COBEM UBERLÂNDIA 2019

ABCM Associação Brasileira de Engenharia e Ciências Mecânicas

25th ABCM International Congress of Mechanical Engineering
October 20-25, 2019, Uberlândia, MG, Brazil

COB-2019-1040
LINEAR MODELS BACKSTROKE START TIME PREDICTION USING EMG

Karla de Jesus
Centre of Research, Education, Innovation and Intervention in Sport, Faculty of Sport, University of Porto, Porto, Portugal; Porto Biomechanics Laboratory (LABIOMEP), University of Porto, Porto, Portugal; Human Performance Studies Laboratory, Faculty of Physical Education and Physiotherapy, Federal University of Amazon, Manaus, Amazon, Brazil; Human Motor Behavior Studies Laboratory, Faculty of Physical Education and Physiotherapy, Federal University of Amazon, Manaus, Amazon, Brazil
karladejesus@ufam.edu.br

Leandro dos Santos Coelho
Industrial and Systems Engineering Graduate Program (PPGEPS), Pontifical Catholic University of Paraná, Curitiba, Brazil
Electrical Engineering Graduate Program (PGEE), Federal University of Paraná, Curitiba, Brazil
leandro.coelho@pucpr.br

Helon Vicente Hultmann Ayala
Deparment of Mechanical Engineering, Pontifical Catholic University of Rio de Janeiro, Rio de Janeiro, Brazil
helon@puc-rio.br

Kelly de Jesus
Centre of Research, Education, Innovation and Intervention in Sport, Faculty of Sport, University of Porto, Porto, Portugal; Porto Biomechanics Laboratory (LABIOMEP), University of Porto, Porto, Portugal; Human Performance Studies Laboratory, Faculty of Physical Education and Physiotherapy, Federal University of Amazon, Manaus, Amazon, Brazil; Human Motor Behavior Studies Laboratory, Faculty of Physical Education and Physiotherapy, Federal University of Amazon, Manaus, Amazon, Brazil
kellydejesus@ufam.edu.br

Pedro Gonçalves
Centre of Research, Education, Innovation and Intervention in Sport, Faculty of Sport, University of Porto, Porto, Portugal
pgoncalves@fade.up.pt

Ricardo Jorge Pinto Fernandes
João Paulo Vilas-Boas
Centre of Research, Education, Innovation and Intervention in Sport, Faculty of Sport, University of Porto, Porto, Portugal; Porto Biomechanics Laboratory (LABIOMEP), University of Porto, Porto, Portugal
ricfer@fade.up.pt; jpvb@fade.up.pt

Abstract. *The start phase is a junction of explosive movements intended to boost the swimmers from the block/wall, representing an important part of the short distance swimming events. It was aimed to apply linear models to predict 15 m backstroke start time using electromyographic (EMG) data. Following a four-week start familiarization with each start variant, 10 male backstroke swimmers randomly performed six maximal 15 m trials with feet parallel and partially emerged, but three with a horizontal handgrip and three with a vertical handgrip (2 min rest in-between trials). Surface EMG of Biceps Brachii, Triceps Brachii, Rectus Femoris, Biceps Femoris, Gastrocnemius Medialis and Tibialis Anterior was recorded and processed using the time integral EMG (iEMG). Eight video cameras (four surface and four underwater) were used to determine backstroke start hands-off, take-off, flight, entry and underwater phases. A Data-driven approach based on regression linear models using iEMG of each backstroke start phase and muscle in both start variants can be useful to predict dynamical behavior related to start component in swimming analysis. The implementation of the linear mathematical model requires optimizing its parameters according to measured data. Preliminary results show that the obtained linear model is able to capture the relationship present in the data. Future submission of the full paper will include the importance of each predictor, different types of learning algorithms for linear models such as Least absolute shrinkage and selection operator, ridge regression, elastic net, and the test on nonlinear model structures.*

Keywords: *muscle activation, machine learning, linear models, swimming start, performance*

1. INTRODUCTION

Swimming events can be decomposed in the start, free swimming and turn phases (de Jesus et al., 2011). For short races, the start, defined between the starting signal and the moment the head vertex passes the 15 m point, can have a significant impact on total race time (Cossor and Mason, 2000). The total start time is dependent upon ~11.5 and 84% of the aerial (i.e., hands-off and take-off), flight and underwater phases (Cossor and Mason, 2000; de Jesus et al., 2011), being crucial to understand the start phase neuromuscular requirements, which enables coaches to gain a better understanding of muscular contributions and control pattern, that will allow technique modification and inform training practices (Ball and Scurr, 2013).

The assessment of maximal effort events affords us an insight in to the neuromuscular limits, capabilities and processes involved in conducting highly-velocity human movement (Ball and Scurr, 2013). The prior upper, lower limb and trunk muscles acting on backstroke start phases have been studied using the surface electromyography (EMG, de Jesus et al., 2011; Hohmann et al., 2008). Findings have revealed the increasing variability of the muscle activation of the swimmers along the different phases of the backstroke start (Hohmann et al., 2008) and the *Rectus Femoris* activation during underwater phase influence on the 5 m backstroke start time (de Jesus et al., 2011).

Authors have described and also predicted backstroke start performance essentially using kinematics and kinetics data (de Jesus et al., 2011; Nguyen et al., 2014). Recent backstroke start studies have applied artificial intelligence algorithms in common used start variants focused on 5 m time prediction revealing errors below 5% for both models (de Jesus et al., 2018). In this paper, it has been have proposed to apply linear models on predicting the 15 m backstroke start time in two commonly used backstroke start variants (i.e. feet partially emerged with hands on vertical and horizontal handgrip) using iEMG data from upper and lower limbs and trunk muscles. Modeling swimming start performance with linear models using neuromuscular data can afford coaches to select proper starts training strategies.

2. METHODS

2.1 Participants

Ten competitive male backstroke swimmers (mean ± SD: age 20.6 ± 6.0 yrs., stature 1.75 ± 0.05 m, body mass 71.6 ± 12.1 kg, training background 12.7 ± 8.0 yrs. and 60.56 ± 2.29 s 100 m backstroke mean performance in 25-m pool representing 80.91 ± 3.09% of the 100-m backstroke short course World Record at that time) volunteered to participate. The University of Porto Research Ethics Committee approved the study design (ethic review: CEFADE 222014), and all experimental procedures corresponded to the Declaration of Helsinki requirements. Swimmers and parents and/or guardians (when participants were under 18 yrs.) provided written informed consent to take part in this study.

2.2 Experimental procedures

Two backstroke start variants with feet parallel and partially emerged were studied (cf. de Jesus, et al., 2018): (i) hands on the highest horizontal and (ii) vertical handgrip. Previous to data collection, a 1-month starting training intervention (3 sessions per week) was conducted to minimize performance bias and to provide similar standards in each of the two variants studied. In each session, swimmers performed 10 x 15 m maximal trials of each starting variant and were supervised two sessions a week to receive qualitative (i.e. video images) and quantitative (i.e. 15 m time) performance feedback.

In a 25 m indoor swimming pool, participants performed randomly six maximal 15 m trials being three of each variant (2 min rest in-between trials), from which a mean value for each swimmer in each variant was calculated for statistical analysis. A starter device (Omega Start Time IV, Swiss Timing, Ltd., Switzerland) produced the starting signals conform to swimming rules (SW4.2, Federatiön Internationale de Natation - FINA) and simultaneously exported a light and trigger to the cameras and the analogue-to-digital (A/D) converter (MP 150, BIOPAC Systems Inc., USA), respectively.

2.3. EMG recording and parameters

Biceps Brachii, *Triceps Brachii*, *Rectus Femoris*, *Biceps Femoris*, *Gastrocnemius Medialis* and *Tibilais Anterior* were right body side selected based on their main function in backstroke start and anatomic location (c.f. de Jesus et al., 2011; Hohmann et al., 2008). Swimmers' skin was shaved and cleaned with alcohol-soaked cotton to reduce skin impedance. Active silver/silver chloride surface electrodes (Dormo, Telic, S.A., Spain) with preamplifiers (AD621 BNZ, Analog Devices Inc., USA) recorded bipolar EMG (2 cm apart) with an eight-channel device (c.f. de Jesus et al., 2011). EMG system presents common rejection mode of 110 dB and a total gain of 1100. Modern pre amplifier design reduces the importance of measuring EMG with low level of electrode skin impedance. Electrodes were placed in the mid-point of the contracted muscle belly, in line with the fiber orientation and a reference electrode was attached to the patella.

Preceding the electrodes insulation and cables immobilization, each swimmer performed three dry land maximal voluntary isometric contractions for each muscle that was held for 5 s (followed by 5 min rest) and verbal encouragement was given to the subjects. The maximum value of the three measurements was defined for normalization. Raw EMG signals were sampled at 1000 Hz per channel with a 16-bit A/D conversion and recording system (BIOPAC System, Inc., USA) and stored on a computer for later analysis. EMG data analysis was performed with MATLAB R2014a (MathWorks Inc., USA; e.g. de Jesus et al., 2011).

Baseline and maximal voluntary isometric contraction values were recorded sequentially and in the same file. After the trigger, baseline was assessed between 1500 to 2500 ms, followed by the maximal voluntary isometric contraction test. Each raw EMG signal was filtered with a 4^{th} order band-pass Butterworth filter with cut-off frequencies of 35 and 500 Hz, full-wave rectified and smoothed with a 4^{th} order low pass Butterworth filter of 10 Hz to get linear envelope. All filtering actions were implemented to assure that zero-phase distortion exists, by processing the input data in both the forward and reverse directions. The mean values plus two standard deviations were calculated from the baseline, and the maximal voluntary isometric contraction values were extracted from above referred files. Dynamic EMG signals were considered active or inactive when located above or below the baseline values, respectively. Integration of the resulting linear envelope signal of active EMG signals (iEMG), in each backstroke start phase (i.e. hands-off, take-off, flight, entry and underwater; cf. de Jesus et al., 2011), was calculated for active EMG normalized time, instead of each respective normalized total phase time. The time normalization results, in any case, in a time vector from 0 to 100%.

2.5 Linear Models

In the present work linear models were used to model the relationship between iEMG and start time. The model equation (Eq. 1) can be described (Friedman et al., 2009) by

$$\hat{y}_i = f(X_i) = \beta_0 + \textstyle\sum_{i=1}^{p} X_{ij}\beta_j \tag{1}$$

where $\hat{y}_i$ denotes the prediction signal, X_i is *n*-dimensional feature vector with *n* components, that is, the inputs of the mathematical model, and β is a *n*+1-dimensional model parameter vector. The model parameters can be estimated using a N-dimensional tuples dataset with regular squared error measures (Eq. 2) such as

$$\mathrm{RSS}(\beta) = \textstyle\sum_{i=1}^{N} y_i - \hat{y}_i = \sum_{i=1}^{N} [y_i - \beta_0 - \sum_{i=1}^{p} X_{ij}\beta_j] \tag{2}$$

where RSS is the residual sum of squares. In this work it is carried out using QR factorization (decomposition) in R statistical language. In linear algebra, a QR decomposition of a matrix is a decomposition of a matrix A into a product A = QR of an orthogonal matrix Q and an upper triangular matrix R. QR decomposition is often used to solve the linear least squares problem and is the basis for a particular eigenvalue algorithm, the QR algorithm.
It was evaluated the accuracy of the predictions using the coefficient of determination R^2, which is calculated through the squared value of the Pearson correlation coefficient between the observed and predicted values. The results generated were created using leave-one-out-cross-validation (LOOCV).

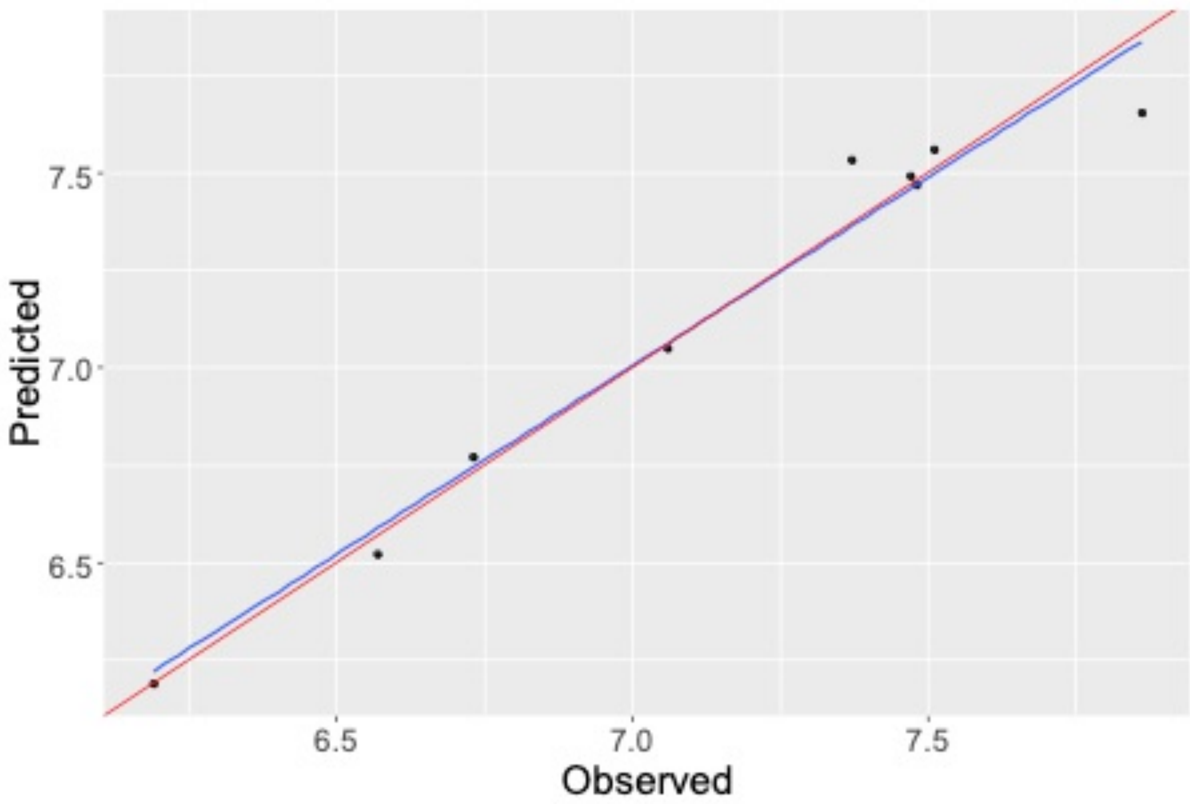
3. RESULTS AND DISCUSSION

Figure 1 depicts observed and predicted 15 m backstroke start time for the variant performed with hands on the horizontal (a panel) and vertical handgrips (b panel) using iEMG data from hands-off to underwater start phase. The R^2 of the presented results are close to unity showcasing the predictive capability of the linear model tested. The knowledge of muscular actions involved in the start phase in all its aspects, its evaluation and feedback allows for the movement optimization, training possibilities and backstroke performance (Ball and Scurr, 2013; de Jesus et al., 2011; Hohmann et al., 2008;).

Performance of backstroke start variant with hands in horizontal and vertical positioning and feet partially emerged were previously modeled with artificial neural networks (de Jesus et al., 2018) and linear models (Hohmann et al., 2008; de Jesus et al., 2018; Nguyen et al., 2014). De Jesus and co-authors (2018) observed errors below 5 % in backstroke start time prediction with non-linear and linear modeling. The small sample size limitations, observed in previous studies (e.g. de Jesus et al., 2018) can be minimized using the support vector to linear regression for performance prediction, due to the shorter training times and greater stability in converging solution (Collazo, et al., 2016).

The present models have 60 iEMG predictors and at generalization, most likely all of these features may be summarized using feature engineering, which also will be a topic for future research. The predictors' importance and term selection are also goals to be included in future studies.

(a)



(b)

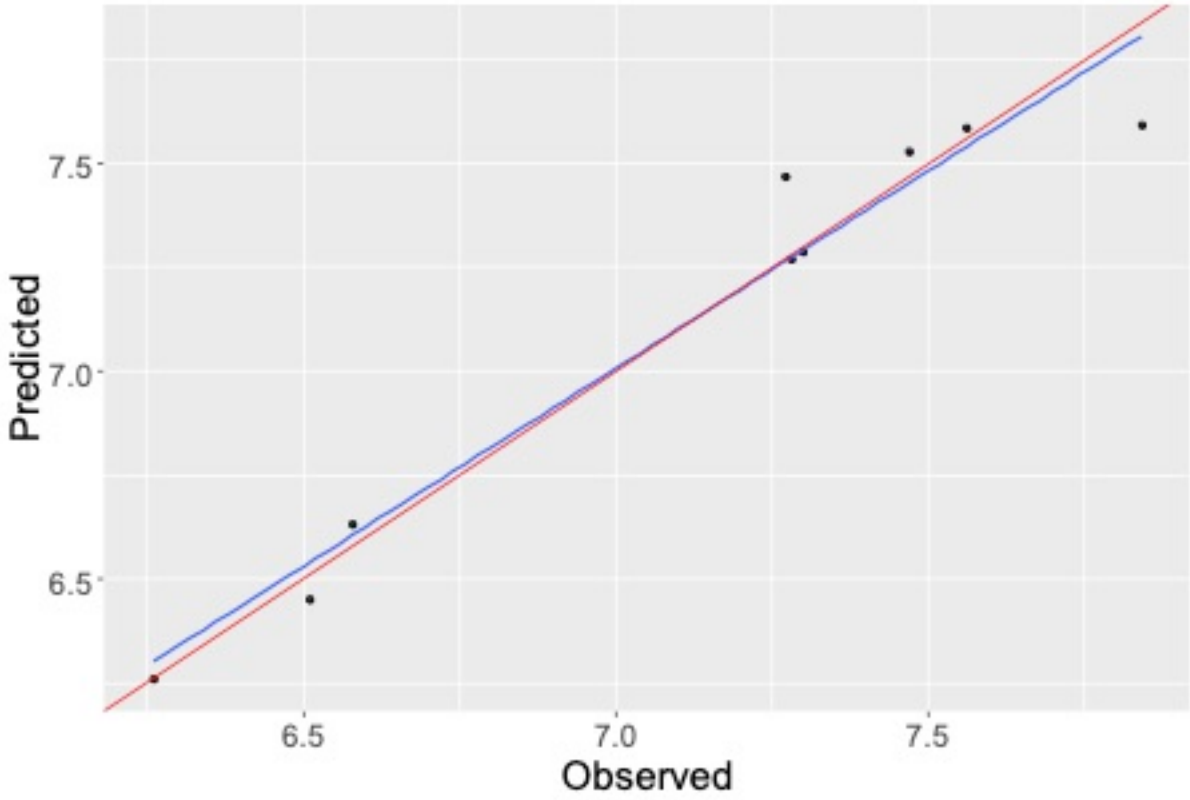


Figure 1. Observed and predicted 15 m start time values based on the iEMG from upper, lower and trunk muscles from the hands-off to the underwater phase in the starting variant with hands positioned on the horizontal (a panel) and vertical handgrips (b panel). Red line is the perfect data reconstruction, blue line is the linear regression of the predicted values (R2=xx), and the black dots draw each model prediction versus the actual value.

4. ACKNOWLEDGEMENTS

This work was supported by the CAPES under Grants (543110-7/2011-2015, 0761/12-5/2012-2015 and 88887.163347/2018-00); FCT under Grant (PTDC/DES/101224/2008 - FCOMP-01-0124-FEDER-00957); CAPES-FCT 039-2014 under Grant (99999.008578/2014-01); CNPq under Grants (303908/2015-7-PQ, 404659/2016-0-Univ, 204893/2017-8-PDE); Araucaria Foundation under Grant (FA 117/2014) and FAPEAM under Grant (3523467452000920102017 PPP 04/2017).

5. REFERENCES

Ball, N., and Scurr, J., 2013. “Electromyography normalization methods for high-velocity muscle actions: review and recommendations”. *Journal of Applied Biomechanics*, 29(5),600-608.

Collazo, R.A., Pessôa, L.A.M., Bahiense, L., Pereira, B.de B., dos Reis, A.F., Silva, N.S., 2016. “A comparative study between artifical neural network and support vector machine for acute coronary syndrome prognosis. Pesquisa Operacional, 36(2), 321-343.

Cossor, J., and Mason, B.R., 2001. “Swim start performances at the Sydney 2000 Olympic Games”. In *Proceedings of the XIX International Symposium on Biomechanics in Sports – ISBS 2001*. San Francisco, USA.

De Jesus, K., De Jesus, K., Figueiredo, P., Gonçalves, P., Pereira, S., Vilas-Boas, J.P., Fernandes, R., 2011. “Biomechanial analysis of backstroke swimming starts”. *International Journal of Sports Medicine*, 32(7), 546-551.

De Jesus, K., Ayala, H.V.H., De Jesus, K., Coelho, L. dos S., Medeiros, A.I.A., Abraldes, J.A., Vaz, M. A. P., Fernandes, R., Vilas-Boas, J.P., 2018. “Modelling and predicting backstroke start perforance using non-linear and linear models”. *Journal of Human Kinetics*, 23(61), 29-38.

Friedman, J., Hastie, T., Tibshirani, R., 2009, “The elements of statistical learning”. 2nd Ed. New York: Springer.

Hohmann, A., Fehr, U., Kirsten, R., Krueger, T., 2008. "Biomechanical analysis of the backstroke start technique in swimming". *E-Journal Bewegung und Training*, 1, pp. 28–33.

Nguyen, C., Bradshaw, E.J., Pease D., Wilson, C., 2014. "Is starting with the feet out of the water faster on backstroke swimming? Sports Biomechanics, 13(2), 154-165.

6. RESPONSIBILITY NOTICE

The author(s) is (are) the only responsible for the printed material included in this paper.