Online Monitoring of Swimmer Training Using a 3D Accelerometer
Identifying Swimming and Swimming Style

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Abstract: In the process of optimizing training efficiency and improving results of the athletes, technology has increasing share. Wearable sensors, especially those measuring motion are lately acquiring more and more interest. In this paper, we aimed to develop online monitoring tool of swimming training, more in particular algorithm for detection of swimming and turning events using 3D accelerometer. Additionally, algorithm should be able to discriminate between performed swimming styles. This study included data of 10 swimmers who swam on predefined protocol for 1200m. Each swimmer was equipped with wireless waterproof 3D accelerometer attached over right wrist. Algorithm showed high accuracy of 100% for detection of swimming and turning activity. Additionally, detection of swimming styles such as crawl, breaststroke and backstroke resulted of 100% true positive rate. However, true positive rate decreased to 95% for detection of butterfly event. To conclude, we demonstrate that swimming activity together with style recognition can be registered using wireless waterproof 3D accelerometer. Furthermore, we show that such detection can be automatized and performed in an online mode. Taken together, this development leads to a useful online monitoring tool of swimming training.

1 INTRODUCTION

With the recent boost in technology development, we are witnessing greater involvement of new technical inventions in the competitions, as well as in the training process of athletes. In the modern sport, it is beneficial not only to test athletes in the laboratory environment, but also to give appropriate guidance of the training process (Maglischo 1993). The latter is essential as it will optimize training efficiency and thus improve results that the athlete can obtain.

The application of accelerometers in sports is increasing either by measuring activity levels using mobile phones (Shumei et al. 2010), characterizing biomechanical activity (Auvinet et al. 2002), or developing specialized accelerometer-based devices to measure energy expenditure (Wixted et al. 2007).

However, the use of accelerometers in swimming, training or competition, is not yet widespread. Most of the work is based on algorithms with complex features to discriminate between limited swimming styles (Siirtola et al. 2011), with algorithms that work only in offline mode (Jensen et al. 2013) or on algorithms with interesting concepts that are yet to be validated in the training process and larger number of subjects (Bachlin and Troster 2012; Le Sage et al. 2010).

Therefore, we aimed to develop an online monitoring tool to follow the swimming training using a three dimensional (3D) accelerometer attached on a swimmer's wrist. Moreover, developed algorithm should be able to detect whether the subject swims or turns, as well as which of the four competitions swimming styles is being used.

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2 METHODS

2.1 Hardware

To perform the experiments, a 3D accelerometer with a MMB Sensor v.1.0.9 (Multimediabox, Netherlands) was placed around the right wrist of the subjects (X axis oriented towards hand, Y on a side and Z upright), as shown in Figure 1. The sensor was placed in the waterproof plastic casing, which was then attached to the wrist using watch strap. The dimensions of sensor are 3cm x 3cm, with a weight of 33g providing an easy-to-use measuring system. The sensor had a sampling rate of 100Hz. To provide a constant communication with a computer, the data were wirelessly transferred via USB receiver.

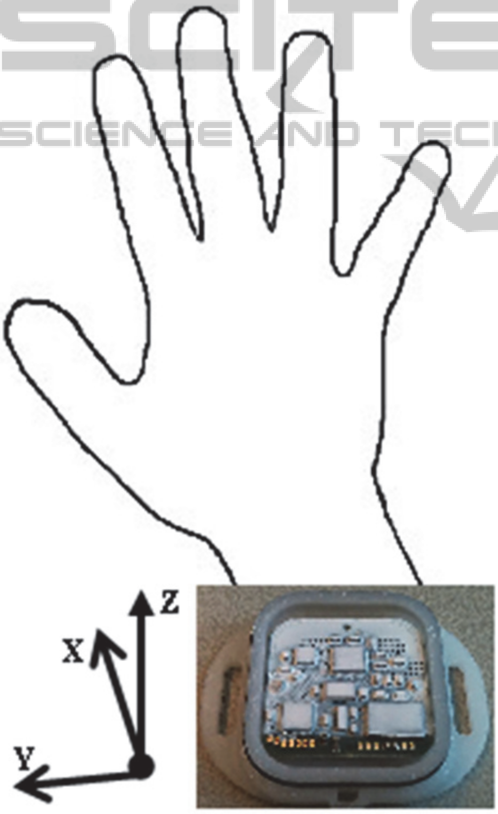

Figure 1: Scheme presenting 3D accelerometer with the orientation of its axes when attached to the right hand.

2.2 Data Collection

For this study we collected the data from 10 swimmers (all European Youth Championship swimming level) during their regular training performance in the sport school in Antwerp, Belgium. The baseline characteristics of the subjects are shown in Table 1.

Table 1: Subjects characteristics (mean ± standard deviation).

	Males (n=5)	Females (n=5)
Age (years)	16.8 ± 0.6	15.9 ± 0.9
Height (cm)	182 ± 4	172 ± 7
Weight (kg)	74 ± 4	64 ± 3

During the development stage, data from 3 swimmers (2 males and 1 female) were collected for algorithm development. Subsequently, data were additionally collected to validate the findings (data of 7 swimmers). All the trainings were performed in an Olympic size pool of 50m. Each of the swimmers trained according to a predefined protocol: 200m medley (combination of all 4 swimming styles: crawl, breaststroke, backstroke and butterfly) of their regular training pace which is then followed by a 200m of same pace and 50m of fast pace for the each swimming style separately. Laps were labelled and measured in parallel with a hand stopwatch.

2.3 Data Processing

The algorithm development was done in an offline framework in MATLAB (7.14, The MathWorks, Natick, Massachusetts). Figure 2 presents data taken from the X axis of the accelerometer at 200m medley swimming. The raw signal (Figure 2, panel A) from each axis was initially filtered using a low pass filter with a cut-off frequency of 2Hz (Figure 2, panel B). Visual differences between swimming styles and turning were already apparent. Based on a trial and error method, we determined thresholds for acceleration on X and Y axis that have to be reached to recognize swimming (shown in Figure 3). In panel C we indicate with 0 when a period is recognized as not swimming, while with 1 when it is recognized as swimming. Pulse train mainly comes from each stroke that the swimmer made, hereof high frequency of pulses. Evidently, most of zeros are false negative, thus if the time difference between two pulses is less than 2.5s they are being merged (shown in panel D, Figure 2).

To determine the style, in addition to already identified swimming, new thresholds were defined. Flow chart for swimming and stroke recognition is shown in Figure 3. To detect crawl and butterfly, average on X axis had to be lower than 0.7G. Moreover, to distinguish between them, minimum of acceleration on Y axis had to be lower/higher than 0.8G. In contrast, for breaststroke and backstroke,

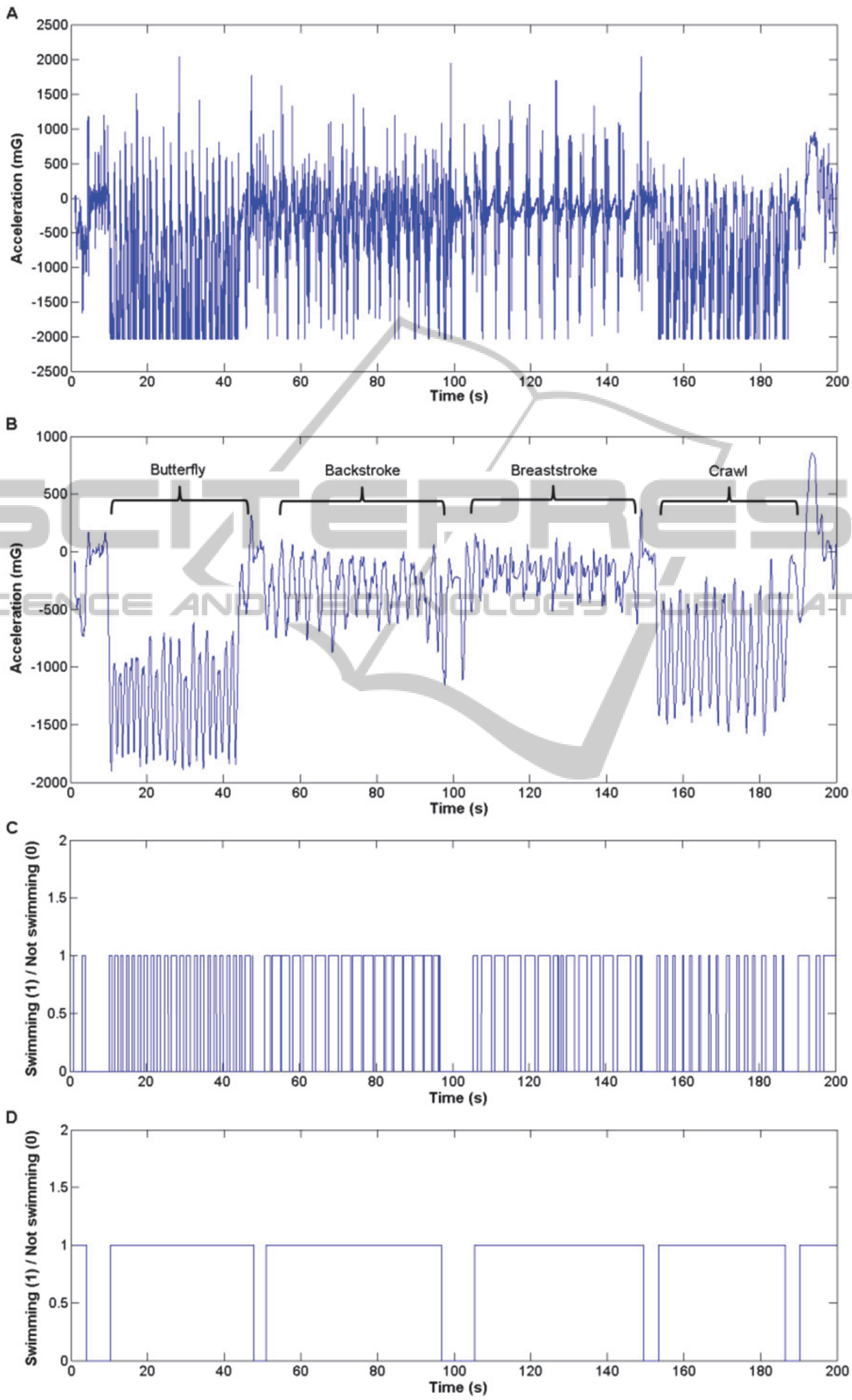

Figure 2: Obtained data from X axis of accelerometer during 200m medley; Panel A/ Raw signal; B/ Filtered signal with labels; C/ Swimming (1) or not (0) upon applying thresholds on the X and Y axis; D/ Swimming sessions after correction.

besides X axis threshold average on Y axis as positive/negative was observed for style recognition.

To validate the algorithm, simulation of online monitoring was performed. New data were released to run through the algorithm continuously. The first window was 20s long which was sliding over the data.

3 RESULTS

For the 7 validation subjects, we had in total 42 laps of swimming, each was 50m long. Our algorithm showed highest performance by identifying all 42 swimming intervals and all 42 turning points. Moreover, we achieved high accuracy when it comes to detecting different swimming styles (Table 2). The algorithm detected all crawl, breaststroke and backstroke laps, however identifying butterfly failed in 2 out of 42 laps. Taken together, true positive rate reaches 99%.

Table 2: Stroke recognition (TP = True positive; FP = False positive, TN = True negative; FN = False negative).

	TP	FP	TN	FN
Crawl	42/42	1/126	125/126	0/42
Breaststroke	42/42	1/126	125/126	0/42
Backstroke	42/42	0/126	126/126	0/42
Butterfly	40/42	0/126	126/126	2/42

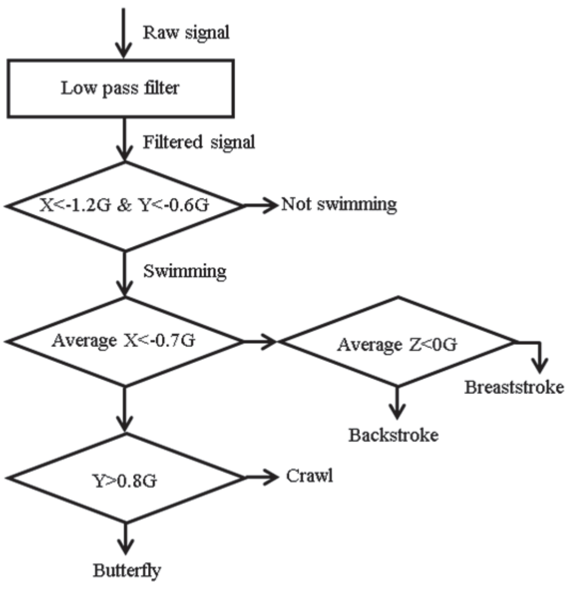

Figure 3: The flow chart of the stroke recognition process, together with used cut-off's.

4 CONCLUSIONS

In this study we are demonstrating that swimming events together with swimming styles may be registered with high certainty using wireless 3D accelerometers. Moreover, we show that the whole process could be performed in online mode, which could be beneficial for coaches when overviewing training performance.

More outputs, such as stroke frequency, stroke length, stroke duration etc., are to be developed. Identifying those variables would complete the online monitoring tool, providing the coach all the necessary information to analyse and improve swimmers training and performance. In practice, whether such a system could be useful to the coaches is not yet explored. However, having a constant feedback on a swimming effort and quantification of each motion can only provide sufficient measurements for more efficient performance (Smith et al. 2002). As addition, suchlike monitoring tool should not be limited to one swimmer, but secure a multi-swimmers monitoring feature.

Substantial improvement of the developed algorithm could be achieved by applying device and algorithm on larger number of subjects. This would either provide stronger validation of the monitoring tool, or result in fine tuning of the used cut-off's which should again confirm high accuracy of the algorithm for monitoring swimming performance.

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