SWIMMING PHASE-BASED PERFOMANCE EVALUATION USING A SINGLE IMU IN FRONT CRAWL

Mahdi Hamidi Rad[1], Vincent Gremeaux[2], Farzin Dadashi[3], Kamiar Aminian[1]

[1]Laboratory of Movement Analysis and Measurement, EPFL, Lausanne, Switzerland
[2]Institute of Sport Sciences, University of Lausanne, Lausanne, Switzerland
[3]Huma Therapeutics LTD, London, UK

The purpose of this study was to assess the potential of using a sacrum-worn inertial measurement unit (IMU) for performance evaluation in each swimming phase (wall push-off, glide, stroke preparation, and swimming) of national-level swimmers in front crawl technique. Nineteen swimmers were asked to wear a sacrum IMU and swim four one-way 25-m trials in front crawl, attached to a tethered speedometer and filmed by cameras in the whole lap for validation. Based on the literature, several goal metrics were defined over speedometer data, each one representing the performance of the swimmer either in one phase (maximum velocity of wall push-off phase) or several phases (time of 15 meters for wall push-off, glide, stroke preparation phases). Following a macro-micro approach, the IMU parameters of each swimming phase were used to predict the goal metrics. The selected IMU parameters were in line with the characteristics of movement within each phase and can estimate the corresponding goal metric with an R^2 over 0.8 and relative RMSE lower than 10%.

KEYWORDS: swimming, wearable sensor, performance evaluation, speedometer

INTRODUCTION: Continuous monitoring of performance is essential in swimming. The swimmer passes different swimming phases from wall to wall, including a dive into the water or wall push-off (*Push*), then glide (*Glid*) and stroke preparation (*StPr*) and finally swimming (*Swim*) up to the following turn. Various goal metrics are used to evaluate the performance of the swimmer in each phase, such as flight distance (Ruschel et al., 2007) for start, time to 15m for under water phases, average velocity per stroke (Dadashi et al., 2015), swimming average velocity (Mason and Cossor, 2000) or lap time. Inertial Measurement Units (IMU) are widely used for parameter extraction in various swimming phases, as IMUs overcome the limitations of traditional methods such as cameras. Moreover, novel orientation analysis algorithms estimate the 3-D orientation of IMU sensor (Madgwick et al., 2011), to extract even more detailed parameters in swimming (Guignard et al., 2017).
Despite the substantial potential of IMU for motion features extraction, this data is rarely used for estimating the performance-related goal metrics of swimming phases. By monitoring the swimmer with a single IMU placed on sacrum, the main objective of this study was to investigate the association between IMU parameters and goal metrics in different swimming phases. This association will allow to better understand the kinematics features involved in each goal metric and to identify IMU parameters as proxy for performance evaluation.

METHODS: 19 elite swimmers took part in this study (9 males, 10 females, age 19 ± 3 years, size 177 ± 7 cm, weight 68 ± 8 kg). One IMU (Physilog® IV, GaitUp, CH) was waterproofed and taped to swimmer's sacrum recording 3-D angular velocity and acceleration at 500 Hz. A functional calibration was performed after IMU fixation to make the data independent of sensor placement (Dadashi et al., 2015). The swimmers performed four one-way front crawl trials with progressive speed (from 70% to 100% of their best time) in a 25m indoor pool.
Two systems, synchronized with the IMU, were used as references in this study. A set of four 2-D cameras (GoPro Hero 7 Black, GoPro Inc., US), attached to the pool wall to videotape all the lap underwater with a 60 Hz rate, used for swimming phase detection and a tethered speedometer (SpeedRT®, ApLab, Rome, Italy), attached with a belt to the swimmer. The speedometer calculated the displacement and velocity of the swimmer at a rate of 100 Hz, and

was used as the reference to estimate eight goal metrics in different swimming phases detected by cameras. During *Push* phase, the ***Push* maximum velocity** was used as the goal metric to assess push-off strength (Stamm et al., 2013). In *Glid* phase where the swimmer should try to lose less velocity (Vantorre et al., 2014) ,***Glide* end velocity** is a goal metric. In ***StPr*** phase, the **average velocity** has negative correlation with 15-meter time of the swimmer (Cossor and Mason, 2001). Two goal metrics are defined for *Swim* phase: the **average velocity per cycle** providing valuable information of swimmer's performance in every cycle (Dadashi et al., 2015), and **average velocity of the whole *Swim* phase**. Three more goal metrics were used, which relate to more than one phase: the time to reach five meters ($\boldsymbol{T_{5m}}$), affected mainly by *Push* and *Glid* phases (Zatsiorsky et al., 1979), the time to reach 15 meters ($\boldsymbol{T_{15m}}$) was used to evaluate *Push*, *Glid* and *StPr* phases (Vantorre et al., 2014). Finally, the **Lap average velocity** was used as the goal metric for the whole lap.

IMU data were processed following the macro-micro analysis approach (Hamidi Rad et al., 2021). Swimming bouts, laps and technique were identified in macro level. Afterwards in micro level, each lap was segmented into swimming phases of *Push*, *Glid*, *StPr* and *Swim* from wall to wall. As a continuation of this approach, the kinematic parameters within each swimming phase (micro parameters) were extracted and used for performance evaluation. The study flowchart is displayed in **Figure 1**. IMU data preparation transfers the IMU data from sensor to the global frame to achieve the true acceleration, angular velocity and orientation of sacrum, using a gradient-descend based optimization algorithm (Madgwick et al., 2011). Global X, Y and Z axes are aligned respectively in vertical, forward and left direction of swimming lane.

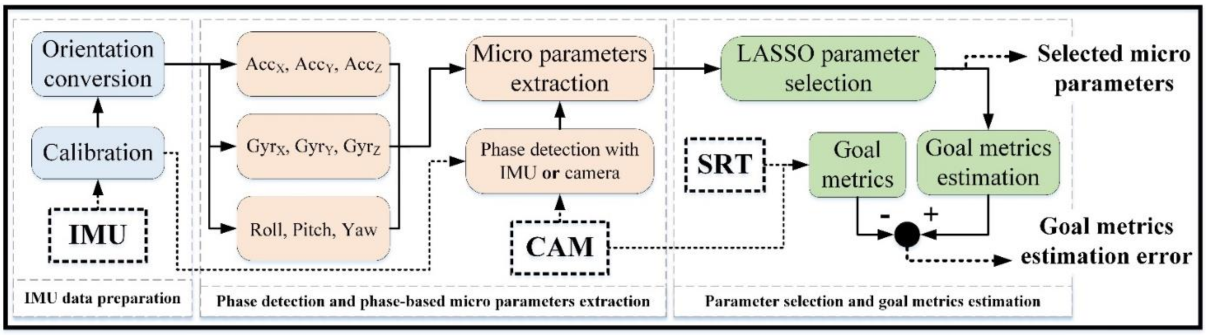

Figure 1: ***Flowchart of the performance evaluation approach. IMU data preparation (left), phase detection by cameras (CAM) or IMU calibrated data and micro parameter extraction from IMU (middle) and parameter selection from micro parameters and the goal metrics estimation (right).***

To observe the effect of IMU-based phase detection error on performance evaluation, the rest of the analysis was performed once with swimming phases detected by cameras and once by IMU for comparison. Then, by analysing the IMU data in global frame within the detected swimming phases, micro parameters were extracted in each swimming phase. Fast swimming depends on generating high propulsive forces, keeping the correct posture for less drag, while swimming with the highest efficiency (Toussaint and Truijens, 2005). Therefore, knowledge of the propulsion, posture and efficiency is useful for performance optimization. Propulsion category is reflected in parameters defined on acceleration in forward direction. Posture category is relevant to the parameters defined over roll and pitch angle signals, and efficiency category relates to the ratio of propulsive to non-propulsive acceleration (such as the ratio of forward acceleration to acceleration norm). The parameters related to the duration or rate of movement, e.g. angular velocity or stroke rate and count in *Swim* phase, were categorized in a category called duration/rate as they do not fit into the previous categories.

Finally, we used a linear model with LASSO (least absolute shrinkage and selection operator) parameter selection to rank and select the highly-associated phase-based micro parameters with the corresponding goal metrics and use them for goal metrics estimation. This method regularizes model parameters by reducing some of them to zero and keeping only the significant ones. After normalizing the micro parameters, LASSO algorithm is applied with leave-one-out cross-validation to rank the parameters. The parameters with a relative weight more than 5% were selected because of higher significance. The relative weights of selected parameters were summed over the four categories (propulsion, posture, efficiency and duration/rate) to observe how much each category contributes to the estimation. Then the goal metrics were estimated using the corresponding selected micro parameters and the cross-validated R^2, RMSE and its relative value were used to evaluate the regression models.

RESULTS and DISCUSSION: The number of observations used for goal metrics estimation were 1166 (number of cycles) for cycle average velocity in *Swim* phase, and 76 (number of laps) for other goal metrics. **Figure 2** displays the overall contribution of each category in estimating the goal metrics. The dominant categories are in line with the phase characteristics, as high propulsion and correct posture are important in *Push* and *Glid* phases respectively. *StPr* phase is a combination of propulsion, acceleration in forward direction (efficiency) and posture categories. For estimating the average velocity per stroke in *Swim* phase, the duration of the cycle (duration/rate) and the displacement per stroke (efficiency) were selected for predicting the goal metric. However, the average velocity of the whole *Swim* phase was affected by the rate of strokes (duration/rate), forward acceleration (propulsion) and horizontal orientation (posture). T_{5m}, T_{15m} and lap average velocity depend on more than one phase. The selected parameters for these goal metrics were already selected for the local goal metrics, proving the significance of them even in a larger scale.

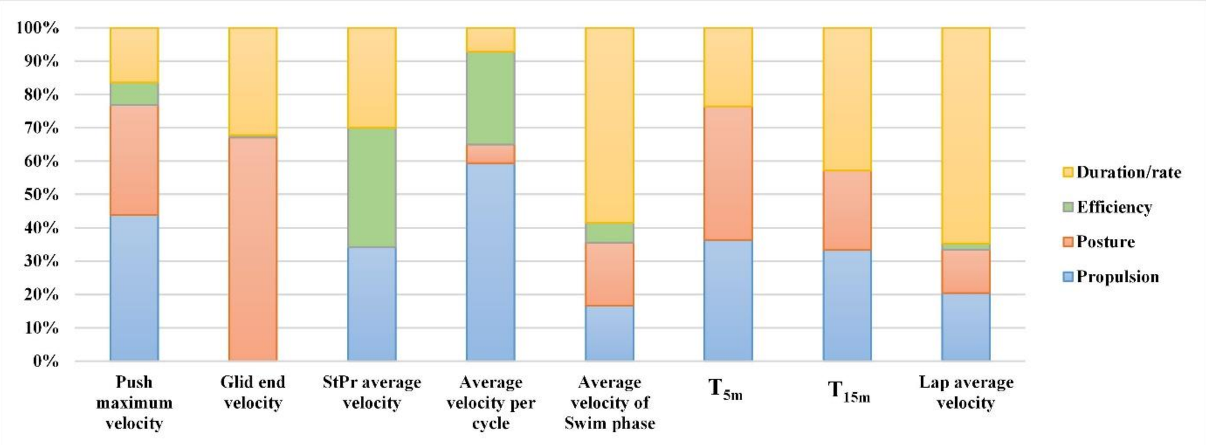

Figure 2: ***Parameter categories contribution to goal metrics estimation for front crawl***

Table 1: R^2, RMSE and relative RMSE (in percent) for goal metrics estimation models (phases detected by camera (CAM) or IMU (IMU))

Goal metrics	**CAM**		**IMU**	
	R^2	RMSE **(%)**	R^2	RMSE **(%)**
Push maximum velocity **(m/s)**	0.80	0.133 **(5.4)**	0.74	0.140 **(5.7)**
Glid end velocity **(m/s)**	0.83	0.105 **(8.7)**	0.76	0.123 **(10.0)**
StPr average velocity **(m/s)**	0.72	0.075 **(4.4)**	0.72	0.075 **(4.4)**
Average velocity per *Swim* cycle **(m/s)**	0.96	0.029 **(4.8)**	0.89	0.050 **(8.3)**
Average velocity of *Swim* phase **(m/s)**	0.90	0.044 **(2.7)**	0.90	0.044 **(2.7)**
T_{5m} **(s)**	0.67	0.155 **(7.5)**	0.64	0.158 **(7.6)**
T_{15m} **(s)**	0.80	0.345 **(4.0)**	0.75	0.369 **(4.3)**
Lap average velocity **(m/s)**	0.95	0.031 **(2.3)**	0.95	0.032 **(2.4)**

The cross-validated R^2, RMSE and relative RMSE (in parentheses) of regression models for each goal metric are reported in **Table 1**, with swimming phases found by cameras and IMU for comparison. The R^2 for estimating all goal metrics was more than 0.8 except for *StPr* average velocity (0.72) and T_{5m} (0.67). The average velocity of *StPr* shows a high variability among swimmers, and the linear model was not efficient enough in reflecting its variation. Only the parameters from *Push* and *Glid* phases were used for T_{5m} estimation, while swimmers might start *StPr* phase earlier than five meters from the wall according to their velocity and T_{5m} is partly affected by *StPr* phase. The relative error was the highest for *Glid* end velocity estimation (11%), because this goal metric had the lowest value in the whole lap. By comparing the results found by the phases detected by camera and by IMU (**Table 1**), the results get slightly worse (lower R^2 and higher error) because of the phase detection error by IMU compared to cameras. However, R^2 has decreased by 0.07 in the worst case, and less than 0.05 for other goal metrics, showing that the IMU phase detection algorithms were reliable enough for phase-based performance evaluation. The parameters, found dominant in this study were already obtained with IMU (such as *Swim* stroke rate (Beanland et al., 2014) or distance per stroke (Bächlin et al., 2008)) but their relationship with the goal metrics were not studied.

CONCLUSION: Using the IMU data, numerous parameters related to propulsion, posture, efficiency and duration/rate of motion were extracted, that were associated with the goal metrics defined over velocity and time of swimming in each swimming phase. These parameters were biomechanically interpretable and were able to predict the goal metrics using LASSO linear regression. The models fit the data with an R^2 value more than 0.8 for most goal metrics. The RMSE of the regression were less than 0.14 $m/_s$ and 10% for goal metrics defined over velocity and 0.369 *s* and 7.6% for goal metrics defined over time. This study showed that a single sacrum-worn IMU has the potential to evaluate the swimmer performance in different swimming phases in line with standard goal metrics. Practically, the proposed method could be useful for the coach to identify the weakness and strength of the swimmer and track their progress during training session with a single IMU. Further studies with different swimmer levels and techniques are needed to improve the estimation and extend the approach.

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