in swimming: Effect of speed and skill level. *Human Movement Science*, *29*(1), 103–113. https://doi.org/10.1016/j.humov.2009.05.003

Silva, A. F., Figueiredo, P., Ribeiro, J., Alves, F., Vilas-Boas, J. P., Seifert, L., & Fernandes, R. J. (2019). Integrated analysis of young swimmers' sprint performance. *Motor Control*, *23*(3), 354–364. https://doi.org/10.1123/mc.2018-0014

Stallman, R. K. (2014). Which stroke first? No stroke first! *International Journal of Aquatic Research & Education*, *8*(1), 2. https://doi.org/10.25035/ijare.08.01.02

Warmenhoven, J., Harrison, A., Robinson, M. A., Vanrenterghem, J., Bargary, N., Smith, R., Cobley, S., Draper, C., Donnelly, C., & Pataky, T. (2018). A force profile analysis comparison between functional data analysis, statistical parametric mapping and statistical non-parametric mapping in on-water single sculling. *Journal of Science & Medicine in Sport*, *21*(10), 1100–1105. Scopus. https://doi.org/10.1016/j.jsams.2018.03.009