A COMPONENT BASED INTEGRATED SYSTEM FOR SIGNAL PROCESSING OF SWIMMING PERFORMANCE

Tanya Le Sage
Sports Technology Institute, Loughborough University, LE11 3TU, Loughborough, U.K.

Paul Conway, Laura Justham, Siân Slawson, Axel Bindel, Andrew West
Wolfson School of Mechanical and Manufacturing Engineering, Loughborough University
LE11 3TU Loughborough, U.K.

Keywords: Swimming, Components, Integrated system, Signal processing.

Abstract: Research presented in this paper details the development of an integrated system, which allowed presentation of meaningful data to coaches and their swimmers in a training environment. The integrated system comprised of a wireless sensor node, vision components, a wireless audio communication module and force measurement technologies. A trigger function was implemented onto the sensor node which synchronized all of the components and that allowed relative processing of the data. Filtering approaches and signal processing algorithms were used to allow real-time data analysis on the sensor node.

1 INTRODUCTION

The majority of methods used to analyse swimming technique are vision-based systems. Quintic is an example of vision-based software where the analyst uses a pre-recorded video file and then manually digitises key occurrences within the recording (Quintic). The disadvantage of this and other vision systems are the parallax errors introduced by the use of video cameras, inaccurate measurements due to light reflections on the water surface and the large amount of time it takes to process the data. Manual digitisation is a time consuming process and does not allow real-time feedback to the coaches or swimmers. The process provides limited quantitative data and requires operator expertise. There is inherent variability within the results due to the reliance of human judgement.

Force measurement platforms are an additional technology used for measuring swimmer performance. Force data can be integrated with video data during the block phase (time from the start trigger to leaving the block) of the dive to enable more complete analysis.

Accelerometer sensor devices have also been developed for use in a swimming environment. An example of this was presented by Davey (2005), where a system was developed using a tri-axis accelerometer to monitor stroke technique. Ohgi used a similar system to measure wrist acceleration of swimmers (Ohgi, 2002). Both systems used a data logging accelerometer system to capture the data, which meant that the data could not be viewed in real time. These existing systems focus on post processing that again increases the analysis time significantly and subsequently coaches are unable to offer immediate feedback to the swimmers based on these data. Neither case used a wireless sensor network (WSN) to allow data to be captured from multiple swimmers, nor an integrated system to allow full analysis of the stroke technique.

Research presented within this paper, carried out at Loughborough University, UK, was concerned with the development of a component based integrated system for monitoring elite athletes in the water. The main results of the initial feasibility study are presented in this paper. This study considered a variety of different sensing and measurement devices and an integrated system was constructed to capture the data. The integrated system comprised of a WSN, real time audio communications to the swimmer, a vision analysis system using real-time image processing, an underwater camera and a force measurement platform. The WSN was chosen due to

Le Sage T., Conway P., Justham L., Slawson S., Bindel A. and West A. (2010).
A COMPONENT BASED INTEGRATED SYSTEM FOR SIGNAL PROCESSING OF SWIMMING PERFORMANCE.
In *Proceedings of the International Conference on Signal Processing and Multimedia Applications*, pages 73-79

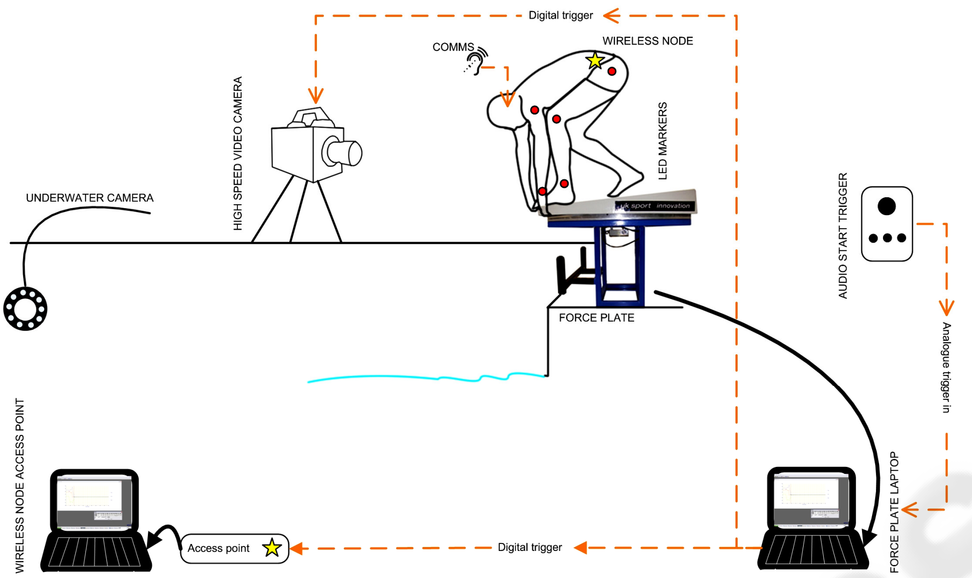


Figure 1: Integrated system.

its ability to transmit and feedback data in real-time. It also allowed multiple swimmers performances to be analysed simultaneously. Furthermore it was possible to synchronize the network with other data capture methods used within the integrated system. The high-speed and underwater cameras were used because of their ability to provide the coach with visual information with regards to the athletes' performance. This made analysing the data from the accelerometer and the force platform much simpler. The audio communications were chosen because they allowed the coach to feedback information to the swimmer in real-time, based on the data gathered.

The WSN was designed with a star topology, a number of nodes communicated with a poolside personal computer (PC) via an "Access Point" that collated the wireless data transmissions from the wireless nodes and had a hardwired connection to the PC. A trigger function was implemented onto the sensor node to allow synchronised processing of data obtained from all components. A Butterworth filter and signal processing algorithms to extract the relevant swimming features were embedded onto the node which allowed the coach to extract useful data with regards to each individual swimmer's performance in real time.

2 METHODOLOGY

The force measurement system was used to augment the information available from a high speed camera and the WSN during the start process. The force measurement system was comprised of a start platform instrumented with four Kistler force transducers (9317B) sampling at 100Hz. The force measurement platform was used to ascertain the following parameters:

- Horizontal force
- Vertical force
- Time: to first movement, to back foot leaving, to front foot leaving, overall block time
- Centre of pressure

A high-speed camera and a WSN were synchronised with the force measurement platform using a TTL trigger function. The function was implemented in the embedded programming of the node which sent an interrupt to the access point (AP) when the trigger was enabled. Sending a TTL signal to a port on the AP triggered the system. The embedded code initialised the trigger, starting the trigger on the rising edge of the signal. The integrated system can be seen in Figure 1 and has been used to determine the characteristics of an accelerometer trace based on the data gathered from the high speed video camera and force plateThe camera used was a Photron SA1 colour camera with a 1024x1024 resolution, sampling at 50 frames per second (fps). Automated vision processing was used to track wearable LED markers placed on body key body landmarks, for example, the hip. This was done via spatial thresholding algorithms, developed in Matlab. An underwater bullet CCTV camera sampling at 25 fps was also used. Vision data was used to supplement the data gathered from the WSN, allowing stroke recognition and real-time analysis of the accelerometer signal.

For many low-g (<2g) inertial sensing applications the signal-to-noise ratio is low and thus any un-modelled error in the physical parameters undermine the effectiveness of the intended application over time (Ang, 2004). A common method to minimize the errors associated with the accelerometer signal is the use of filtering (see for example Koukoulas 2005, Jo 2004, Hernandez 2000). For the current system a low-pass finite impulse response (FIR) filter was implemented to filter out frequencies greater than a pre-defined threshold while retaining the low frequency components (Ketharnavaz, 2005). Filtering also reduces the errors associated with integration of a signal, in this case integration of the accelerometer data in order to obtain velocity and double integration to obtain position. Edwards (2005) demonstrated that seemingly small aliased content could cause appreciable errors in the integrated waveforms.

The raw accelerometer values were fed into a real-time Butterworth filter and signal processing equations, which were embedded onto the node. This enabled analysis to take place robustly, in real-time, so that the results could be sent directly from the node rather than sending raw data. This was preferable because the raw data file was large and therefore filled the available bandwidth. A low pass Butterworth filter was chosen to smooth the data collected and to minimize the noise components of the signal. It was chosen over a Chebyshev filter due to its ability to be implemented in real time and embedded on the sensor node. Lap count identification was automatically determined by setting a low filter frequency on the Butterworth filter and using a 'zero crossing' algorithm. Signal processing algorithms were developed to analyse filtered data, including a 'zero crossing' algorithm to determine the stroke durations and stroke rates, which were identified to be the variables of most interest to the end users. Pulse analysis of the filtered data was also calculated and used to determine the rise and fall times of each stroke. Circular buffers were used to allow real-time implementation of the filter and signal processing algorithms.

A wireless audio communication module was attached to the swimmer and a UART interface to the host device was used to configure the module operation and then transfer data between the host and the communication end-point via the wireless interface. Once the devices were connected the coach used the microphone input to provide feedback to the swimmer (who wore earphones attached to the wireless module) on their performance throughout their training. The module transmitted wirelessly up to a depth of 10cm over a distance of more than 50m underwater.

3 RESULTS

Initially the results are used to highlight the implementation of the synchronised system and data capture. The filtering technique used on the synchronised data is then considered. Finally determination and analysis of the stroke characteristics from the filtered data are reviewed.

The TTL trigger function embedded on the sensor node was used to capture data simultaneously from the force measurement platform, the high speed video camera and the sensor node. These data can be seen in Figure 2. The high speed video was used to supplement the data gathered from the force platform and allowed determination of the key points that occurred during the dive, for example, time of back foot leaving the force platform. The times on the video were correlated with those of the accelerometer data, identifying time to entry, the point where the stroke was initiated and the time at 15m (where the start officially ends). In addition, the WSN was used to consider elements such as lap count, stroke rate, stroke duration in free swimming and to distinguish the different phases of the turn.

Initially a Butterworth filter was used to ascertain the lap count of the swimmer. Setting a low filter frequency achieved this. A comparison of the raw unfiltered data and the real-time embedded filtered data on 4 lengths of front crawl stroke can be seen in Figure 3. The largest peak in the data was identified as the swimmer's turn at the wall at the halfway point. By setting a threshold the filter and signal processing algorithms were used to pick out the lap count. For these data the four laps were identified.

Different filter frequencies were required for the different swimming strokes. In order to retain the peaks in the breaststroke and butterfly data a higher cut off frequency was used. The signal processing technique used for one length of front crawl can be seen in Figure 4. It was found that pre processed data could be analysed to establish timing information, stroke count, stroke durations, rise times and fall times. This analysis may then be collated to give an indication of the swimmers performance. Four 100m trials have been analysed

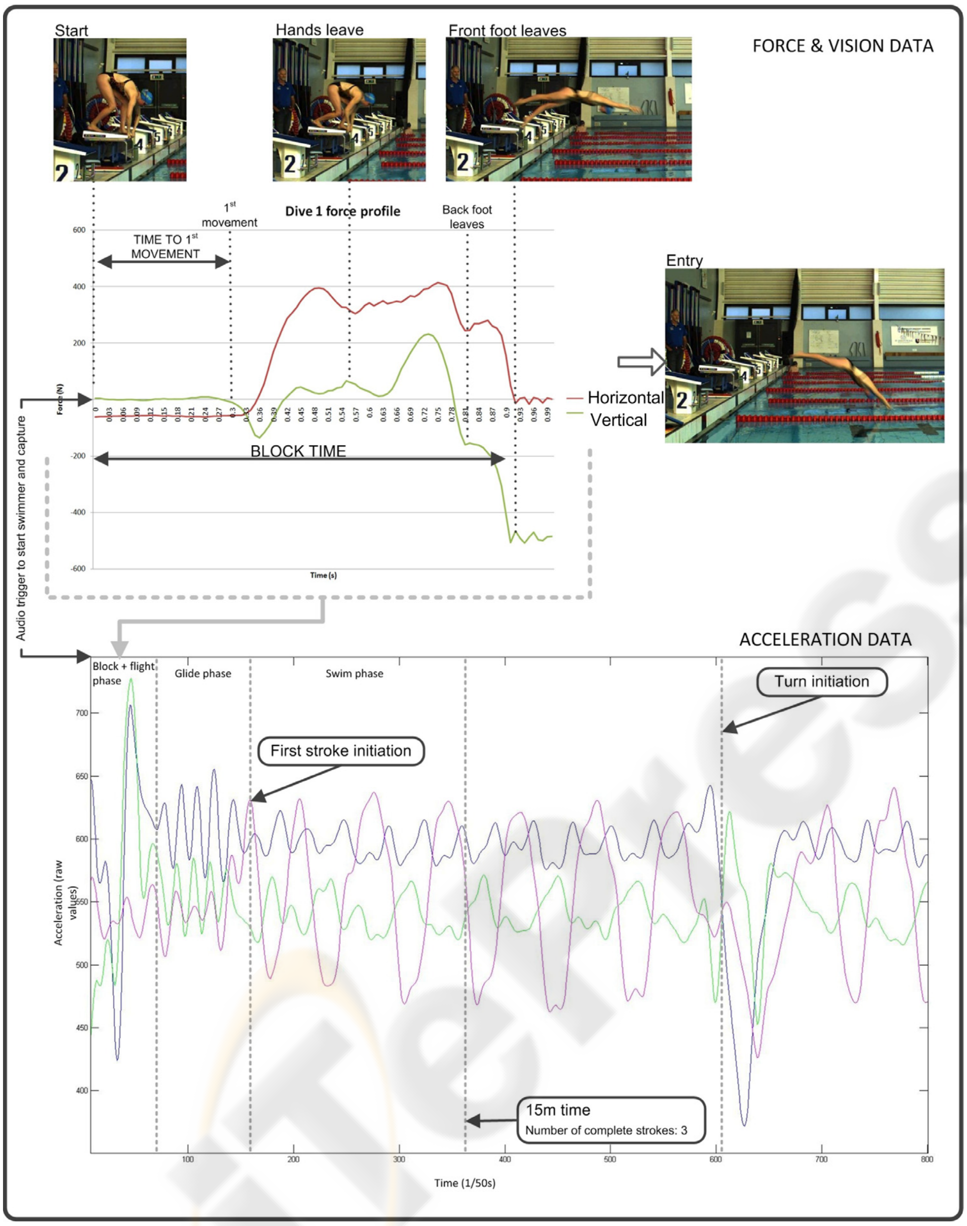


Figure 2: Integrated system for starts.

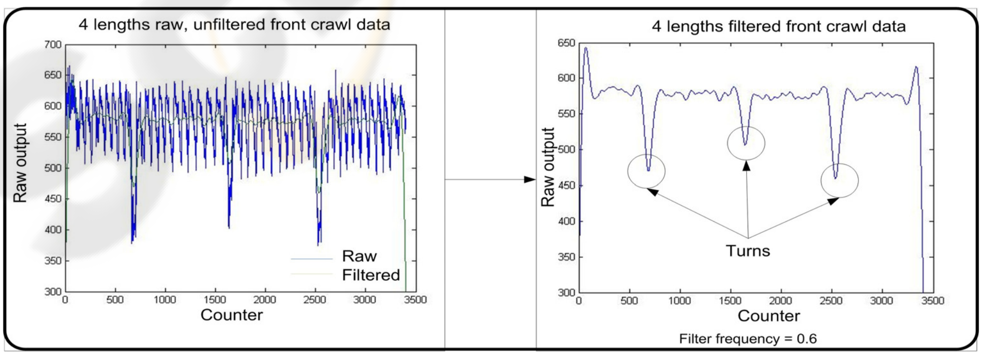


Figure 3: Butterworth filter on 4 lengths of front crawl data.

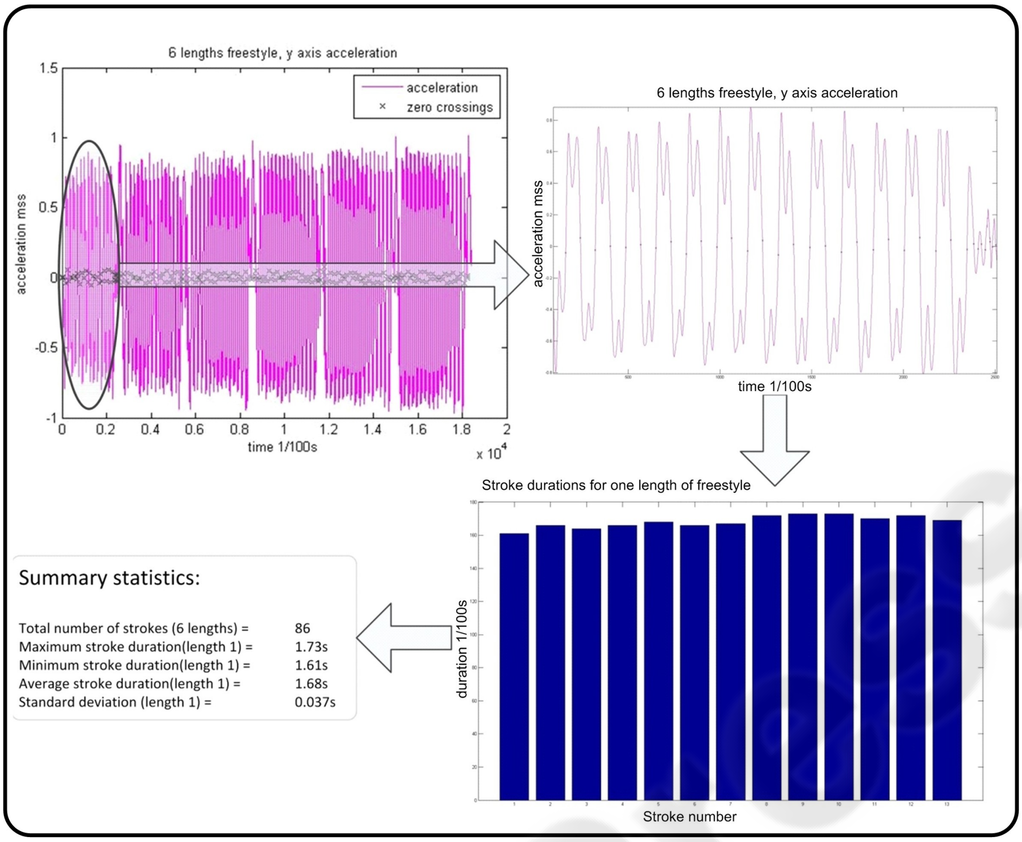
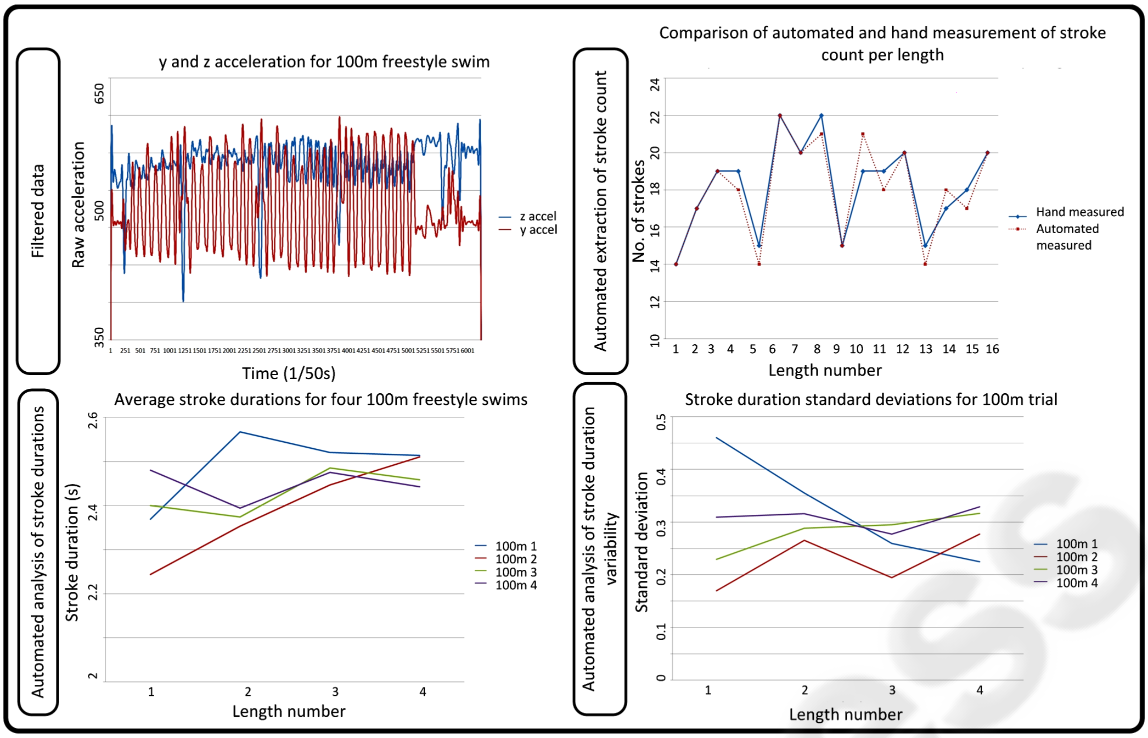


Figure 4: Analysis of the front crawl stroke using video and accelerometer data.

to derive all of the discussed parameters, Figure 5. Automated timing was found to be within 1 second of hand timing on average. Hand timing is undesirable since it is subject to human judgement and variability and cannot be readily scaled to support the monitoring of multiple swimmers in training sessions. Average stroke durations gave an idea of a swimmer's typical stroke and provided a measure to determine if they had changed their technique.

The underwater video camera was used to chracterise phases of the turn with the accelerometer data. The x axes represented the forward motion, the y axis the roll of the swimmer laterally and the z axis the vertical movement of the swimmer. On the swimmer's approach to the wall the acceleration in the z axis remained fairly constant. When the swimmer initiated the turn the z axis rotated through 90 degrees, which meant that the x axis experienced the major gravity component and the z axis tended towards zero. When the swimmer turned onto their back the z component experienced a negative contribution from gravity. As the swimmer turned back onto their front the z acceleration returned to fluctuating about 1g. This process can be seen from the video and accelerometer data in Figure 6.

A comparison of manual and automatic tracking was carried out to determine the efficiency of the automated code. The time it took to analyse one 100m IM manually, i.e. to determine lap count, stroke rate, stroke duration and rise and fall times, was approximately 45 minutes. An elite swimmer swims around 4-6km in a two hour session. If each length was analysed for the parameters discussed it would take up to 45hours to analyse one swimmer's two hour training session! The embedded coding enabled these same values to be obtained in real-time throughout the swimmer's training session.



Filtered data
y and z acceleration for 100m freestyle swim
Raw acceleration
650
500
350
z accel
y accel
Time (1/50s)
Automated extraction of stroke count
Comparison of automated and hand measurement of stroke count per length
No. of strokes
Hand measured
Automated measured
Length number
Automated analysis of stroke durations
Average stroke durations for four 100m freestyle swims
Stroke duration (s)
100m 1
100m 2
100m 3
100m 4
Length number
Automated analysis of stroke duration variability
Stroke duration standard deviations for 100m trial
Standard deviation
100m 1
100m 2
100m 3
100m 4
Length number

4 CONCLUSIONS

A multimedia system and signal processing techniques for monitoring swimmer performance has been presented in this paper. It provides a significant advantage over current methods used because it allows results from multiple components to be integrated and analysed simultaneously in real-time. The signal processing techniques used on the accelerometer offer feedback to swimmers in real-time and parameters are derived automatically on the sensor node.

5 FUTURE WORK

An inertial navigation system (INS) will be used in which measurements from embedded accelerometers and gyroscopes will be used to track the position and orientation of a swimmer relative to a known starting point, orientation and velocity. An INS comprising of a tri-axis accelerometer and a tri-axis gyroscope, measuring angular velocity and linear acceleration respectively, will be attached as a strapdown system to a swimmer. By processing signals from these devices it is possible to track the position and orientation of a device (Woodman, 2007). The output of the gyroscope provides the attitude of the swimmer. Strapdown navigation equations will be used to combine the accelerometer and gyroscope data, compensating for the effect of gravity on the system. The output will then be integrated twice (once in order to obtain velocity, and again in order to obtain position).

The results from the IMU will then be fed into an extended Kalman filter. The Kalman filter combines noisy sensor outputs to estimate the state of a system with uncertain dynamics (Grewal, 2007). The noisy sensors in this research will be INS accelerometers and gyroscopes. The system state includes position, velocity and attitude rate of the swimmer. It also includes the accelerometer and gyroscope biases and scale factors. The uncertain dynamics includes unpredictable disturbances of the swimmer, for example, waves in the water. A GPS receiver may be used to calibrate the system initially (before the swimmer enters the building), increasing the accuracy of the initial error predictions.

The integrated system will be presented in a graphical user interface (GUI) thus allowing the coaches and swimmers to visualise the results with ease, allowing unique insight into the skill and performance capabilities of elite swimmers.

REFERENCES

Ang, W., 2004. Physical model of a MEMS accelerometer for low-g motion tracking applications. *Proceedings of the 2004 IEEE International Conference on Robotics and Automation*. New Orleans, LA.

Arellano, R., et al., 2005. A comparison of CMJ, simulated and swimming grab-start force recordings and their relationships with the start performance. *Proceedings of XXI International Society of Biomechanics in Sport.* China

Brown, R., Hwang, P., 1992. *Introduction to random signals and applied Kalman filtering.* John Wiley & Sons, Inc.

Davey, N., 2005. An accelerometer-based system for elite swimming performance analysis. *Proceedings of SPIE the International Society for Optical Engineering.,* vol. 5649, no. 1.

Edwards, T., 2005. Effects of aliasing on numerical integration. *Mechanical systems and signal processing,* vol. 21. Elsevier.

Galbraith, H., et al., 2008. Biomechanical comparison of the track start and the modified one-handed track start in competitive swimming: an intervention study. *Journal of Applied Biomechanics,* vol. 24.

Grewal, M., 2007. *Global positioning systems, inertial navigation, and integration*. Hoboken, New Jersey. John Wiley & Sons, Inc.

Hernandez, W., 2000. Improving the response of an accelerometer by using optimal filtering. *Sensors and actuators A,* vol. 88. Elsevier.

Jo, G., 2004. Underwater navigation system with velocity measurement by a receding horizon Kalman filter. *Seiken symposium conference 38,* vol. 3.

Ketharnavas, N., 2005. *Real-time digital signal processing*. Bulington, MA, USA. Elsevier.

Koukoulas, T., 2005. Binary low, high and band pass amplitude filters will full and quantized phase in the presence of disjoint noise. *Lasers in Engineering.* Old City Publishing Inc, vol. 15.

Maglischo, E., 1993. *Swimming even faster.* Mountain View, CA. Mayfield Publishing Company.

Mason, B., et al., 2007. A kinematic analysis and recommendations for elite swimmers performing the sprint start. *Proceedings of XXV International Society of Biomechanics in Sport.* Brazil.

Ohgi, Y., 2002. Microcomputer-based data logging device for accelerometry in swimming. *Engineering of Sport.,* vol.4.

Quintic Consultancy Ltd. *Putting sports science into practice.* Available: http://www.quintic.com [Accessed: 10th October 2009]

Woodman, O., 2007. An introduction to inertial navigation. *Technical Report,* no. 696. University of Cambridge.