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Regression-based analysis of front crawl swimming using upperarm mounted accelerometers

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Abstract

Wearable accelerometers can be used to quantify movement during swimming, enabling objective performance analysis. This study examined arm acceleration during front crawl swimming, and investigated how accelerometer-derived features change with lap times. Thirteen participants swam eight 50m laps using front crawl with a tri-axial accelerometer attached to each upper arm. Data were segmented into individual laps; lap times estimated and individual strokes extracted. Stroke times, root mean squared (RMS) acceleration, RMS jerk and spectral edge frequencies (SEF) were calculated for each stroke. Movement symmetry was assessed as the ratio of the minimum to maximum feature value for left and right arms. A regularized multivariate regression model was developed to estimate lap time using a subset of the accelerometer-derived features. Mean lap time was 56.99±11.99s. Fifteen of the 42 derived features were significantly correlated with lap time. The regression model included 5 features (stroke count, mean SEF of the X and Z axes, stroke count symmetry, and the coefficient of variation of stroke time symmetry) and estimated 50m lap time with a correlation coefficient of 0.86, and a cross-validated RMS error of 6.38s. The accelerometer-derived features and developed regression model may provide a useful tool to quantitatively evaluate swimming performance.

Introduction

Wearable inertial sensors allow for unobtrusive, low cost and objective analysis of human movement in any environment. This is particularly useful when comparing movements over time, such as a prescribed clinical test [1-3], or as a sports training tool [4, 5], where subtle changes in movement patterns may not be obvious to the human eye. In swimming, waterproof wearable accelerometers facilitate quantitative assessment of swimming technique, within a training session and between different training sessions.

Previous studies have reported methods to distinguish stroke types, and to estimate standard training measures such as stroke count, stroke rate, number of laps, swimming duration and distance [6-9]. Sensor location determines what measures may be extracted from the recorded data. Most research in this field has used accelerometers on the lower back, due to lower variation of axes orientation during swimming compared to sensor worn on the limbs. Lower back mounted accelerometers have been used to examine stroke rate and duration [6], to identify swimming strokes and turns, count strokes and estimate swimming intensity [11], and to investigate symmetry of stroke times [12, 13]. Wristmounted accelerometers have previously been used to examine stroke phase characteristics [10]. Sensor placement on the arms may enable detailed and accurate assessment of arm movement during each swimming stroke.

Front crawl swimming velocity has previously been estimated using accelerometer data recorded at the sacrum [7, 14, 15]. Dadashi, et al. [15] proposed a method for drift-free integration of forward acceleration to estimate swimming velocity, and reported RMS error in instantaneous velocity of 11.3 cm/s, and a Spearman's correlation coefficient of 0.94. Dadashi, et al. [16] later presented an updated method, and reported a swimming velocity root mean square (RMS) error of 9.0 cm/s and high linear correlation compared to a commercial tethered reference system. Stamm, et al. [17] estimated instantaneous swimming velocity by integrating total acceleration and using a correction based on recorded lap times and pool length, and reported good agreement compared with a tethered velocity meter. However, armmounted accelerometers have not yet been used to estimate swimming times or velocities.

The aim of this study was to quantitatively examine arm movement during front crawl swimming. To quantify changes in swimming technique with lap times, a range of accelerometer-derived features were examined for each stroke. The relationship between lap times and each feature was examined. Regularized multivariate linear regression was then used to estimate lap time.

Methods

A. Participants

Thirteen healthy subjects (7 male, 6 female; aged: 26.38±9.53 years; height: 1.76±0.09 m; BMI: 22.34±2.42 kg/m^2) gave their informed consent and participated in this study. Ethical approval was obtained from University College Dublin. Four participants (1 male, 3 female; aged: 23.50±0.58 years; height: 1.73±0.11 m; BMI: 21.20±2.32 kg/m^2) had previously swam at a competitive level. All of these participants reported that they currently swim once monthly. The remaining nine participants (6 male, 3 female; aged: 27.67±11.40 years; height: 1.77±0.08 m; BMI: 22.84±2.42 kg/m^2) had always been purely recreational swimmers. Six of these participants reported that they currently swam less than once per month, one participant swam once per month, and two participants reported that they swam twice per week.

B. Protocol

A waterproof, wearable sensor (BiostampRC, MC10 Inc., Fig. 1) was attached to the left and right upper arms (on the belly of the biceps brachii muscles) of each subject, secured to the skin using double sided adhesive stickers. Additional taping was used to ensure the sensors stayed in place during the protocol. The sensors were programmed to record triaxial accelerometer data sampled at 31.25 Hz (±4g).

The flexible sensor measured 6.6 cm in length, 3.4 cm in width and 0.45 cm in height. The X axis of the sensor was positioned along the humeral line; the Y axis was then perpendicular to the X axis, aligned with the medial-lateral anatomical axis, and the Z axis was perpendicular to both the X and the Y axes, Fig. 1.

After performing their usual warm up, participants were asked to complete eight laps (total: 400 m) of an indoor 50 m pool using front crawl stroke. Each participant was asked to perform the first seven laps at their normal pace, followed by one final lap at their maximum pace. Rest periods were taken between lengths if desired.

C. Data analysis

Data for each subject were captured as one recording which included all 8 laps and rest periods. Data were stored locally on the sensor. After the test they were downloaded and exported to MATLAB (The MathWorks, Inc, Natick, MA) for offline analysis.

1) Lap detection

A lap was defined here as one length of the swimming pool, 50 m in this case. To detect turns between laps with no rest periods, a Butterworth low pass filter with cut off frequency 0.2 Hz was applied to the Y axis acceleration signal, and the peaks corresponding to turns were detected. Similar methods were previously reported [9].

To detect start and end points of laps which preceded or followed by a rest period, an algorithm based on peak to peak amplitude was developed. A subject-specific threshold was applied to the peak to peak amplitude of the X axis acceleration, with limits applied to reflect the minimum and maximum plausible lap times.

Lap start and end times were verified by visual inspection of the data. Lap times were then calculated as the time between the start and end points. These values were then used as reference measures for further analysis.

2) Stroke identification

A stroke was defined here as a complete cycle for one arm, with data for each arm examined individually. For each lap, individual strokes were extracted from the X axis acceleration using a peak detection algorithm. The minimum acceleration in each stroke was detected, which may correspond to the point when the arm entered the water [10]. Subject-specific thresholds for peak amplitude, prominence, and distance between consecutive peaks were applied.

3) Feature extraction

In total, 42 accelerometer-derived features were extracted from the data for each stroke. These features are as follows:

Standard features (3): Stroke count was calculated as the sum of all strokes for the left and right arms. The mean and coefficient of variation (CV) of stroke time were calculated for each lap as the mean of results for all left and right arm strokes.

Detailed features (18): For each stroke, root mean squared (RMS) acceleration, RMS jerk and spectral edge frequency (95% power frequency, SEF) [1] were calculated for each axis. These features were selected to provide quantitative temporal- and frequency-based measures of movement smoothness. For each lap, the mean and CV of each feature across all strokes for both arms was computed.

Symmetry features (21): For all standard and detailed features, the lower value between the left and right arms, was divided by the higher value. A resultant value of one would therefore indicate a perfectly symmetrical feature, with increasing asymmetry for lower values.

4) Statistical analysis

One way analysis of variance was used to assess differences in lap times between male and female swimmers, and between previously competitive swimmers and purely recreational swimmers.

The correlation of lap time and each individual accelerometer-derived feature was then examined. Additionally, regularized linear least squares regression was used to estimate 50 m lap time using a combination of accelerometer-derived features. Lasso regularization was used to reduce the number of features included in the model [18]. The regularization strength (lambda) was selected using ten-fold cross-validation, balancing low cross-validated mean squared error with predictor variable sparsity. To assess model performance, cross-validated RMS error (RMSE) and mean absolute error (MAE) were calculated.

Pearson's correlation coefficient (R), the lower and upper limits of the 95% confidence interval, and the significance level (p value) were reported for each individual feature correlation, and the correlation of the multivariate regression model. P-values less than 0.001 were considered statistically significant [19].

Results

Left and right arm tri-axial accelerometer data recorded during all 104 laps were included in the final analysis. The mean recorded 50 m lap time was 56.99 s with a standard deviation (SD) of 11.99 s, ranging from 38.00 s to 81.00 s. These correspond to swimming velocities in the range 0.62- 1.32 m/s. Lap times did not significantly vary between male and female swimmers ($p=0.50$). Previously competitive swimmers were significantly faster than the remainder of the cohort ($p<0.001$).

Sample stroke data for a representative subject illustrating a distinctive acceleration pattern in each axial direction is presented in Fig. 2.

Fifteen features were significantly correlated with lap time, Table 1, with the mean and SD for the cohort. Correlation coefficients, their lower and upper 95% confidence intervals, and p values are also reported. Results of the regularized linear least squares regression model are presented in Fig. 3, and the model features are indicated in Table 1. Lasso regularization reduced the features included in the final model to 5, Table 1. The final model was significantly correlated with reference lap time ($R = 0.86$ (0.80, 0.91), $p<0.001$. The cross-validated RMS error was 6.38 s and the MAE was 4.75 s.

Discussion

In this study, tri-axial accelerometer data were used to quantitatively examine arm movement during front crawl swimming. In particular, a comprehensive range of features were examined, their correlations with swimming lap times were investigated, and a regularized regression model was developed to estimate 50 m lap times using a subset of the derived features. Superimposed stroke data for a representative lap are presented in Fig. 2, showing a distinctive acceleration pattern for each arm and each axis. Similar results have been reported previously by studies which examined the acceleration profile during front crawl swimming [10, 12]. Fifteen, of the forty-two accelerometer-derived features examined, were significantly correlated with lap time. Strong significant positive correlations with lap time were observed for stroke count and mean stroke time. These findings indicate that, in this cohort, lower stroke counts and faster stroke rates resulted in faster lap times, consistent with the literature [7, 8]. Additionally, significant negative correlations with lap time were observed for mean RMS acceleration in all axial directions, mean jerk in all axial directions, and mean SEF for the X and Z axes. This suggests that higher accelerations, increased rate of change of acceleration and movements with higher frequency content are features of faster swimming. Previous studies have used similar detailed accelerometer-derived features to quantify gait, balance and turning, and have applied these features to classify movement disorders [1, 2]. However, to our knowledge, these features have not previously been examined in relation to swimming.

Two symmetry measures (both based on RMS acceleration along the Y axis) were also found to be significantly correlated with 50 m lap time, indicating that these features may provide a useful method to measure arm movement symmetry during front crawl swimming. Two additional symmetry features (stroke count symmetry, and variation in stroke time symmetry) were included in the regularized regression model, selected by lasso regularization, despite not being significantly correlated with lap time, see Table 1. Their inclusion indicates that, when combined with the other model features, they add value to the ability of the model to estimate lap time.

Previous studies have estimated instantaneous swimming velocity using integration-based methods and sacrum mounted sensors, reporting Spearman's Rho of 0.94 [16]. The model presented here estimated 50 m lap time with a Pearson's correlation coefficient (R) of 0.86. However, by using upper arm acceleration and a range of descriptive features this method provides insights into arm movement patterns and the underlying reasons for changes in swimming velocity.

The final regression model included stroke count, mean stroke time, and mean SEF Z. The associations between stroke count and swimming speed, and stroke time and swimming speed are well established. However, frequencybased measures of movement have not previously been shown to vary with swimming speed. Identifying accelerometer-derived features which are strongly correlated with swimming velocity may help to develop a useful training tool, allowing training analysis to move beyond simple measures such as stroke number, stroke rate and stroke time. Using such features, arm acceleration patterns could be objectively analyzed during a training session, and compared between training sessions.

A limitation of the current study is the low sampling rate used, 31.25 Hz. This was a constraint of the sensors which were simultaneously collecting electromyography data at 500 Hz. Sampling above 100 Hz would be recommended, and may identify changes in features associated with higher frequency components of the acceleration signals. This study did not account for breathing patterns, which may have influenced symmetry measures [13, 20].

This study did not control for the duration of rest periods between laps, or the method used to turn. Methods to detect events at the pool wall using low pass filtering of wrist worn accelerometer data have been reported previously [9], and a similar approach to detect turns with no rest periods was implemented here. Classification methods have also been used to detect turns using wrist or upper-back worn accelerometer data [11]. The method proposed here detects swimming laps with an undefined rest period between laps, and would be suitable to monitor unstructured protocols.

The accelerometer-derived features and regularized linear regression model developed in this study to estimate lap times based on three of these features. The reported method has potential for use in swimming performance analysis by providing insights into subtle changes in movement at different swimming speeds, thereby providing a novel method to track improvements in swimming technique.

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Figures

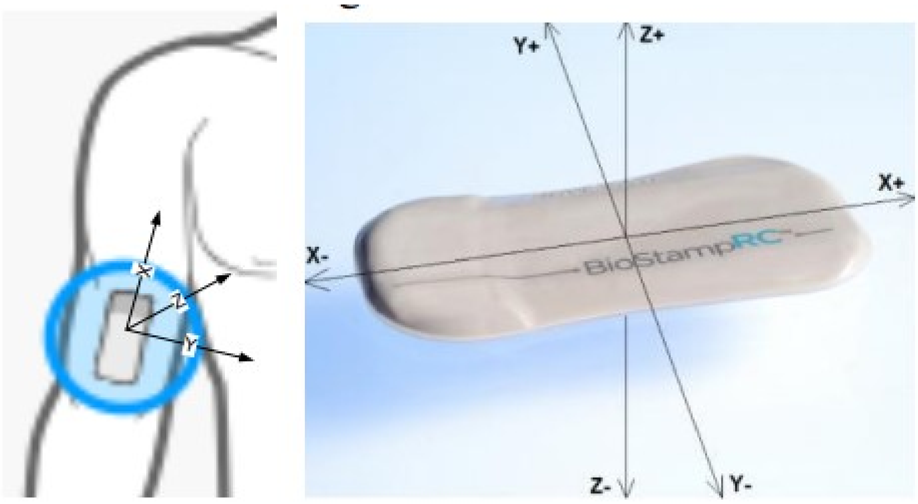

Figure 1: Left: Sensor placement, Right: Sensor axes.

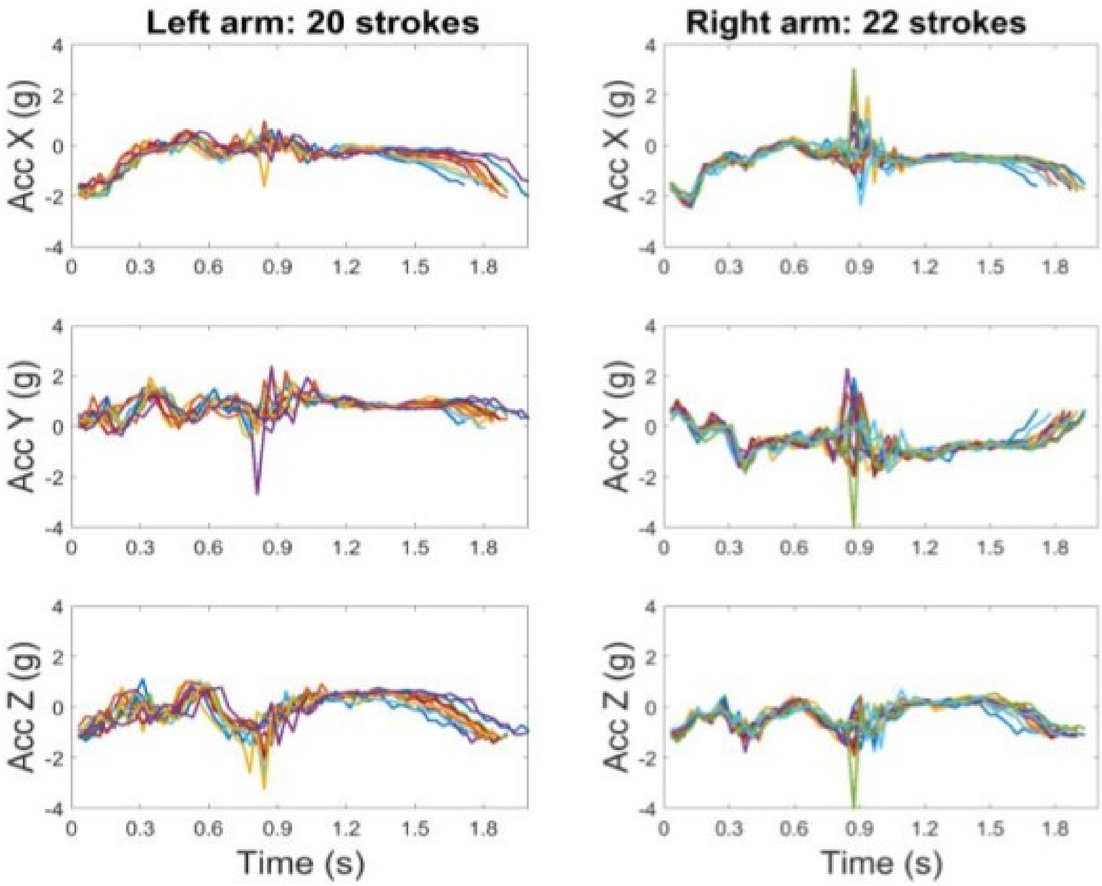

Figure 2: Superimposed raw data for each stroke are presented from one lap performed by a previously competitive female swimmer (age = 23 years; height = 1.81 m; BMI = 20.3 kg/m^2).

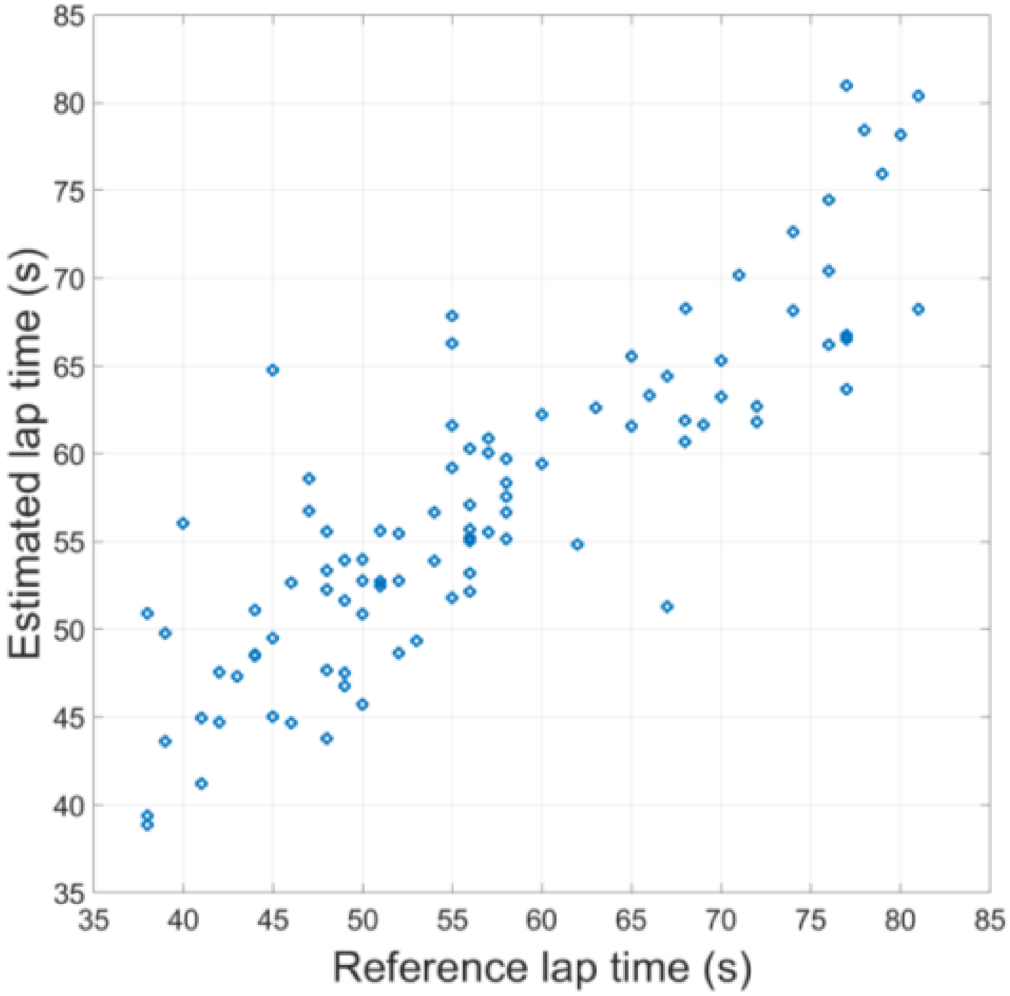

Figure 3: Reference time to complete 50 m swim versus the time estimated by the regression model.

Tables

TABLE 1. THE MEAN AND SD OF FEATURES WHICH WERE SIGNIFICANTLY CORRELATED WITH LAP TIME, ALONG WITH ADDITIONAL FEATURES INCLUDED IN THE REGRESSION MODEL (*). PEARSON'S CORRELATION COEFFICIENT (R), THE LOWER AND UPPER BOUNDS OF THE 95% CONFIDENCE INTERVAL, AND THE SIGNIFICANCE LEVEL (P) ARE PRESENTED

Feature	Mean (SD)	R (lower,upper)	P
Stroke count *	54.11 (10.93)	0.75 (0.65,0.83)	<0.001
Mean stroke time (s)	1.98 (0.28)	0.46 (0.28,0.61)	<0.001
Mean Acc X (g)	0.80 (0.11)	-0.25 (-0.43,-0.06)	0.01
Mean Acc Y (g)	0.77 (0.05)	-0.35 (-0.52,-0.16)	<0.001
Mean Acc Z (g)	0.61 (0.07)	-0.34 (-0.51,-0.15)	<0.001
CV Acc X (g)	0.12 (0.03)	-0.28 (-0.46,-0.09)	0.01
CV Acc Z (g)	0.16 (0.03)	-0.29 (-0.46,-0.09)	<0.001
Mean Jerk X (g/s)	0.28 (0.10)	-0.36 (-0.53,-0.17)	<0.001
Mean Jerk Y (g/s)	0.42 (0.11)	-0.33 (-0.50,-0.14)	<0.001
Mean Jerk Z (g/s)	0.45 (0.12)	-0.37 (-0.53,-0.18)	<0.001
CV Jerk Z (g/s)	0.41 (0.09)	0.27 (0.08,0.45)	0.01
Mean SEF X (Hz) *	3.61 (1.71)	-0.38 (-0.54,-0.20)	<0.001
Mean SEF Z (Hz) *	10.43 (1.64)	-0.29 (-0.46,-0.09)	<0.001
Mean Acc Y symmetry	0.93 (0.03)	-0.34 (-0.51,-0.15)	<0.001
CV Acc Y symmetry	0.72 (0.16)	0.29 (0.09,0.46)	<0.001
Stroke count symmetry *	0.92 (0.09)	-0.08 (-0.27,0.13)	0.46
CV stroke time symmetry*	0.53 (0.28)	-0.07 (-0.27,0.13)	0.51