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

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## 21 **Abstract**

22 Wearable accelerometers can be used to quantify movement during swimming, enabling  
23 objective performance analysis. This study examined arm acceleration during front crawl  
24 swimming, and investigated how accelerometer-derived features change with lap times.  
25 Thirteen participants swam eight 50m laps using front crawl with a tri-axial accelerometer  
26 attached to each upper arm. Data were segmented into individual laps; lap times estimated and  
27 individual strokes extracted. Stroke times, root mean squared (RMS) acceleration, RMS jerk  
28 and spectral edge frequencies (SEF) were calculated for each stroke. Movement symmetry was  
29 assessed as the ratio of the minimum to maximum feature value for left and right arms. A  
30 regularized multivariate regression model was developed to estimate lap time using a subset of  
31 the accelerometer-derived features. Mean lap time was  $56.99 \pm 11.99$ s. Fifteen of the 42 derived  
32 features were significantly correlated with lap time. The regression model included 5 features  
33 (stroke count, mean SEF of the X and Z axes, stroke count symmetry, and the coefficient of  
34 variation of stroke time symmetry) and estimated 50m lap time with a correlation coefficient of  
35 0.86, and a cross-validated RMS error of 6.38s. The accelerometer-derived features and  
36 developed regression model may provide a useful tool to quantitatively evaluate swimming  
37 performance.

## 38 **Introduction**

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

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

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

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

## 70 **Methods**

### 71 *A. Participants*

72 Thirteen healthy subjects (7 male, 6 female; aged:  $26.38 \pm 9.53$  years; height:  $1.76 \pm 0.09$  m; BMI:  
73  $22.34 \pm 2.42$  kg/m<sup>2</sup>) gave their informed consent and participated in this study. Ethical approval  
74 was obtained from University College Dublin. Four participants (1 male, 3 female; aged:  
75  $23.50 \pm 0.58$  years; height:  $1.73 \pm 0.11$  m; BMI:  $21.20 \pm 2.32$  kg/m<sup>2</sup>) had previously swam at a  
76 competitive level. All of these participants reported that they currently swim once monthly. The  
77 remaining nine participants (6 male, 3 female; aged:  $27.67 \pm 11.40$  years; height:  $1.77 \pm 0.08$  m;  
78 BMI:  $22.84 \pm 2.42$  kg/m<sup>2</sup>) had always been purely recreational swimmers. Six of these  
79 participants reported that they currently swam less than once per month, one participant swam  
80 once per month, and two participants reported that they swam twice per week.

### 81 *B. Protocol*

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

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

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

### 95 *C. Data analysis*

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

#### 99 *1) Lap detection*

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

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

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

### 111 2) *Stroke identification*

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

### 117 3) *Feature extraction*

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

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

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

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

131 4) *Statistical analysis*

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

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

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

146 **Results**

147 Left and right arm tri-axial accelerometer data recorded during all 104 laps were included in the  
148 final analysis. The mean recorded 50 m lap time was 56.99 s with a standard deviation (SD) of  
149 11.99 s, ranging from 38.00 s to 81.00 s. These correspond to swimming velocities in the range  
150 0.62- 1.32 m/s. Lap times did not significantly vary between male and female swimmers  
151 ( $p=0.50$ ). Previously competitive swimmers were significantly faster than the remainder of the  
152 cohort ( $p<0.001$ ).

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

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

## 162 Discussion

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

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

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

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

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

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

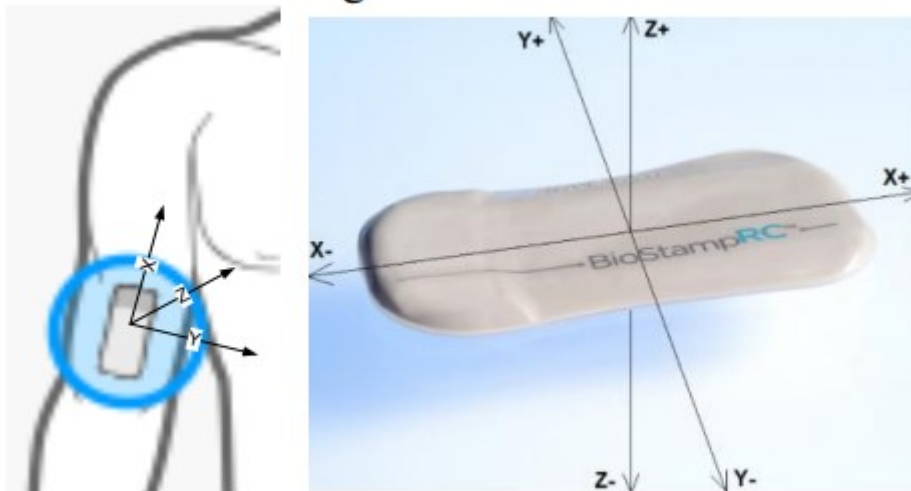
215 The accelerometer-derived features and regularized linear regression model developed in this  
216 study to estimate lap times based on three of these features. The reported method has potential  
217 for use in swimming performance analysis by providing insights into subtle changes in  
218 movement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

220

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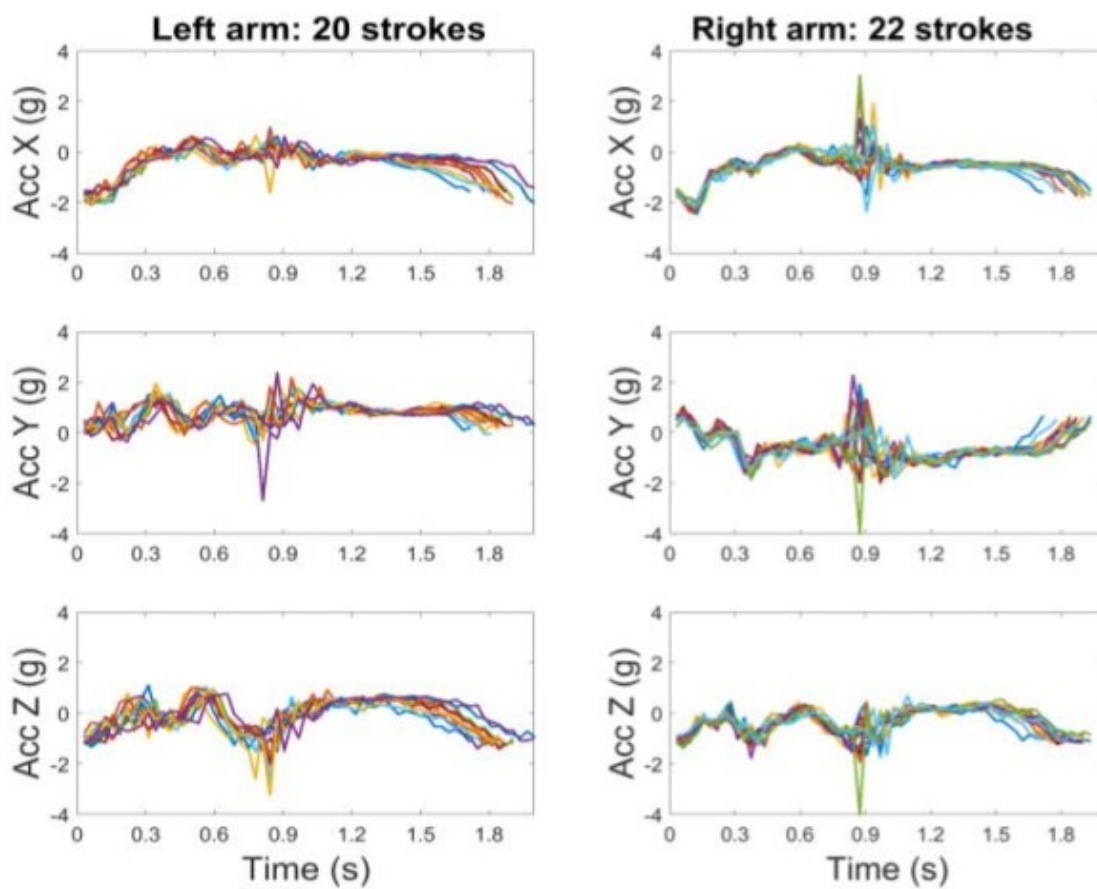
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276 **Figures**

277

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

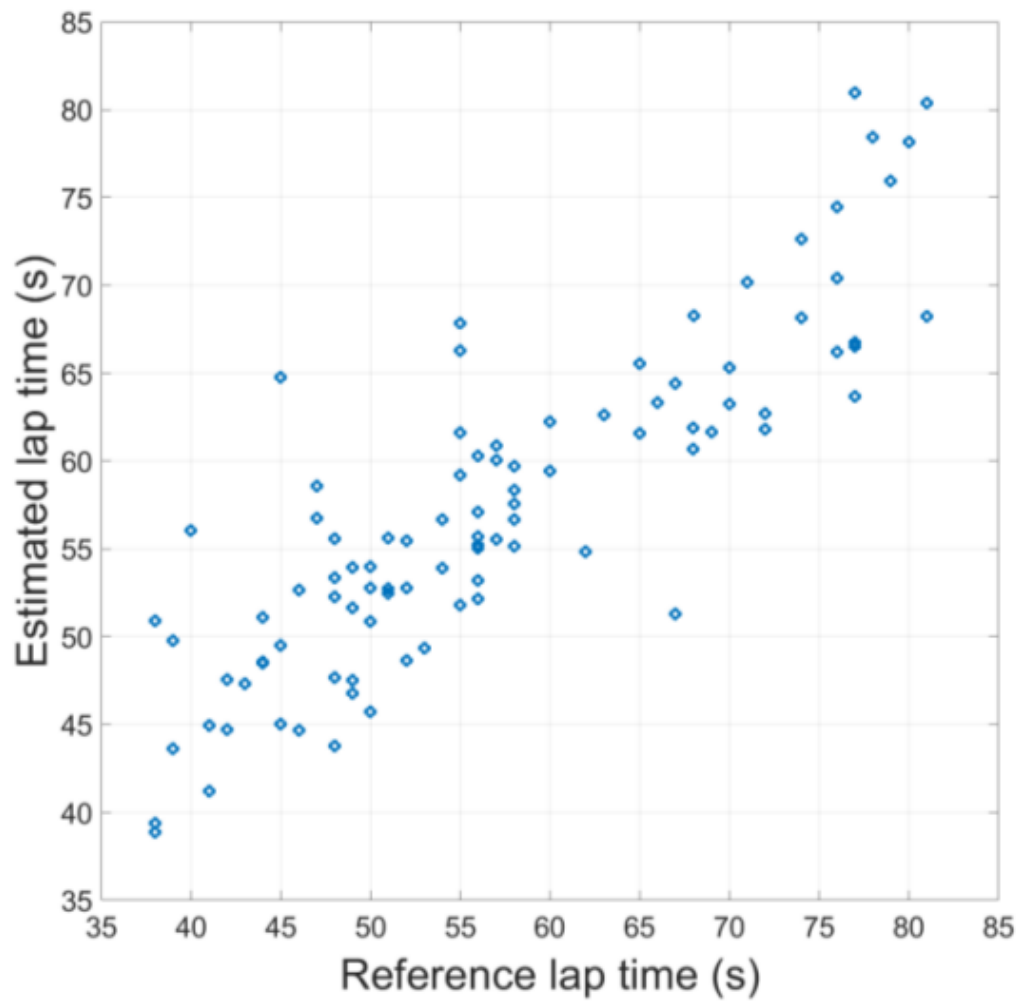
279



280

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

283



284

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

287

## 288 **Tables**

289 **TABLE 1.** THE MEAN AND SD OF FEATURES WHICH WERE SIGNIFICANTLY  
 290 CORRELATED WITH LAP TIME, ALONG WITH ADDITIONAL FEATURES INCLUDED  
 291 IN THE REGRESSION MODEL (\*). PEARSON'S CORRELATION COEFFICIENT (R),  
 292 THE LOWER AND UPPER BOUNDS OF THE 95% CONFIDENCE INTERVAL, AND THE  
 293 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