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The Use of a Cap-Mounted Tri-Axial Accelerometer for Measurement of Distance, Lap Times and Stroke Rates in Swim Training

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Abstract

This paper will report some of the findings from a trial which recorded accelerometer data from six elite level swimmers (three female and three male, varying primary event stroke and distance) over the course of a regular 15 week training block. Measurements from a head-mounted accelerometer are used to determine when the athlete is swimming, marking of turning points (and therefore distance and lap-time measurements), and is processed by frequency analysis to determine stroke-rate. Comparison with video where available, and with training plans and literature where not, have proven this method to be accurate and reliable for determining these performance metrics. The primary objective of this project was to develop a low-cost, simple and highly usable system for use in swim coaching, feedback from elite coaches has indicated that development of this could be an extremely useful addition to their training regime.

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Keywords: Swimming; Inertial Sensor; Performance Analysis; Training

1. Introduction

With the availability and prevalence of technical knowledge in sports increasing exponentially, along with the reduction in costs of technological equipment required for implementing training plans based on such technical knowledge, it is becoming increasingly important for athletes and coaches to implement data acquisition and analysis into daily training if the athlete is to achieve and maintain elite status. The principles of physiological training remain relatively constant from sport to sport (adjusted for intensity and duration); however methods of performance measurement vary due to limitations of each sport. Swimming is an example of a sport in which it is particularly challenging to take direct performance measurements.

Currently, performance measurement in swimming during training is done through stopwatch lap-time measurement by coaches, combined with distance measurement and athlete-reported ratings of perceived exertion. But despite the limitations inherent to the activity, performance measurement in swimming has room to become more technical, due to swimming taking place in a predictable, controlled environment with a consistent, repeatable technique. Due to this, the use of acceleration-measuring inertial sensors (or inertial measurement units, IMUs) is highly appropriate for tracking swimming, especially as this technology has now reached the stage where a device can be small, lightweight, waterproof, and therefore fully wearable without interfering in any way with the athlete, as well as battery and memory life increasing to a state where a week of data can be recorded and stored with minimal interaction from coach or athlete, improving usability. Use of more technical measurement methods involving IMUs will result in more accurate, consistent and comprehensive data collection, which in turn can lead to more advanced analysis, allowing faster and better identification of critical features in an athlete's training progression.

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2. Literature Review

A comprehensive review of IMU usage in swimming was conducted by (Mooney et al. 2015). In a technical evaluation of 87 papers on the subject of IMU use in elite swimming, they found that most successful recent work has been conducted processing accelerometer data using relatively simple techniques, such as peak detection. Specific to distance and lap-time identification, Davey et al. found that using a sacrum-mounted accelerometer, lap times could be derived with equal or greater accuracy than manual stopwatch measurement, although detection of starts and finishes proved difficult (Davey et al. 2008). Stroke rates were estimated with good accuracy by a number of research teams also using sacrum-mounted accelerometers (Sage et al. 2011; Chakravorti et al. 2013). A number of groups have also attempted evaluating head-mounted accelerometers for swimming analysis. Pansiot et al. developed a head-mounted system which could detect stroke type, lap counts and times, and proposed using the system for stroke timing (Pansiot et al. 2010). However, no solution has been designed for full usability. To achieve this, the solution would be required to work consistently and be convenient in real world conditions. A requirement for precise mounting and assumption of parameters such as pool length restrict this from being the case for current systems

2.1. Summary

This report aims to demonstrate the potential ease of operation and use of resulting data analysis from a set of IMUs inserted into a group of elite athlete's daily training regime, when the system is designed primarily for maximum ease of use and accessibility.

3. Methods

To begin designing this trial, a number of key objectives were defined and prioritized. The primary objectives for this trial was to ensure that the system could be introduced into an athlete's regular training with minimal interference for either the athlete or associated staff. Secondly, the data gathered needed to be extensive enough to ensure that feature extraction could be conducted to an accurate and consistent level. And finally, the data needed to be of high enough quality to ensure accuracy of any metrics reported could be satisfactory for the requirements of the coaching staff. Using these objectives, hardware needed to be selected and positioned, software written, and an athlete trial organised.

3.1. Hardware Selection

When selecting hardware, the reduction of interference with the athlete's regular stroke was the primary consideration. To achieve this, the hardware was required to be lightweight, waterproof, have a long battery and memory life, and be easily and robustly connectable to current computing hardware. To reduce unit size and maximise battery and memory life, it was decided that a tri-axial accelerometer would be a sufficient type of IMU. Other papers (Lecoutere & Puers 2014; Jensen et al. n.d.) have shown that the use of gyroscopes can be useful in feature extraction in swimming, however this was deemed an unnecessary addition to this project due to the success of accelerometer-only systems discussed in section 2.

The final chosen hardware which matched all requirements was the Axivity AX3 unit (http://axivity.com/).

Figure 1 - Axivity AX3 IMU (http://axivity.com/)

3.2. Positioning

Referring again to the objectives of the trial, interference with the athlete had to be considered when selecting the positioning of the sensor during activity. Previous projects and current commercial solutions have mounted their sensors on the wrist, however when questioning the athletes involved in this study, there was a clear dislike for this solution as it was felt to interfere with the way their hand felt during the swimming motion. Another popular location is the sacrum, and some trials were conducted with this position, however it was difficult to ensure the sensor remained in position (particularly with male athletes) without adding a bespoke item of clothing, which it was decided would interfere with regular procedures too much. The final chosen mounting position was the back of the head, underneath the swimming cap. This position allows the unit to be easily and consistently mounted using no additional mounting system, and the unit is undetectable by the athlete once in position. The disadvantage of this position is that while the fore-aft acceleration of the head is largely representative of the centre of mass of the body, the Euler angles (primarily roll and pitch) are not representative of the majority of the body. However, this project does not aim to deal directly with the roll and pitch of the body, and therefore this was not considered an issue. Body roll and pitch could be used in feature extraction, so not having this information available is a limitation when compared to using the sacrum as the mounting point, however having head roll and pitch available could itself be used as an identifier which wouldn't be available if the sacrum or wrist were used.

Another issue given consideration was the orientation of the sensor. There were two options regarding this. Firstly, a specific orientation is described to the athlete, and they are asked to ensure that the IMU is mounted in this orientation for every session. This option allows a simpler and potentially more reliable procedure to be used for feature extraction, as determining the orientation of the body at any point in the data trace becomes relatively trivial. The second option was to not dictate an orientation to the athlete, allowing them to mount the sensor freely, and use assumption in post-processing to take a best guess at the orientation of the sensor relative to the athlete before continuing on to feature extraction. The advantage of this method is that it eliminates the possibility that the athlete could forget to orient the sensor correctly and invalidate the data. It also eliminates the reliance on the sensor being mounted accurately in the prescribed orientation. And finally, it reduces the amount of interaction the athlete has with the sensor, thus reducing the impact on their regular training procedure. Because of these advantages, it was decided not to dictate an orientation to the athlete, and rather estimate the orientation during post-processing.

3.3. Software Development

For processing and analysing the IMU data, a bespoke software package was developed using the MATLAB™ (The Mathworks Inc., Natick, Massachusetts, USA) development environment. This software was nicknamed Swimming Training Analysis, or SWIMTAN for short. The process SWIMTAN follows in converting raw data to useful performance metrics is outlined in Figure 2.

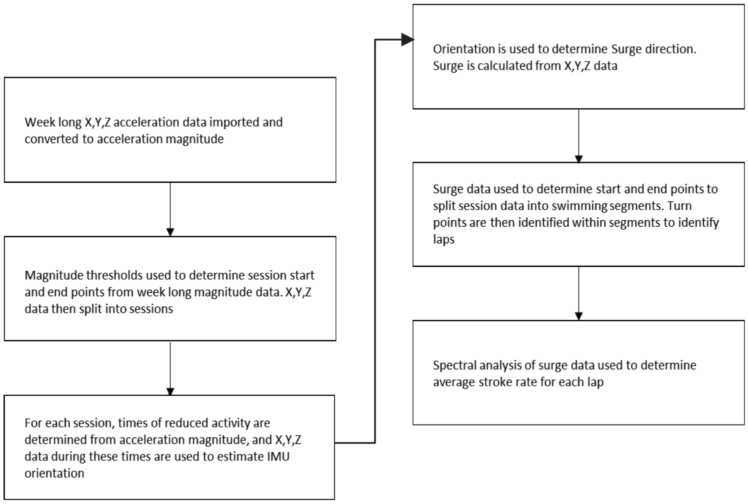

Figure 2 - Process of performance data extraction from raw acceleration data

To reduce impact on athlete and coach workload to the bare minimum, data is recorded in week-long batched. Stage one of processing this data is to convert the X, Y and Z acceleration component data into a single trace of acceleration magnitude data. At stage two, a boundary is set which determines whether the sensor is active, and therefore whether a swimming session is underway, and the data is then cropped to segregate these sessions from each other, and from periods of inactivity between sessions. Sessions are defined as periods of activity longer than 30 minutes (any shorter periods of activity are discarded).

Stage three uses the cropped session data to determine on a session-by-session basis how the sensor is oriented having been mounted under the swimming cap. This is done using an acceleration magnitude threshold below which the athlete is assumed to be in their neutral position (head upright so that eyeline is along the pool surface in the direction of swimming. Observation indicated that athletes assuming this position regularly between sets during training sessions). Several periods of relative inactivity are taken during the session and the average of the most common position is taken. It was decided to take this approach to sensor orientation determination rather than prescribing an orientation to the athletes primarily to reduce the workload/input required from the athlete, but also because consistency of mounting between athletes and over the course of the trial period could not be ensured.

Stage four consists of the conversion of X, Y and Z acceleration data, combined with the calculated sensor orientation, into surge (acceleration in the direction of travel) and Euler angles.

At stage five, the session data is split into individual sets and laps, and a multitude of derived data is extracted. The primary step in splitting the data is using surge spikes to estimate starts and turns, which allows laps to be identified (the exact point of completion of a set is determined by an unusual change in pitch as the athlete touches the wall and stops). Set and session distances are now calculated, as are lap times. By performing a Fourier transform on the surge data of a given lap, spectral density analysis can be used to determine the peak frequency of surge, which corresponds to the average stroke-rate of the lap. The verification of segments identified by surge data analysis is done in what will be referred to as “uncertainty analysis”. This consists of comparing a set of metrics (such as stroke rate, swimming velocity, etc.) of the potential segment to known realistic values for a swimming segment. If too many of the metrics of the potential segment fall outside of these known values, the segment is discarded.

Key features of the software are ability to identify swimming sessions from a week long data stream, identification of specific swimming segments during sessions and laps during those segments, calculation of surge direction regardless of mounting position, automatic estimation of the pool length for each session, and estimation of stroke rate per lap. The software currently does not attempt to identify which stroke is associated with either swimming sessions or segments, as this is not necessary for the level of analysis required here, and would add extra complexity to the software which could cause consistency issues.

3.4. Athlete Trial

All data used in this project was recorded during an elite athlete trial based at the University of Bath Sports Village using six UK-based full time, elite, internationally competitive swimmers.

3.4.1. Participants and Timing

Six International-level athletes, three male and three female, were used during the trial, which was intended to include every swimming session for 3 months. Not all datasets are complete, however, due to influences such as hardware malfunction, or athletes attending events where the use of such sensors would be impractical or illegal. A summary of the data collected is given in Table 1.

Table 1 - Summary of data collected per athlete

Athlete/Sensor ID	Date Range of Data	Number of Sessions
14242	15/09/15 – 10/11/15	69
14268	15/09/15 – 11/11/15	59
14272	15/09/15 – 24/11/15	71
14349	15/09/15 – 26/09/15	11
18325	22/09/15 – 15/12/15	101
20174	05/10/15 – 15/12/15	79
	Total	390

3.4.2. Participant Instructions

The participants were given no instructions other than to fit the sensors under their swimming caps in a consistent location on the back of the head during every session, to store their sensor in their own locker between sessions unless instructed otherwise (e.g. for data download and battery charging), and to otherwise continue with their training regime as normal.

3.4.3. Comparison Data

Copies of corresponding training plans were provided for each session included in the IMU trial. These session plans were matched to the relevant IMU data, and used to validate and assess the data derived.

4. Results

With such a large pool of highly detailed data available, both short and long term comparisons can be made between training plans and measured data. First, an individual session is chosen semi-randomly (sessions involving complicated or unusual drills such as changing stroke mid length or kick-only drills were not included for selection) for detailed comparison, analysing the accuracy of number of segments, segment distances, and segment lap times derived from IMU data compared to those prescribed in the session plan. Secondly, long term data is given, and the usefulness of the data discussed.

4.1. Comparison: Individual Session Features

Two example sessions have been chosen at random for detailed analysis of the SWIMTAN output, and comparison to the corresponding training plan. Figure 3 shows the SWIMTAN output from athlete 14242 for the session completed on 03/10/15.

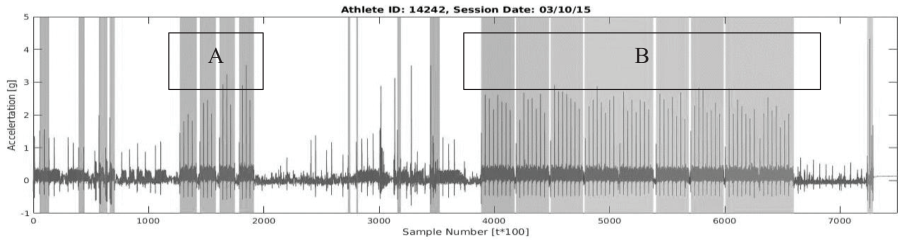

Figure 3 - Surge data from session completed by athlete 14242 on October 3rd 2015 with relevant segments identified

Represented by the x-axis is sample number (sample rate is 100 Hz), and on the y-axis is surge (acceleration in the down-pool direction). The shaded areas on the plot represent SWIMTAN identified swimming segments. The largest spikes in the surge trace (clearly visible) are caused by the athlete pushing off the wall (or a dive start in some cases). Therefore these spikes can be used to identify segment starts and turns, differentiated by the nature of the activity before and after the spike.

Identified in Figure 3 are the two main sets prescribed on the session training plan: a 4x200m on 3 minute turnaround aerobic test set (labelled ‘A’), and a 10x400m on 5 minutes threshold set (labelled ‘B’, note the athlete appears to have only completed 9 repeats of 400m, despite the training plan prescribing 10). Not fully identified are the warmup (mostly consisting of short low intensity swimming, with a few mid-length bursts), and a speed-kick set after the 4x200 (kick drills do not generate enough of an acceleration impulse to trigger segment recognition under the current algorithm, and the athlete performs much slower starts and turns during these sets). The athlete appears to also perform a low intensity cool-down swim after the threshold set. This highlights that the segment extraction algorithm does not currently identify low intensity swimming with great reliability. Whether this is practically important from a training analysis standpoint is debatable, as these segments may not be considered to contribute greatly to the accumulation of training stress. Detection of these segments could be improved however by developing a separate algorithm to search extended areas of low activity for these low intensity sets.

SWIMTAN reports the session distance to be 5000m, which considering the known missed segments, brings it close to the prescribed session distance of 6100m.

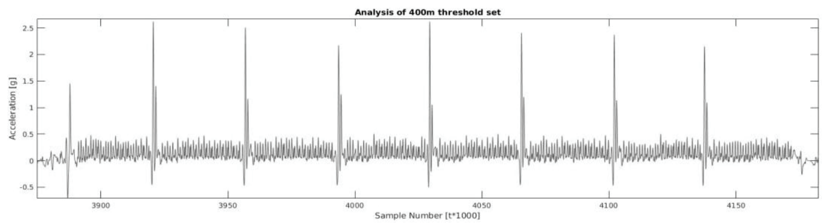

Figure 4 - Surge Analysis of a single set of a 10x400m Threshold set

Figure 4 shows a single set of the 10x400m Threshold set identified in Figure 3. By analysing the surge data at greater detail, turns can be easily identified and time between measured, and the periodic nature of surge becomes more obvious. This periodicity can be analysed using spectral analysis techniques to identify the athlete’s stroke rate for each lap. Therefore, a detailed analysis of this example segment can be made.

Table 2 - Analysis of Single 400m Threshold set

Lap	1	2	3	4	5	6	7	8
Lap Time [s]	32.76	36.29	36.70	35.87	36.13	36.51	35.49	38.21
Stroke Rate [strokes/min]	26.6	29.4	27.5	28.3	27.1	28.1	27.3	26.7

Maglischo conducted research into average stroke rates at various swimming velocities. A stroke rate of between 26.5 and 29.5 (53-59 stroke cycles per minute) for an athlete swimming at a pace of roughly 72 seconds per 100m corresponds well with his findings (Maglischo 2003). SWIMTAN identified the total segment time as 289 seconds, which matches well with the 5 minute (300 second) turnaround time prescribed in the training plan. Further validation of these metrics against video recordings is required for complete confidence.

4.2. Longitudinal Analysis

When tracking the training of an elite athlete, it is important that data on time spent and distance covered in training is logged and utilised in planning future training activities. This is usually achieved by manually keeping track of the mileage prescribed in the athlete's training program. SWIMTAN is able to output total session distance and time actually completed by the athlete, which can then be used to track distance and time longitudinally.

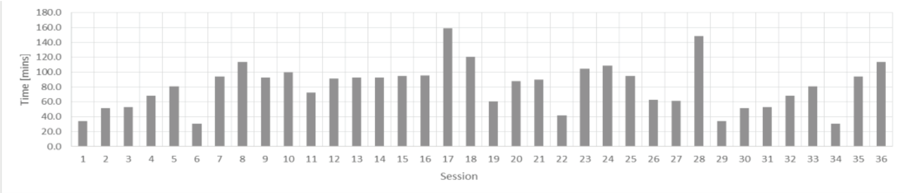

Figure 5 - Athlete 14242 Training Time per Session over 36 sessions of Trial Period

Figure 5 shows the length of time of each training session. Note that this calculation is based on activity detected in the acceleration signal, therefore is not directly related to the session distance calculation. Taking a random sample of 16 sessions from the full range of athletes, the SWIMTAN derived average session length was 90.3 minutes (minimum of 45.3 minutes, maximum of 134.7 minutes), which compares to the manually-measured average session length of 98.4 minutes (minimum 60.0 minutes, maximum 134.0 minutes). For session distances over the same 16 sessions, SWIMTAN derived average distance was 3339m (minimum 1700m, maximum 6350m) compared to the average distance from training plans of 5678m (minimum 4000m, maximum 6200m). This discrepancy in distance calculation is likely due to the SWIMTAN algorithm currently ignoring low intensity drills such as kick drills, which can make up significant portions of some sessions. A better comparison would be between session training load.

5. Conclusions

Having confirmed the findings of Moody et al., that a head-mounted tri-axial accelerometer has the potential to provide sufficient data to extract all relevant performance metrics from an elite swimmers training session in a relatively accurate and consistent manner, it was important to prove that this could all be done in a framework which would reduce workload for coaches and athletes. By achieving the stated objectives with a system which requires no special equipment or particular consideration to mount, and with absolute minimal interaction from coaches, a first step towards this goal has been reached. Continuation of the development of the feature extraction algorithms to improve accuracy and robustness further, along with thorough validation and verification against real world data should yield a highly useful and practical system based on this model.

6. Acknowledgements

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