IMU PHASE-BASED PERFORMANCE EVALUATION SENSITIVITY TO THE PROGRESS OF YOUNG FRONT CRAWL SWIMMERS

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The aim of this study was to evaluate the sensitivity of a phase-based performance assessment method obtained from a sacrum IMU to assess swimming progress. Five IMU-based goal metrics were extracted from the literature for the main swimming phases of wall push-off, glide, strokes preparation, swim, and total lap. Sixteen young competitive swimmers completed five one-way front crawl laps at maximum speed with an IMU attached to the sacrum while the coach recorded lap time as the main indicator of performance level. To monitor the swimmers' performance improvement, the same test was repeated once a week for 10 weeks. The minimum 0.5s change in lap time was calculated as the minimum worthwhile enhancement. The results showed that the goal metric of whole lap and swim phase closely predict swimming progress (e.g., accuracy, precision, sensitivity, and specificity of 0.91, 0.89, 0.94, and 0.95 for the whole lap goal metric, respectively). Other goal metrics achieved high precision and specificity (≥ 0.79) for detecting the progress, indicating that they can be reliably used for further improvement of swimmers in the level of swimming phases. The results showed that coaches can use the goal metrics in training sessions to track the progress of the swimmers in each phase.

KEYWORDS: IMU sensor, phase-based evaluation, performance progress

INTRODUCTION: The main goal of a swimming coach is to monitor the swimmers' performance and improve it through intensive training. Each and every phase of swimming (wall push-off, glide, strokes preparation, swim and turn) is important, as swimmer's flawless performance in all of these phases is necessary to win a competition (Mooney et al., 2016). IMUs have been widely used to extract swimming kinematic variables in different phases and swimming techniques (Dadashi et al., 2012; Brackley et al., 2017). However, in most studies, the extracted kinematic variables were not associated with swimming performance. In a recent study, IMUs were used to automatically segment swimming laps into wall push-off (***Push***), glide (***Glid***), stroke strokes preparation (***StPr***), and swim (***Swim***) phases using a novel approach (Hamidi Rad et al., 2021b), and then estimated performance-related goal metrics in all swimming phases (Hamidi Rad et al., 2021a).
The main objective of this study was to evaluate how the IMU-based goal metrics react to swimmer’s performance progress during training sessions, so the coach can use them for performance monitoring. Using a similar approach, five goal metrics were calculated across multiple training sessions for a team of swimmers: *Push* maximum velocity (Stamm et al., 2013), *Glid* end velocity (Vantorre et al., 2014), *StPr* average velocity (Cossor and Mason, 2001), *Swim* average velocity (Dadashi et al., 2015), and lap average velocity. Lap time was used as the representative of performance level to define meaningful progress. The relationship between the five goal metrics and lap time will be examined.

METHODS: Sixteen swimmers from the same swimming team (9 males, 7 females, age 14.6±0.8 years, height 172±7 cm, weight 56±10 kg, front crawl record for 50m 28.60 ± 2.04 s) were asked to wear a sacrum-worn IMU (Physilog® IV, GaitUp, CH.) using a waterproof band (Tegaderm, 3M Co., USA). The sensor recorded 3D angular velocity and acceleration at a sampling rate of 500 Hz. After IMU fixation, functional calibration was performed to make the

data independent of sensor placement (Dadashi et al., 2013). After the warm-up, each swimmer completed five laps of front crawl in one direction at maximum speed in a 25m pool, completing all phases of swimming so that a complete analysis could be obtained. The coach was responsible for recording the lap time for each attempt with a stopwatch. The swimmer rested for five minutes between laps to avoid fatigue. The same measurement was repeated once a week for ten weeks to monitor swimming performance over the long term.
During each training session, the swimming phases were separated during each swimming bout (Hamidi Rad et al., 2021b). Then, using a selected set of kinematic variables from IMU data, the five phase-based goal metrics were estimated (Hamidi Rad et al., 2021a). To evaluate the sensitivity of the IMU goal metrics to progress, two main steps were performed on each swimmer's data. Following the structure of our dataset, during the weekly measurements, the swimmer's performance in each session was compared to all of his other sessions to find pairs of sessions with significant improvements based on lap time change. Five values (for each goal metric and for lap time) were obtained for each participant in each session. Since the sample size for quantifying the progress of each swimmer is small (five values in each session), we used Cliff's Delta effect size analysis as a nonparametric method (Macbeth et al., 2011) to identify pairs of sessions with significant improvements (lap time change). Each comparison set was assigned an effect size value to quantify the change. The confidence interval (at a 95% confidence level) was then calculated to determine whether or not the change was significant. To reflect true performance improvement, we assumed that the smallest worthwhile enhancement (***SWE***) should occur in comparison pairs separated by at least 3 weeks (Hopkins et al., 1999). Therefore, in the second step of our sensitivity analysis, we calculated a *SWE* as the minimum threshold for meaningful progress. The median lap time of comparisons that were 3 weeks apart (e.g., sessions 1 and 4 or sessions 2 and 5, etc.) was calculated and then averaged as the *SWE*. Of all the significant changes identified in step one of the sensitivity analysis, only those whose change was above the *SWE* were counted as meaningful progress. The main question we sought to answer with this analysis was, "Do the IMU goal metrics detect meaningful progress as lap time does?" To answer this question, we looked at the pairs that showed meaningful progress and determined whether each goal metric had also significantly changed (i.e., improved) (i.e., true) or not (i.e., false). The ability of goal metrics to detect progress is assessed using a confusion matrix defined as follows:

- True positive (***TP***): the goal metric shows a significant change when there is a meaningful progress.
- True negative (***TN***): the goal metric does not change significantly while there is no meaningful progress.
- False positive (***FP***): the goal metric changes significantly but there is no meaningful progress.
- False negative (***FN***): meaningful progress, while the goal metric does not show significant change.

The unitless values for accuracy, precision, specificity, and sensitivity of the goal metrics to predict meaningful progress were calculated for goal metrics using the equations in **Table 1**.

Table 1: Equations used to calculate accuracy, precision, sensitivity and specificity.

Variable	Accuracy	Precision	Sensitivity	Specificity
Equation	$\frac{TP+TN}{TP+TN+FP+FN}$	$\frac{TP}{TP+FP}$	$\frac{TP}{TP+FN}$	$\frac{TN}{TN+FP}$

RESULTS: A data set of 750 swimming laps was collected during the ten test sessions. As each participant was compared to themselves, 642 comparisons were made. Comparing sessions three weeks apart yielded an *SWE* of 0.5±0.2s, giving us 122 pairs of sessions with meaningful progress. For these comparisons with meaningful progress, the accuracy, precision, sensitivity, and specificity of each goal metric change are shown in **Figure 1**.

Among the five phase-based goal metrics, lap average velocity and *Swim* average velocity achieved the highest values for accuracy, sensitivity, precision, and specificity (≥0.87). However, for the other three goal metrics representing swimming performance during the initial phases of *Push*, *Glid* and *StPr*, the accuracy, precision, and specificity were relatively high (≥0.82, ≥0.79, ≥0.90, respectively), while sensitivity was low (between 0.45 and 0.65).

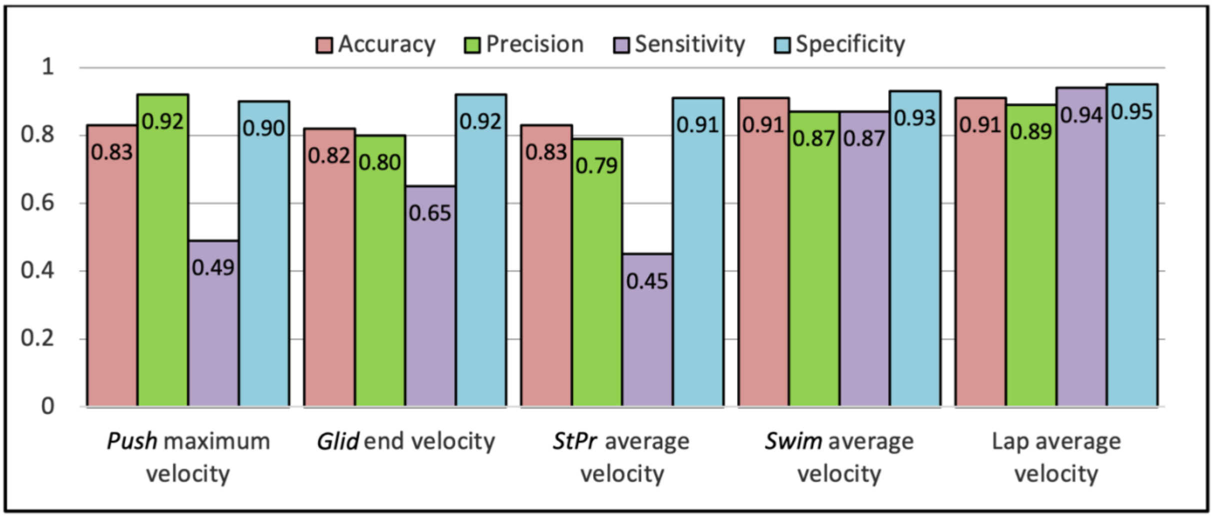

Figure 1: ***accuracy, precision, sensitivity and specificity of IMU goal metrics for detecting meaningful performance progress (lap time change)***

DISCUSSION: In this study, a single sacrum-worn IMU was used to initially separate the four main swimming phases of a lap using a new approach (Hamidi Rad et al., 2021b). The kinematic variables from the signals were then used to estimate a set of performance-based goal metrics based on previously validated algorithms (Hamidi Rad et al., 2021a). These phase-based goal metrics were hypothesised to be related to swimmer progress. Our results from ten weeks confirmed our hypothesis that IMU goal metrics can monitor a swimmer's progress in training sessions, but with different sensitivities and different levels of association in each phase.

As shown in Figure 1 lap and *Swim* average velocity achieved the highest accuracy, precision, sensitivity, and specificity (≥ 0.87) among all target metrics to predict a meaningful performance progress. Lap average velocity was expected to be highly associated with progress because lap time was used as a representative of performance level. Due to the error usually associated with traditional lap time measurement and the associated effort for the coach, this goal metric can replace lap time. Since the *Swim* phase is typically the longest phase of a lap, it should contribute more to a swimmer's overall performance compared to other phases.

Although the sensitivity of *Push* maximum velocity, *Glid* end velocity, and *StPr* average velocity for detecting progress are determined to be low, their specificity and precision are either close to or above 0.80. The definition of these two indices shows that high specificity and precision are due to a low number of false positives. It can be inferred that the three initial goal metrics can detect pairs with meaningful progress less than lap and *Swim* average velocity. However, when they do detect meaningful progress, it is correct and shows their relevance to progress scoring, despite their low sensitivity. The fact that a change in lap time is not essentially due to better performance in the initial phases increases the number of false negatives and lowers the sensitivity of the initial goal metrics for overall progress.

It is clear that all phases of swimming are important and contribute to improving overall swimming performance, and progress is the result of mastering all phases. Instead of the time-consuming recording of lap times, the coach can use the lap goal metrics as a substitute and then use the phase goal metrics to gain a more detailed view of the swimmer's performance. Training strategies are highly dependent on the swimmer's profile and the coach's experience. By integrating the sensor into the swimming suit, the phase-based performance assessment can be obtained and reported after every lap and help the coach find the personalized optimal training strategy. He can adjust the training of each swimmer to focus on the weakest phase.

CONCLUSION: In this study, we investigated the possibility of objectively assessing swimmers' progress during training sessions by using IMU-based goal metrics in the front crawl to monitor the performance of members of a swimming team. A change in lap time of more than 0.5s is considered as a meaningful progress. Of the five goal metrics used in this study, lap average velocity and *Swim* average had the highest accuracy, precision, sensitivity, and specificity (≥ 0.87) for detecting progress in swimming. The goal metrics relevant to *Push*, *Glid* and *StPr* phases achieved high specificity and precision (≥ 0.79) for progress, demonstrating the role of the initial phases in overall performance. Because lap average velocity and *Swim* average velocity are as sensitive to progress as lap time, they can be used as precise indicators of overall swimming performance. Other goal metrics provide an additional quantitative assessment of phase-based performance that is not possible with traditional coaching approaches and tools. In summary, with the help of a single IMU, which can be integrated into the swimsuit, the coach can get a comprehensive view of the swimmer's performance by using the phase-based performance assessment report. This study opens new horizons for training swimmers by providing objective feedback based on goal metrics and analysing the impact of the feedback on the swimmer's performance.

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