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A Bayesian approach for pervasive estimation of breaststroke velocity using a wearable IMU

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ABSTRACT

A ubiquitous assessment of swimming velocity (main metric of the performance) is essential for the coach to provide a tailored feedback to the trainee. We present a probabilistic framework for the data-driven estimation of the swimming velocity at every cycle using a low-cost wearable inertial measurement unit (IMU). The statistical validation of the method on 15 swimmers shows that an average relative error of 0.1 ± 9.6% and high correlation with the tethered reference system ($r_{X,Y} = 0.91$) is achievable. Besides, a simple tool to analyze the influence of sacrum kinematics on the performance is provided.

1. Introduction and motivation

Pervasive performance monitoring is a crucial element of training in different sport disciplines. By shrinking the gap between the performance levels of elite athletes, new rooms are opened for technological developments in order to be able to observe previously unseen details during the workout sessions. Equally, the improvements in size, cost and reliability of self-assessment wearable systems attracted a broad range of individuals to use these systems. Two main questions related to viability of using a device as a monitoring system are accuracy and delay of the system in data collection and processing.

During the past decade various systems were developed for pervasive over-ground activity monitoring from daily activity recognition [1,2] to the sport training as in physical exercising [3], spatial coordination assessment in ski jumping [4], skiing kinematics assessment [5], rowing performance monitoring [6] and running kinematics assessment [7,8]. Nevertheless, the developments in swimming could not adequately address the existing need of an easy-to-use monitoring system due to the complexities of the measurement in water.

Swimming velocity is the most intuitive hallmark of the performance. Having an accurate and timely estimation of velocity, the coaches can provide the trainees with corrective feedback and will significantly increase the efficiency of training sessions. The most common system for quantitative assessment of swimming velocity is the video based system [9]. The kinematics can be measured by manual digitization of the video footage to extract the position of markers attached to the body segments on a frame-by-frame basis [10]. This process can be excessively time consuming. Recently, an underwater optical motion capture system (Qualisys AB, Gothenburg, Sweden) was developed that reduces the tracking time significantly [11]. Nonetheless, the system installation and calibration, controlling the changes in the illumination of the environment and light refraction in the water are issues that limit the use of camera based systems in water [12]. In

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Table 1
Demographics of swimmers.

Parameter	All participants ($n = 15$)	Well-trained	Recreational
Age (year)	17.9 ± 4.3	20.7 ± 3.5	14.2 ± 1.0
Height (cm)	174.8 ± 12.0	181.0 ± 7.9	166.5 ± 12.0
Weight (kg)	66.1 ± 13.3	74.1 ± 7.3	55.5 ± 12.2

addition, it is well documented that movement variability influences the metabolic responses in swimming [13]. Yet, the field of view of a fixed video-based system is restricted to 3 or 4 cycles and makes variability assessment based on such a few number of cycles misleading [14,15].

The tethered speedometer is another system that is frequently used in the swimming pools to provide a more accurate and automatic estimation of instantaneous velocity [16]. The system is generally composed of a tachometer and a fishing-reel, measuring the velocity via a thin nylon line tied to the swimmer's waist. The swimmer can be monitored just in one direction and an extra force is constantly applied to the swimmer in order to alleviate the nylon line's slack during the decelerations of the swimmer [17].

Contrary to the standard motion capture systems which are restricted to the laboratory conditions, inertial measurement unit (IMU) can be employed as a wearable monitoring device in a variety of human movement studies [18,19]. Moreover, recent advances in microelectromechanical systems (MEMS) manufacturing have made IMU a low-cost option compared to the standard laboratory settings. As for the estimation of the swimming velocity using IMU, a wrist-worn 3D accelerometer was used to extract the average swimming speed of one lap [20]. Stamm et al. used a 3D sacrum-worn accelerometer for instantaneous velocity estimation [21]. The main drawback of the methods using a single 3D accelerometer is that the orientation information in global frame of movement cannot be retrieved [22]. Therefore, the projection of gravity on the acceleration in direction of movement is inseparable from movement acceleration that leads to high inaccuracies. On top of that, the method is highly sensitive to the sensor placement on the body and makes the repeatability of the method questionable. The instantaneous velocity of front-crawl swimming was estimated using a sacrum-worn IMU comprising a 3D accelerometer and a 3D gyroscope by applying the strap-down estimation of the IMU orientation using the angular velocity data [23]. The velocity drift, induced by the time integration of the IMU acceleration and angular velocity, was attenuated by using a biomechanical constraint of front-crawl and prior knowledge about the pool length. However, using the pool length for the velocity pattern offset correction restricts the application of the method to the full lap indoor conditions. It has been shown that velocity and its variation are key parameters to estimate the swimming energy expenditure [24]. In [25], we used an approximation of global frame acceleration in a Gaussian process regression framework to estimate the cycle by cycle velocity of the front-crawl without using any prior knowledge of the pool length. The computational cost of the Gaussian process regression as a nonparametric approach is $O(N^3)$ where N is the number of training samples. Consequently, the direct application of Gaussian process for large training sets can be intractable.

In this paper we propose a Bayesian framework to estimate breaststroke swimming velocity using a wearable IMU without a priori knowledge of pool length. To avoid the errors that arise from integration of inertial signals when estimating velocity, we assumed that in the breaststroke swimming there are some features in the inertial signals of sacrum movement at each cycle that can be precisely mapped to the velocity of that cycle. We employ the Bayesian linear regression for this mapping and compare the estimator result in terms of generalization and computational cost with a linear least-square estimator and Gaussian process regression (GPR). The proposed data-driven velocity estimation method does not require kinematics constraints of the breaststroke contrary to our previous studies in the front-crawl swimming where a movement constraint was used as a part of the estimation algorithms [23,25].

2. Methods

2.1. Participants, protocol and the velocity reference system

Eight well-trained national level swimmers (6 males and 2 females) and seven recreational swimmers (3 males and 4 females) participated in our study. Demographic information including age, height and weight of the swimmers is shown in Table 1. The experimental procedure was approved by the Ethics Committee of the Faculty of Biology and Medicine, University of Lausanne (protocol #87/10) and followed the Declaration of Helsinki. The experimental procedure was explained to the swimmers, who then signed informed consent.

Each swimmer performed four 25 m breaststroke trials consecutively from 70% to 100% of their personal maximum speed (V_{max}), considering their actual 100 m record, by starting in water with a push off on the wall. As the reference system, we used a tethered speedometer (SpeedRT®, ApLab, Italy, 100 Hz) that was attached to the waist of swimmers with a belt. A resistance of 5N was applied to keep the nylon line tight via a clutch on the pulley compartment of the apparatus. According to the SPEEDRT (reference) specs the resolution of displacement is 0.08 mm. Therefore, at average personal V_{max} (in our measurement: 1.32 m/s) the velocity error of the SPEEDRT is 1.0 mm/s. To control the trials speed, a technical assistant used the average of the velocity recorded by SpeedRT®. If the swimming velocity was not within 5% of target velocity, the swimmer was asked to repeat the trial. The choice of 5% is due to the fact that the difference between two successive trials is 10% V_{max} of each participant.