Preliminary study: IMU system validation for real-time feedback on swimming technique

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1. Introduction

The use of Inertial Measurement Units (IMU) for sport performance monitoring has grown in the previous decade due to its ease of use and the growth of private market applications. In swimming monitoring, it has been highlighted (Dadashi et al. 2012; Callaway et al. 2015) that measuring performance with traditional 2D and 3D video-based systems have many downsides (light refraction, bubbles, time-consuming). Other alternative methods are also mentioned such as speed measurement using a tighten cord, but they disturb the swimmer’s technique and only provides feedback on the forward speed. The main problem of those solutions is that the data must be post processed and they do not provide an instant feedback to the swimmer. In this context, IMUs appear to be a low-cost solution, easy to use and not interfering with the swimmer’s technique, even if its data analysis requires a complex data mining process. Such real-time feedback for gesture and sport training is a solution that has been used many times: for instance karate training (Takahata et al. 2004), and various other sports (Spelmezan et al. 2008; Drobyn et al. 2009). It has been shown (Zatoń et al. 2014) that an immediate feedback can improve swimming technique. Measuring the performance is something much in demand for sportsmen to be able to keep track of their progress. For swimming, the most common performance criterion tends to be stroke length, stroke count and lap count (Dadashi et al. 2012), which are often summarized by coaches as the ‘Swim Golf’ (SWOLF) criteria (Perego et al. 2015). Those have been used in several scientific publications as references of the swimmer’s level (Perego et al. 2015; Lemkadem et al. 2016), but it also has been shown (Cardelli et al. 2000) that there is a significant correlation between the breathing characteristics and the swimmer’s skills plus the stroke characteristics. From this statement we wanted to validate an IMU devices mounted on the head of a swimmer to measure its breathing characteristics, and experiment on an instant feedback to correct those movements.

The tested device is a Swimbot (Meudon, France), based on Newton 2 smart watch core (Ingenic, Beijing) including a 1.2 GhZ M200 CPU running a custom Android 5.1 with a 16 bits 9 axis IMU (MPU-9250 (InvenSense, San Jose, California) embedded, using the Android sensors fusion algorithm to provide a rotation quaternion at a sampling rate of 50 Hz. The other data provided are: accelerometer, magnetometer and gyroscope and two software sensors provided by Android: linear acceleration (without the gravity) and quaternion orientation. The device is placed under the swimming cap at the back of the head and also includes two bone conduction headphones placed just behind the ears for instant feedback under water, with an on-board memory of 2 Gb of data to store logs and data.

2. Methods

Measurements were validated both with manual video analysis (VIRB cameras, Garmin, Schaffhausen) and with a motion capture (MoCap) system: OptiTrack (NaturalPoint, Corvallis). Makers have been placed on the head of a mannequin and on the device. The OptiTrack has been calibrated with a mean tracking error of 8.46e-4 mm on markers position and provides rotation quaternions of the head. The second monitoring device was two VIRB cameras and movement was reconstructed by tracking markers position with image processing software (Blender, Blender Foundation, Amsterdam).

From both MoCap system and Swimbot we extracted quaternions then converted to Euler angles and from the video file, the position of two markers in the alignment of the face to get an orientation vector from which we deduced the roll.
easy to use system for roll analysis and real time feedback. However, this study must be completed with more test subjects in order to perform statistical performance and error analysis.

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\[ \theta = \arctan \left( \frac{v_y(2)}{v_x(2)} \right) \]

Where \(v_x(1)\) and \(v_y(2)\) are respectively coordinates of the vector along X and Y axis (see Figure 1).

We ran ten experiments with a breathing movement, and for each one removed the offset and used a manual synchronisation (selecting manually identical instants of the IMU, video and MoCap curves) and a cross-correlation to synchronize the time more precisely.

3. Results and discussion

The relative error between Swimbot, motion capture and video has been statistically analysed which gave the following results:

It must be noted that for one value in the 7th experiment, the Swimbot provided a false value for two consecutive samples which represents 0.03% of the samples (see Figure 2). Despite this problem, error was low on each measurement device.

4. Conclusion

We have shown that in laboratory conditions, for offset compensated and time synchronized signals, the error on rotation values provided by the Swimbot were under 5 degrees, performing as good as video analysis. It must be highlighted that an error on rotation reconstruction may occur (which happened on 0.03% of our samples), resulting in a fleeting roll change. We issued the hypothesis that it could be due to the internal fusion algorithm but further research should be done on this topic. For its field of application (swimmer’s feedback and performance monitoring), the Swimbot is relevant as we are not interested in very precise values but more on the relative progression of head rolls. We also shown that it performs much less noisy roll analysis than video tracking in underwater conditions. Assuming that the IMU device accuracy is not influenced by a sub aquatic environment (or that the degradation is negligible), we shown the Swimbot device is a valid and

Table 1. Comparison of relative errors for each measuring devices.

|                      | Absolute mean error (deg) | Absolute error standard deviation (deg) |
|----------------------|---------------------------|----------------------------------------|
| Swimbot rel. to MoCap| 1.876                     | 5.329 e^{-2}                           |
| Swimbot rel. to video| 2.184                     | 5.949 e^{-2}                           |
| Video rel. to MoCap  | 1.990                     | 4.450 e^{-2}                           |

Figure 1. Test conditions.

Figure 2. One-off error on Swimbot rotation.