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Development of a real time system for monitoring of swimming performance

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Abstract

This research was conducted to allow real-time transmission, processing and presentation of data to swimming coaches and subsequently their swimmers in a training environment. This was done using an integrated system which comprised of a wireless sensor node, vision components and both force and pressure measurement technologies. Filtering approaches and signal processing algorithms were used to allow real-time data analysis on the node. Immediate feedback to the coach and sports scientist on poolside allows for a swimmer to be given quantifiable coaching tips and enables them to adjust their performance based on the results obtained. The system has reduced the time for processing acquired data and has delivered novel monitoring devices suitable for the harshness of the pool environment.

Keywords: swimming; embedded programming; real-time; stroke recognition

1. Introduction

The four competition strokes in swimming can be identified as front crawl, butterfly, backstroke and breaststroke. These strokes can be characterized by four basic sweeps of competitive swimmers' arms [1]:

- Outsweep: initial underwater sweep in butterfly and breaststroke
- Downsweep: initial underwater sweep in front crawl and backstroke
- Insweep: second sweep used in all competitive strokes
- Upsweep: final sweep of front crawl and butterfly

The relative durations of each phase alter depending on the duration of the swim, the amount of fatigue experienced by the swimmer and on the stroke being used.

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Research has been conducted in a number of areas to enable analysis of the swimming stroke. In swimming, velocity depends on stroke rate and stroke length (the number of metres the swimmer's body moves forward during each stroke cycle, measured in metres per stroke cycle). Maglischo produced typical velocity profiles of a swimmer's hand for each individual stroke [1]. Seifert used such profiles to identify that an abrupt change in the coordination pattern of the front crawl occurred at the critical velocity of 1.8m/s, which corresponds to the 100m pace for elite swimmers, and at this stage they switch from catch-up (which consists of a lag time between the propulsive phases of the two arms) to relative opposition (i.e. one arm begins the pull at exactly the same time as the other finishes the push phase) [2]. Thompson used velocity profiles to demonstrate that as the pace of breaststroke trials increased, the stroke rate was found to increase proportionally with stroke count [3]. All of these studies have focused on post processing of the data rather than in real-time.

The majority of methods used to analyse swimming technique are vision based or sensor based systems. Quintic is an example of vision-based software where the analyst uses a pre-recorded video file and then manually digitizes key occurrences within the recording [4]. The disadvantages of this and other such systems are the parallax errors induced by the use of video cameras, inaccurate measurements due to light reflection on the water surface and the large amount of time it takes to process the data. Manual digitization is a time consuming process and does not allow real-time feedback to the coaches or swimmers. Wireless sensor devices have also been developed for use in a swimming environment. An example of this was presented by Davey [5], where a system was developed using a tri-axis accelerometer to monitor stroke technique. An algorithm was determined which allowed a positive peak to be counted when a maximum occurred, and which stated that another maximum couldn't occur until a minimum had been counted. Ohgi used a similar system to measure wrist acceleration of swimmers [6]. Although both these systems used sensor devices for monitoring the swimmer, neither used a wireless sensor network (WSN) nor embedded processing to analyse the stroke technique in real-time. Both systems used a data logging accelerometer to capture the data, which meant that the data could not be viewed in real time. These systems focus on post processing that increases the analysis time significantly and subsequently coaches are unable to offer immediate feedback to the swimmers based on these data.

The research presented within this paper has been carried out at Loughborough University, UK, and has been based upon real-time monitoring of elite athletes in water. An initial feasibility study was conducted, considering a variety of different sensing and measurement devices and an integrated system was constructed to capture the data. The system was comprised of a WSN, a vision analysis system using real-time image processing, and both force and pressure measurement technologies. Force transducers have been embedded into a swimming start block and pressure transducers into a pad which can be attached to the pool walls. The focus of the current paper was the development of the node that was developed in-house and based upon the identified user-requirements. In accordance with these requirements, the node included a tri-axis accelerometer and a dual-axis gyroscope. It was developed to provide real-time data feedback to the poolside for ongoing analysis, and it was designed to be as non-invasive to the swimmers as possible. It was developed to operate as a network of nodes to allow analysis of multiple swimmers performance during a training session. The prototype node was packaged to ensure it was waterproof for the application. Initial validation testing was then carried out at the pool. A Butterworth filter and signal processing algorithms were embedded onto the node that allowed the coach to extract useful data with regards to each individual swimmer's performance. These algorithms provided the coach with the stroke rate, stroke duration and lap count of the swimmer.

2. Methods

To develop the WSN a suitable Microcontroller (MCU) with integrated transceiver was chosen. The transmission range was tested in water and shown to be robust upto 35m at 25cm depth, which was found to be suitable for the application. The integrated MCU contained an in-built wireless protocol stack used for the development presented within this paper. The topology of the chosen network architecture was a star configuration with multiple sensor nodes acting as End Devices (ED) and a single coordinator node or Access Point (AP). The sensor nodes transmit the data at a configurable sampling rate (currently set to 50Hz) with 10bit resolution. The current protocol is based on a single-hop network, which has been adapted for the swimming application. The protocol stack is presented in Figure 2.

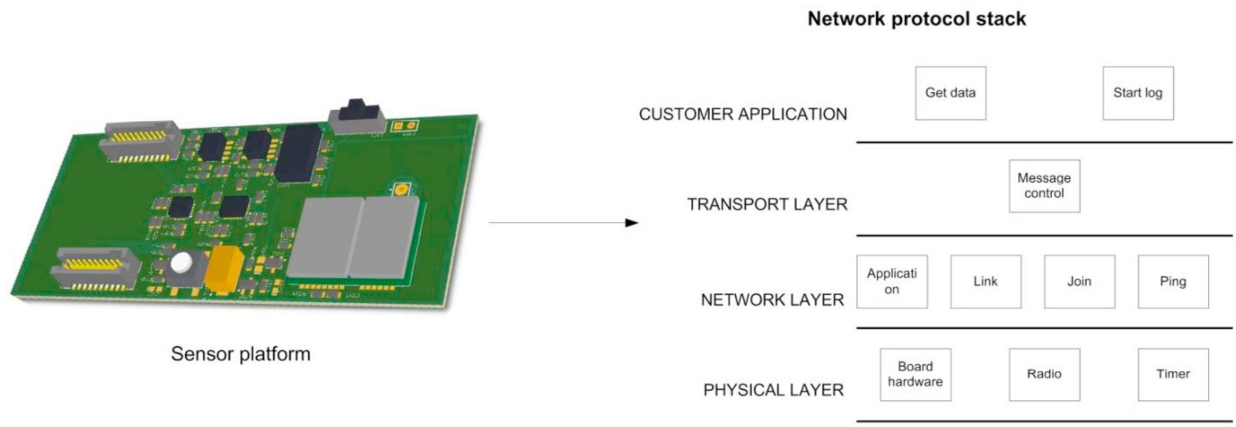

Fig. 2. The network protocol that has been adapted for the swimming application.

The board hardware consists of a radio, microprocessor and general purpose inputs/outputs (GPIO). The MCU was chosen due to its low power consumption, built in memory and processing power. The network applications on the ports are *objects* used to manage the network. The Ping application detects the presence of a specific device. It sends a message from one device to another. The receiver echoes the payload contents back to the transmitter. A timeout parameter is also applied [7]. The link application is the means by which an application connection is established. Once the link has been established the ED can send messages to the AP. When the network has an AP, each device must join the network. Upon joining, a device is supplied with an encryption context to prevent intrusion by rogue devices, and a join token to ensure that, when there are two APs, that they do not both respond to a new device trying to join a network [7].

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 [8]. A common method to minimize the errors associated with the accelerometer signal is the use of filtering [9, 10, 11]. A low-pass finite impulse response (FIR) filter was designed to filter out frequencies greater than a pre-defined threshold and retain the lower frequency components [12]. 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 [13] demonstrated that seemingly small aliased content could cause appreciable errors in the integrated waveforms. Testing was accomplished with the accelerometer by positioning it stationary on a flat, vibration isolated surface, which allowed determination of the noise components present.

The accelerometer was placed onto a swimmer's back and the raw accelerometer values were fed into a real-time Butterworth filter and signal processing equations. The filter was implemented to enable the analysis to take place robustly, in real-time, so that the results of the analysis could be sent directly from the node rather than the raw data. This is particularly important because the raw data file is large and fills the available bandwidth too quickly for a whole squad of swimmers to be analysed simultaneously. 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 to avoid ripples in the passband. Its low filter order allowed it to be approximated to real time and embedded on the sensor node. The coefficients for the filter were determined and fed into the equation in Figure 3, where *bi* and *aj* are the coefficients of the Butterworth filter, *X(n)* are the raw data values and *y(n)* are the previously filtered values. Circular buffers were used to allow real-time implementation of the filter. The filtered data was then used to implement the signal processing algorithms. A zero crossing algorithm was used to determine the stroke durations and stroke rates, which were identified to be the variables of most interest to the end users. The maximum values of the filtered data were also calculated and were used to determine the rise and fall times of each stroke. The process used to convert the raw data through to the output parameters can be seen in Figure 4.

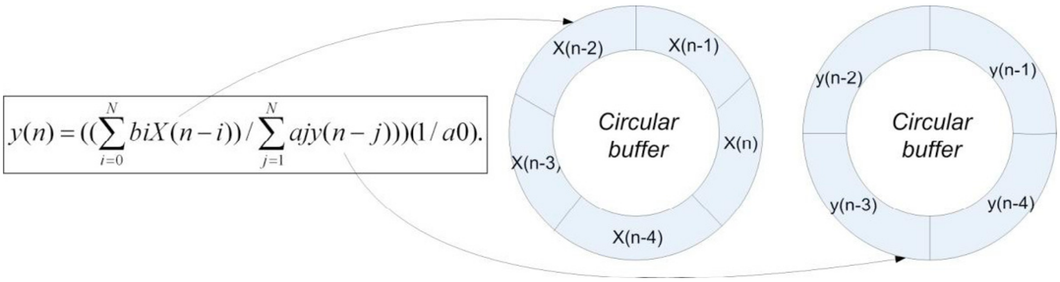

Fig. 3. Filter process.

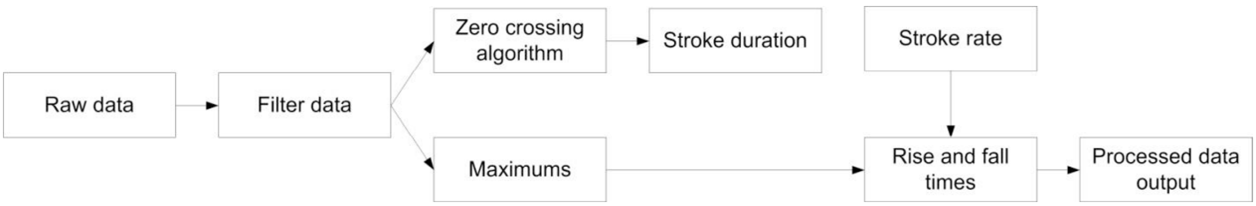

Fig. 4. Processing path of raw data through to the output parameters.

The WSN was developed as a platform to support integrated real time data capture on swimming performance. As mentioned previously, the WSN is part of a larger system with additional functionality in the form of vision components (high speed video) and both force and pressure measurement using appropriate transducers. The WSN was synchronized to these components using a trigger. The function was implemented in the embedded programming which sent an interrupt to the AP when the trigger was enabled. Sending a TTL signal to a port on the AP triggered the system. The embedded code initialized the trigger, starting the trigger on the rising edge of the signal. The synchronized system can be seen in Figure 5 and has been used to determine the characteristics of an accelerometer trace based on data gathered from the high speed video camera and a force plate.

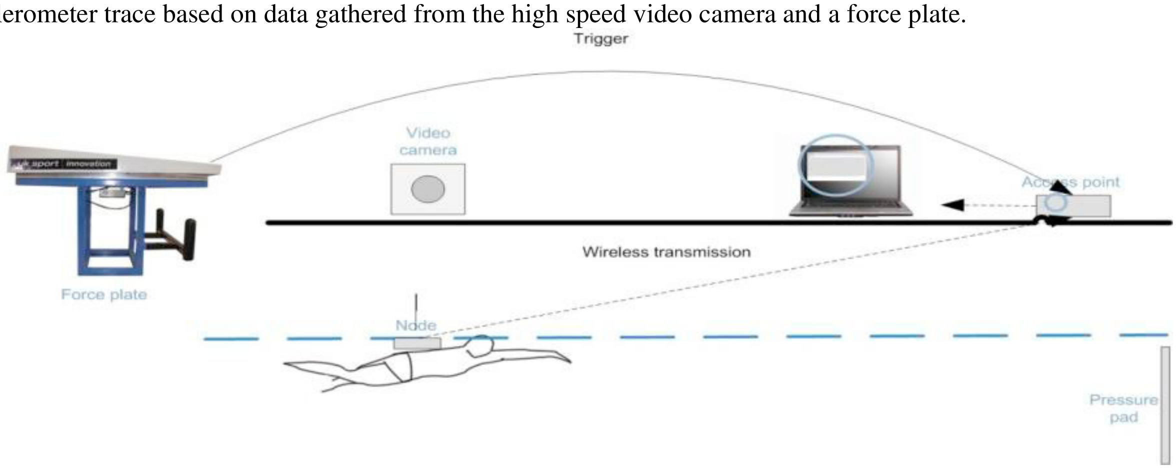

Fig. 5. Integrated system.

3. Results

Initially the 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 6.

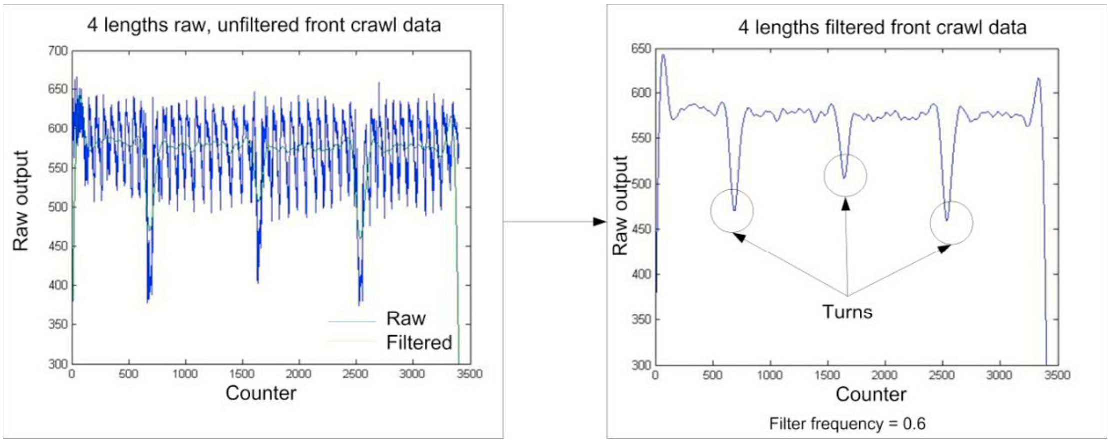

Fig. 6. Butterworth filter on 4 lengths of front crawl acceleration data.

The lowest values of minimum relative peaks in the data have been identified as the swimmer's turn at the wall at the halfway point. The sharp drops at the beginning and the end of the data occur due to the filtering applied to the window. By setting a threshold the filter and signal processing algorithms were used to pick out the lap count. For these data above the lap count was identified as 4. Different filter frequencies were required for the different swimming strokes. For front crawl and backstroke a cut-off frequency of 2Hz was used whereas for breaststroke and butterfly higher cut-off frequencies were required. This is because when a cut-off frequency of 2Hz was used for breaststroke and butterfly the data was smoothed too much. The filter implementation on different strokes using different frequencies can be seen in Figure 7.

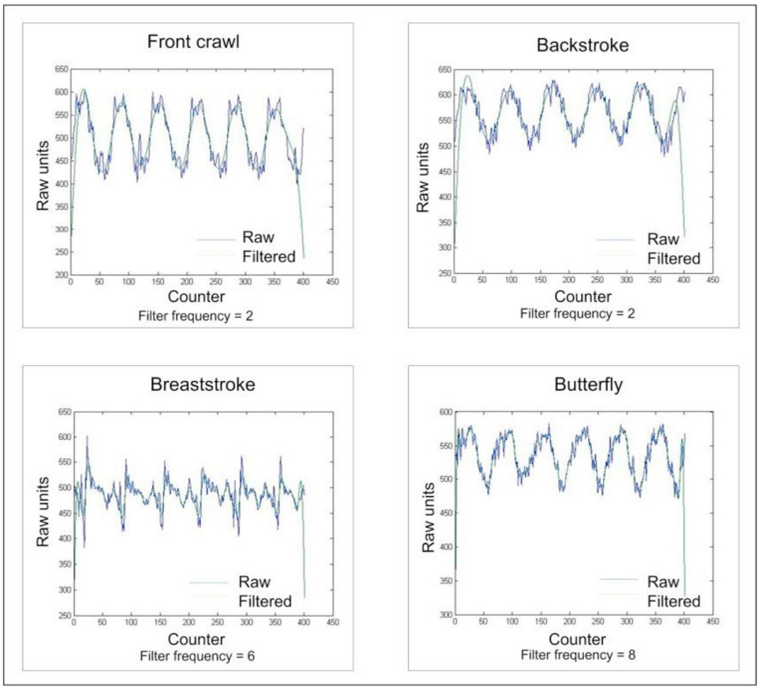

Fig. 7. Butterworth filter on 5 or 6 strokes of front crawl, backstroke, breaststroke and butterfly data.

The relative stroke durations for one length of front crawl, which were calculated using the zero crossing algorithms, can be seen in Figure 8. Algorithms were also used to calculate the stroke rate and rise and fall times of each stroke. Thresholds were set to determine minimum and maximum acceptable values for the stroke duration. Values that fell outside of these thresholds were omitted.

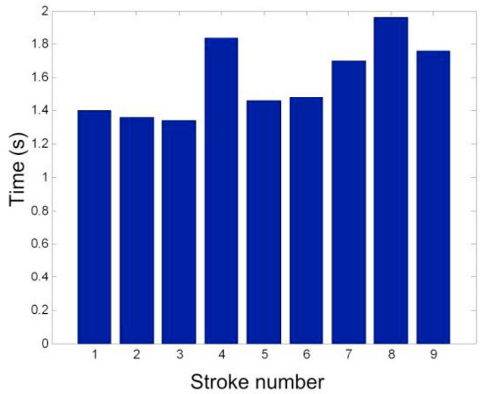

Fig. 8. Stroke durations for one length of front crawl.

4. Conclusion

This paper presents a novel approach to monitoring swimming performance based on the use of a WSN with embedded real-time filtering and signal processing. It is advantageous over current analysis techniques because they do not offer feedback to swimmers in real-time and must be manually processed in order to determine the stroke characteristics of each swimmer. The research completed at Loughborough University provided a method for allowing swimmers to obtain feedback with regards to their performance in real-time. It was based on the user requirements and the objective to save time during analysis. It does not replace the role of the coach but aids them in their analysis of swimmers' strokes. The results from the testing have shown that the Butterworth filter can be implemented in order to minimize the noise components of the signal. It allowed smoothing of the data that in turn allowed accurate determination of the stroke characteristics of the swimmer. Ongoing and future work involves additional validation tests to ensure that the signal processing algorithms are representative of different swimmers and all the different competition strokes. Further development of the integrated system is also required to include pressure measurement technologies, predominantly for turns analysis.

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