Thesis Access Form

Copy No…………...…………………….**Location**……………………………………………….……………...…

Author…SIÂN SLAWSON…………………………………………………………...…….

Title…A NOVEL MONITORING SYSTEM FOR THE TRAINING OF ELITE SWIMMERS

Status of access ~~OPEN~~ / RESTRICTED / ~~CONFIDENTIAL~~

Moratorium Period: 5 years, ending MAY/2015

Conditions of access approved by (CAPITALS):…………………………………………………………………

Supervisor (Signature)…………………………………………...…………………………………...

Department of Mechanical and Manufacturing Engineering

Author's Declaration: *I agree the following conditions:*

Open access work shall be made available (in the University and externally) and reproduced as necessary at the discretion of the University Librarian or Head of Department. It may also be digitised by the British Library and made freely available on the Internet to registered users of the EThOS service subject to the EThOS supply agreements.

*The statement itself shall apply to **ALL** copies including electronic copies:*

This copy has been supplied on the understanding that it is copyright material and that no quotation from the thesis may be published without proper acknowledgement.

Restricted/confidential work: All access and any photocopying shall be strictly subject to written permission from the University Head of Department and any external sponsor, if any.

Author's signature…………………………………….Date…………………………………...…………...……...

users declaration: for signature during any Moratorium period (Not Open work): ***I undertake to uphold the above conditions:***			
Date	Name (CAPITALS)	Signature	Address

A NOVEL MONITORING SYSTEM FOR THE TRAINING OF ELITE SWIMMERS

A Doctoral Thesis Submitted in Partial Fulfilment of the Requirements for the Award of Doctor of Philosophy of Loughborough University

By

Siân Slawson

Wolfson School of Mechanical and Manufacturing Engineering
Loughborough University
United Kingdom
March, 2010

Certificate of Originality

This is to certify that I am responsible for the work submitted in this thesis, that the original work is my own except as specified in the acknowledgements or in footnotes, and that neither the thesis nor the original work contained therein has been submitted to this or any other institution for a higher degree.

.... (Signed)

.... (Date)

Abstract

Swimming performance is primarily judged on the overall time taken for a swimmer to complete a specified distance performing a stroke that complies with current regulations defined by the Fédération Internationale de Natation (FINA), the International governing body of swimming. There are three contributing factors to this overall time; the start, free swimming and turns. The contribution of each of these factors is event dependent; for example, in a 50m event there are no turns, however, the start can be a significant contributor. To improve overall performance each of these components should be optimised in terms of skill and execution.

This thesis details the research undertaken towards improving performance-related feedback in swimming. The research included collaboration with British Swimming, the national governing body for swimming in the U.K., to drive the requirements and direction of research. An evaluation of current methods of swimming analysis identified a capability gap in real-time, quantitative feedback. A number of components were developed to produce an integrated system for comprehensive swim performance analysis in all phases of the swim, i.e. starts, free swimming and turns. These components were developed to satisfy two types of stakeholder requirements. Firstly, the measurement requirements, i.e. what does the end user want to measure? Secondly, the process requirements, i.e. how would these measurements be achieved? The components developed in this research worked towards new technologies to facilitate a wider range of measurement parameters using automated methods as well as the application of technologies to facilitate the automation of current techniques. The development of the system is presented in detail and the application of these technologies is presented in case studies for starts, free swimming and turns.

It was found that developed components were able to provide useful data indicating levels of performance in all aspects of swimming, i.e. starts, free swimming and turns. For the starts, an integrated solution of vision, force plate technology and a wireless

node enabled greater insight into overall performance and quantitative measurements of performance to be captured. Force profiles could easily identify differences in swimmer ability or changes in technique. The analysis of free swimming was predominantly supported by the wireless sensor technology, whereby signal analysis was capable of automatically determining factors such as lap times variations within strokes. The turning phase was also characterised in acceleration space, allowing the phases of the turn to be individually assessed and their contribution to total turn time established. Each of the component technologies were not used in isolation but were supported by other synchronous data capture. In all cases a vision component was used to increase understanding of data outputs and provide a medium that coaches and athletes were comfortable with interpreting.

The integrated, component based system has been developed and tested to prove its ability to produce useful, quantitative feedback information for swimmers. The individual components were found to be capable of providing greater insight into swimming performance, that has not been previously possible using the current state of the art techniques. Future work should look towards the fine-tuning of the prototype system into a useable solution for end users. This relies on the refinement of components and the development of an appropriate user interface to enable ease of data collection, analysis, presentation and interpretation.

'I'd rather be surfing'

Acknowledgements

There are so many people who have contributed to the last 3 (and a half!) years of my life, and consequentially my PhD. First I must thank my supervisors Andy West and Paul Conway. Andy, thank you for being completely passionate about what you do, I couldn't have got to where I am if I hadn't been working with someone who really cares about what they're doing and the team they are part of. Thanks for expecting nothing but the best, for giving me a kicking when I needed it and for giving me the flexibility and trust to do it my way. At times it has been tough, but I wouldn't have had it any other way. Paul, thanks for being there when the going got tough, you're support in the last few months has been invaluable and I appreciate it more than you know.

I would like to thank all of members of the Sports Technology Research 'family', having such a knowledgeable and tight-knit group around me has helped me every step of the way. Equally I must thank 'the team', you know who you are, if in doubt I have always been able to turn to you for honest and straightforward advice. A special mention must go to the boys in the workshop, Rue, Simon, Steve and now Max, what can I say, you have made my job as a researcher infinitely easier. You have come to the rescue when I have needed it the most, I am so lucky to have had your expertise at my disposal.

A big thank you must go to the people who believed enough to fund my research: EPSRC, IMCRC, Wolfson School of Mechanical and Manufacturing Engineering at Loughborough University, UK Sport and British Swimming. I would also like to personally thank the staff at British Swimming and the pool at Loughborough University for their patience during testing and efforts to facilitate our needs; I couldn't have achieved what I have without your help.

Finally I must thank my friends and family who have been there along the way. Thank you for being there, enduring my moans and being my distraction. Without our countless strumming sessions, cheeky pints and trips to the coast, I would never have kept the perspective, motivation and drive required to get to the end. Without you I'm nothing.

Contents

List of Tables

List of Figures

Publications arising from this work

Journal

Development of Feature Extraction Methodologies for Analysis of Swimming Performance: A Case Study to Identify the Phases of the Tumble Turn in Swimming, submitted to IMechE Part P, Journal of Sports Engineering and Technology, April 2010

Conceptualisation of a Component Based Analysis System for Swimming: An Example for the Swimming Start, submitted to IMechE Part P, Journal of Sports Engineering and Technology, April 2010

Development of a Novel Real-Time Wireless Data Communication System for Performance Analysis in Swimming, in preparation for publication in IMechE Part P, Journal of Sports Engineering and Technology [planned submission date June 2010]

Conference

S.E. Slawson, A.A. West, J.D. Smith, L.M. Justham, P.P. Conway, M.P. Caine, R. Harrison, *Accelerometer profile recognition of swimming strokes* Vol.1, pp 81-88, Proceedings of the International Sports Engineering Association (ISEA) 7th International Conference June 3 - 6, 2008, Biarritz, France

L.M. Justham, S.E. Slawson, A.A. West, P.P. Conway, J.D. Smith, M.P. Caine, R. Harrison, *Business Process Modelling and its use within an Elite Training Environment* Vol.1, pp 73-80, Proceedings of the International Sports Engineering Association (ISEA) 7th International Conference June 3 - 6, 2008, Biarritz, France

L.M. Justham, S.E. Slawson, A.A. West, P.P. Conway, J.D. Smith, M.P. Caine, R. Harrison, *Enabling technologies for robust swimming performance monitoring* Vol.1, pp 45-54, Proceedings of the International Sports Engineering Association (ISEA) 7th International Conference June 3 - 6, 2008, Biarritz, France

S.E. Slawson, A.A. West, L.M. Justham, P.P. Conway, T. Le-Sage, *Dynamic signature for tumble turn performance in swimming*, Proceedings of the 8th Conference of the International Sports Engineering Association (ISEA), 12th - 16th July 2010, Vienna, Austria [accepted]

S.E. Slawson, A.A. West, L.M. Justham, P.P. Conway, *The development of an inexpensive passive marker system for the under and over water analysis of starts and turns in swimming,* Proceedings of the 8th Conference of the International Sports Engineering Association (ISEA), 12th - 16th July 2010, Vienna, Austria [accepted]

T. Le-Sage, A. Bindel, P.P. Conway, L.M. Justham, S.E. Slawson, A.A. West, *Real-time Monitoring of Swimming Performance.* Proceedings of the 8th Conference of the International Sports Engineering Association (ISEA), 12th - 16th July 2010, Vienna, Austria [accepted]

J. Cossor, S.E. Slawson, A.A. West, L.M. Justham, P.P. Conway, *The development of a component based approach for swim start analysis* Biomechanics and Medicine in Swimming, 16th – 19th June 2010 [accepted]

T Le Sage, P Conway, L Justham, S Slawson, A Bindel, A West, *A Component Based Integrated System for Signal Processing of Swimming Performance.* International Conference on signal processing and multimedia applications, SIGMAP 2010-03-22 July 26-28 Athens, Greece [under review]

Chapter 1

1. QUANTIFICATION OF STAKEHOLDER REQUIREMENTS

Swimming is the number one participation sport in the UK [Mintel 2009]. Olympic success from the last three Olympiads has increased significantly from 0 medals in Sydney 2000, to 2 Bronze medals in Athens 2004 and most recently a total of 6 medals in Beijing 2008 (2 Gold, 2 Silver, 2 Bronze). This achievement, in addition to the upcoming Olympics in London, 2012, has given rise to an increased investment in the sustained development of the sport, especially at the elite level, to maximise podium success in 2012. To optimise performance, ongoing athlete monitoring is essential to enable the refinement of training strategies at all phases during the build up to the games.

The objective of the research presented in this thesis was to improve performance-related feedback in swimming. The project worked collaboratively with British Swimming, the national governing body for swimming in the U.K., to drive the requirements and direction of research. The primary aim to deliver on the research objective was to establish the feasibility of applying new technologies and methods in swimming performance analysis so as to facilitate the measurement of a greater range of quantitative performance parameters in a timely manner.

1.1 Chapter Overview

The requirements as specified by the swimming stakeholders (i.e. coaches, sports scientists and athletes) are presented within this chapter. These have been divided into measurement and process requirements. Measurement requirements pertain to the physical parameters that need to be measured. Process requirements refer to the way in which these measurements are obtained and processed.

1.1.1 Research Questions (RQs)

RQ1 Stakeholder requirements

a. What are the stakeholder requirements for the system?

b. What methods are currently used for performance analysis in swimming?

c. What are their limitations, with respects to the stated stakeholder requirements?

1.1.2 Chapter Structure

The current chapter, focussed on the stakeholder requirements of the research project, is structured as follows. Research is discussed within the context of an elite training environment, where inputs and outputs are used to optimise athlete performance. Measurement needs, as defined by the user, are specified for each phase of swimming, i.e. start, free swim and turn. Current methods of analysis are reviewed using CIMOSA modelling to evaluate what and how analysis is presently performed. Interviews with the end user are summarised to provide a list of “process needs”. These address the ideal way in which the end user would like systems to operate, for example in real-time. Finally core themes arising from the chapter are summarised.

1.2 Components of an elite athlete system

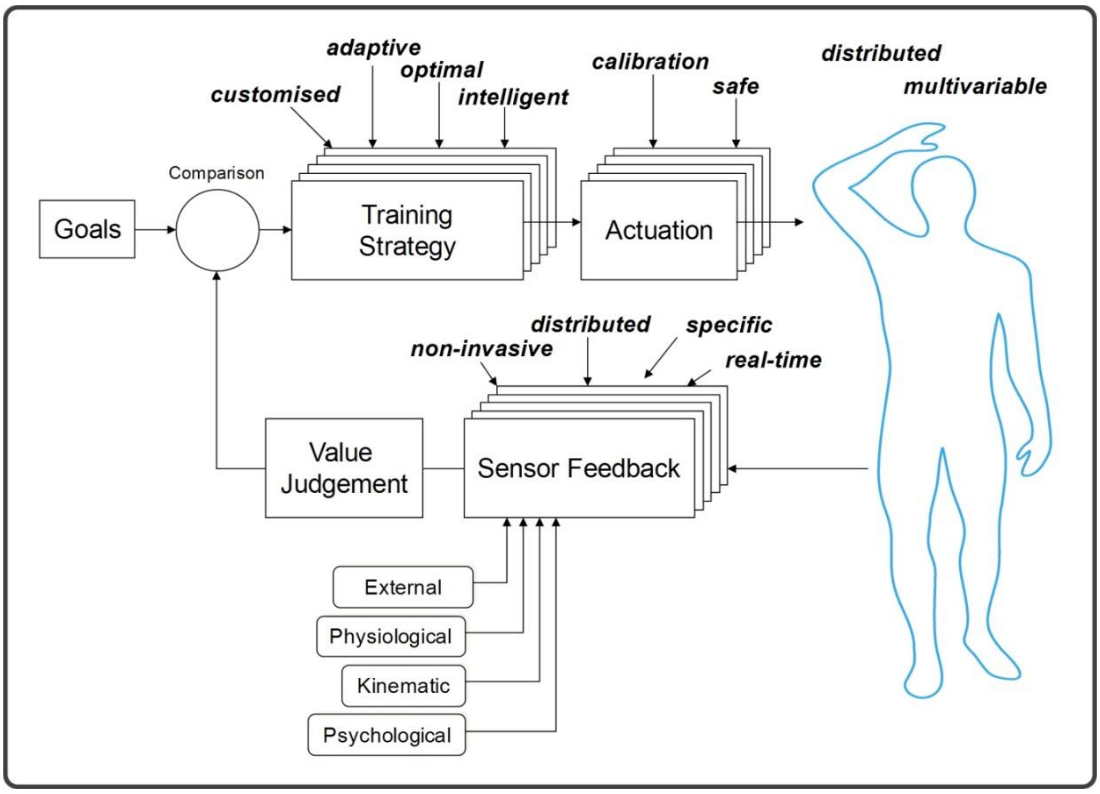


Figure 1-1: The elite athlete 'system'

An elite athlete is driven by quantifiable *Goals* based on their performance within their specific discipline. To reach these goals there are *Inputs* for the athlete, such as *Training Strategies* and *Outputs* from the athlete, which are the performance attributes that can be measured and monitored (via *Sensor Feedback*) to give an indication of capability (see Figure 1-1). These measured parameters may then be used to make *Value Judgements* on how best to adapt future strategies to optimise performance.

For an elite swimmer, goals will predominantly be based around achieving personal best times for their preferred event, at a particular date, e.g. for the Olympic Games. Due to: (i) the differences in the demands of events (e.g. distances (50m, 100m, 400m, 800m and1500m) and style (freestyle, backstroke, breaststroke, butterfly and medleys)), and (ii) the inherent capacity of each athlete, it is essential to customise and individualise training to optimise progress. Equally training strategies must be adaptive to accommodate changes in performance and ensure optimal progression, e.g. if a swimmer improves their times throughout training it is essential to adapt training strategies to maintain the overload level (whilst ensuring adequate rest and recovery is included), otherwise further improvements may not be achieved [McArdle et al, 2001]. *Actuation* in Figure 1-1refers to devices or technologies which may be used to provide a training stimulus for the athlete. For swimming these may be out of water devices such as weights or swimming ergometers [Vasa, 2010, Weba, 2010], whereas in water these could be, for example, snorkels or drag resistance devices. It is essential that these *Actuation* components are calibrated properly and tested to ensure that they are safe for the athlete to use.

The athlete/swimmer has been referred to in Figure 1-1 as a distributed and multivariable component to be actuated and monitored. In this context, distributed refers to a component which is not necessarily a singular object in one space, i.e. there may be multiple swimmers to consider and/or multiple components of a single swimmer. Multivariable describes the fact that there are a number of different variables that have been monitored to determine the performance capability of the athlete.

Sensor feedback provides information regarding athlete specific monitored variables. These variables have been broken into three core areas for consideration, namely, physiological, kinematic and psychological. In addition to these athlete parameters, external factors (e.g. the environment and the technology), also have to be monitored to ensure that information regarding athlete performance can be readily understood within the context of the performance (i.e. environment) and is complete, consistent and correct (i.e. technology). For a swimmer, the environment is relatively well controlled [fina.org, 2010] compared with a sport such as running where terrain, weather and altitude are all important factors that influence overall performance [Saunders et al, 2004, Ely et al 2007]. The most relevant external factors currently faced by swimmers relate to technological changes within the sport, namely swim suit technology and swimming start block form, both of which have experienced influential changes in the last two years [Omega (OSB11), 2010, Speedo, 2010].

Four key requirements have been identified as important features for successful athlete monitoring. Any technology and analysis must be: (i) minimally / non-invasive, (ii) distributed, (iii) sport specific and (iv) real-time. In swimming, aspects such as streamlining, body form and technique are essential for optimum performance and hence tools and technologies used for monitoring athlete performance variables must be non-invasive and non-encumbering to the athlete to minimise the impact on their overall performance. For a sports such as cycling, streamlining, body form and technique are also key contributing factors for performance, however, the presence of the bicycle and helmet mean that there are more available opportunities for implementing monitoring technologies without adversely affecting performance. For a swimmer, equivalent options are limited to direct mounting onto the athlete or within skin tight garments.

Monitoring of athlete performance has to be distributed, i.e. it should not be isolated to a one on one situation. Typical training scenarios involve a coach being required to monitor the timing performance of each of the athletes within their training group. At the elite level this equates to five to ten athletes. To achieve this a coach will have a stopwatch capable of timing multiple events (i.e. splits) for multiple athletes, requiring "distributed" monitoring capability at its most basic level. Note: A monitoring system capable of monitoring a single feature, such as timing, for a single athlete that is not capable of distributing the information cannot provide real-time feedback in a real life training scenario.

It is essential that monitoring is specific for the athlete and sport / event. In swimming, different measurement parameters will be more relevant for certain athletes depending on their strengths and weaknesses in their given event. For example in the 1500m event the swimmers ability to perform consistently when *turning* is essential, as with 14 turns this can greatly impact overall performance. However, for a 50m sprinter, (a race with no turns), optimising the starting performance is vital since small improvements (~1%) are significant when compared with typical winning margins. The information that has to be measured is predominantly driven by the coaches and sport scientists, who have "opinions" and "experiential knowledge" on how to improve overall performance for individual athletes. However to date, the ability to measure these parameters has been limited by capabilities of the technology that can perform within the harsh swimming environment.

Athletes are able to respond and adapt performance better if feedback to the athlete, for example regarding issues with their technique, is supplied at the time of the event [Kirby, 2009] and it has been found that supplementing verbal feedback with visual feedback increases an athlete's ability to effectively make changes [Hume, 2005, Tzetzis, 1999, Sanders, 1995]. For this reason is it a key requirement that feedback is supplied to the athlete as close to the time of observation as possible to optimise the adaptation possible the swimmer.

Based on the real-time observations, a coach, sports scientist or athlete can make timely judgements on swimmers progression and performance and hence more readily develop adaptive training strategies that focus the athlete on the optimum progression towards their goals.

1.3 Stakeholder measurement requirements

Table 1-1: Free swimming measurement parameter requirements

	Simple	Compound
Starts	• Time from gun to first movement • **Block time** • Angle of entry • **Time to entry** • Distance of entry • Maximum depth • Break out distance • Break out time • First stroke timing	• Velocity off blocks • Velocity of glide • Velocity at break out
Free swimming	• Stroke count • **Distance per stroke** • Stroke duration • Rotation during the stroke: longitudinal and vertical	• **Stroke rate** • Swimming velocity • Variations in velocity throughout a stroke cycle
Turns	• **Last stroke to wall timing** • Rotation information • **Time of wall contact** • Wall contact duration • Depth profile • Break out distance • First stroke timing	• Velocity into/out of the turn, also glide, start of initial swimming

Stakeholder requirements were derived via interviews, questionnaires and protocol analysis of key members of the British swimming team [Kerrison et al, 2007] (see Table 1-1). The outcome is a number of variables that British Swimming would ideally monitor during training sessions, if it were possible. These variables deal exclusively with the kinematic aspect of athlete performance monitoring. They have been divided into two subgroups (i.e. simple and compound) pertaining to each phase of swimming (i.e. start, free swimming and turns) (see Table 1-1). Firstly, *simple* measurements refer to “one dimensional” parameters such as time and distance. *Compound* measurements are predominantly concerned with velocities, which require a combination of simple measurements (e.g. time and distance) for their evaluation. Measurements that are currently routinely monitored (e.g. block time, time to entry, distance per stroke, stroke rate, last stroke to wall timing and time of wall contact) are highlighted in bold type in Table 1-1. It must be noted that significant manual effort is required to support the quantification of these parameter typically derived from the raw video data [Davey et al, 2008]

1.4 Evaluation of current performance analysis techniques using the CIMOSA reference architecture

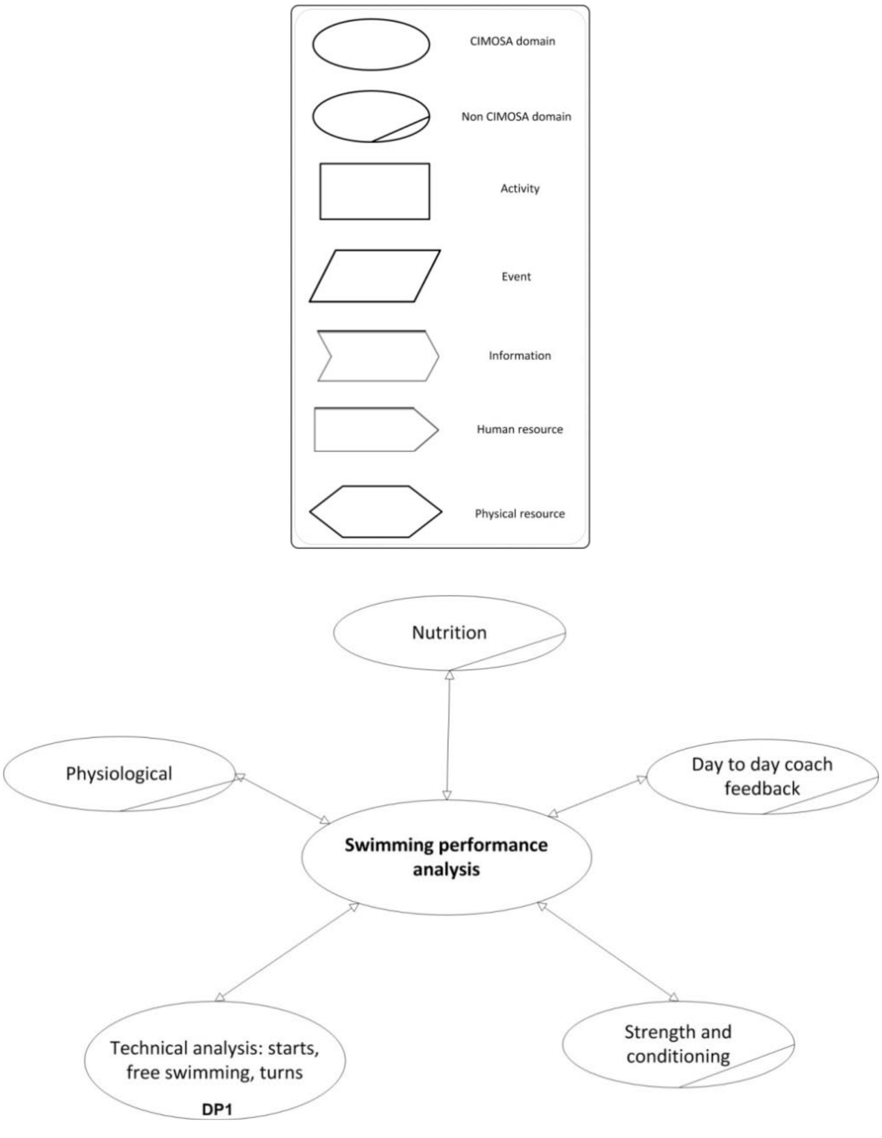


Figure 1-2: CIMOSA context diagram for swimming domain

In order to appreciate the current *AS-IS* performance monitoring processes, formal modelling of the activities, information, resource utilisation and organisation has been undertaken using the Computer Integrated Manufacturing Open System Architecture (CIMOSA) [ESPRIT Consortium, 1993]. The CIMOSA approach (usually utilised in enterprise modelling projects [Berio and Vernadat, 200, Rahimifard and Weston 2007]) was adopted over alternative modelling architectures (e.g. PERA, GERAM [IFAC-IFIP Task Force, 1999, Williams and Li, 1998]) since there is significant experience of its usage and value at Loughborough University in defining the requirements of sporting, healthcare and software systems [Justham et al, 2008, West et al, 2007].

CIMOSA was developed by the ESPRIT Consortium AMICE for enterprise modelling [ESPRIT Consortium, 1993]. The CIMOSA framework provides a language enabling end user domains to be modelled utilising a small set of core constructs representing, for example, activities, events, information, human resources and physical resources (see Figure 1-2). Complexity is addressed by structuring a hierarchical breakdown of the interactions of the constructs on a number of linked diagrams (e.g. context diagrams, structure, interaction [Monfared et al, 2002]). Lifecycle analysis can be readily accommodated within the CIMOSA architecture [Molina et al, 1998].

The CIMOSA context diagram supplies an overall vision of the core components (or domains) relating to swimming performance analysis (see Figure 1-2). The scope of this research is focussed on developing an ability to monitor the technical aspects of swimming (i.e. domain process (DP1)). Knowledge of the technical aspects is critical to supporting advances in the other components of analysis (e.g. physiological, strength and conditioning and nutrition) which will ultimately provide a complete picture of a swimmers performance and optimised training strategy.

There are three main elements contributing to technical aspects of swimming performance analysis: starts, free swimming and turns. The aim of this research is to establish robust testing technologies and protocols to accommodate analysis in all of these elements to enrich current knowledge of performance and technique and how they can impact on overall performance.

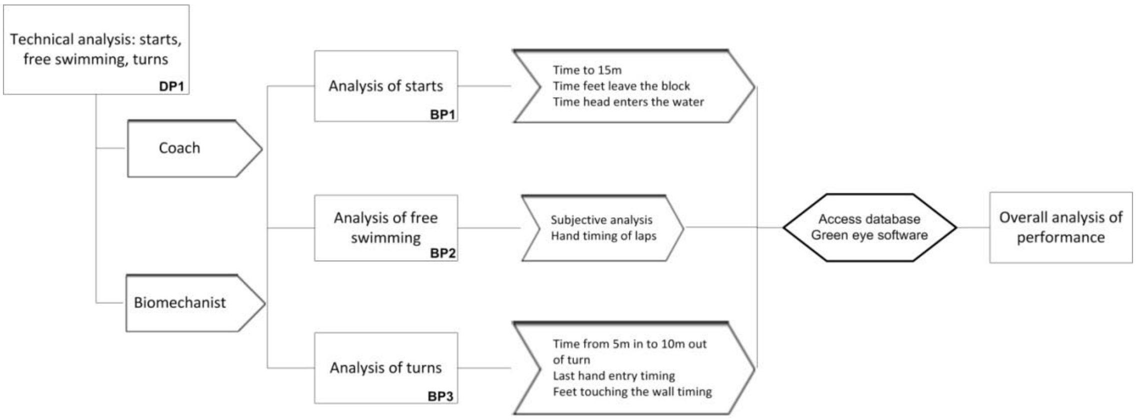


Figure 1-3: CIMOSA Interaction diagram for swimming domain

The technical analysis domain process (DP1) can be broken into three individual business processes (BP's): analysis of starts (BP1), free swimming (BP2) and turns (BP3) (see Figure 1-3). The high-level interaction diagram illustrated in Figure 1-3, helps to demonstrate the flow of information between each element of the domain process, i.e. how the business processes link and generate the relevant information to support the overall performance analysis of the technical aspects of swimming. In the example given, staff at British Swimming collate analysis from each of the swim phases into a single Access database.

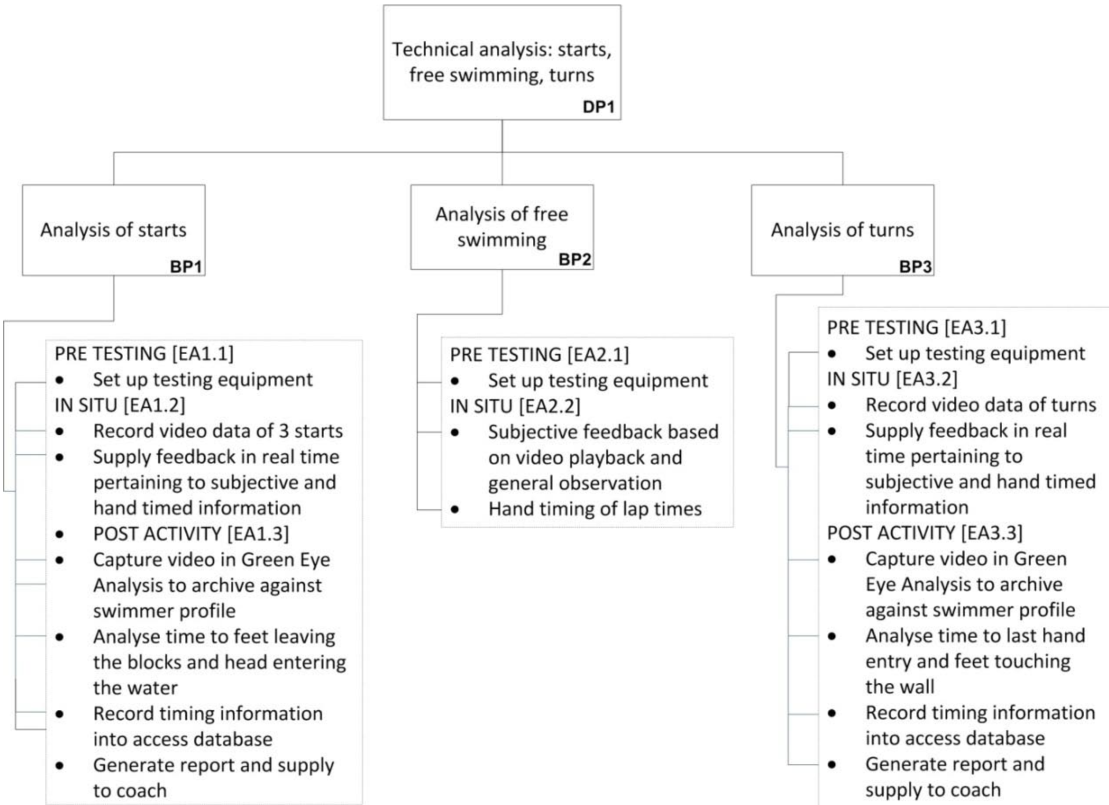


Figure 1-4: CIMOSA Structure diagram for swimming domain

A structure diagram (Figure 1-4) is used to illustrate how each of the business processes are decomposed into individual enterprise activities (EA), i.e. the core activities that have to be performed to support the overall business and domain processes. These enterprise activities are different for each BP and can be further decomposed into discrete tasks and flows of information. For each of the BP's the EA's have been divided into activities supporting *PRE-TESTING*, (i.e. involving equipment set up), *IN SITU* (i.e. recording video and supplying real-time feedback on timing), and *POST ACTIVITY* (i.e. activities and events supporting post processing of data or entry of results into a database). An interaction diagram illustrating this decomposition for the *Analysis of Starts* (BP1) is given below in Figure 1-5.

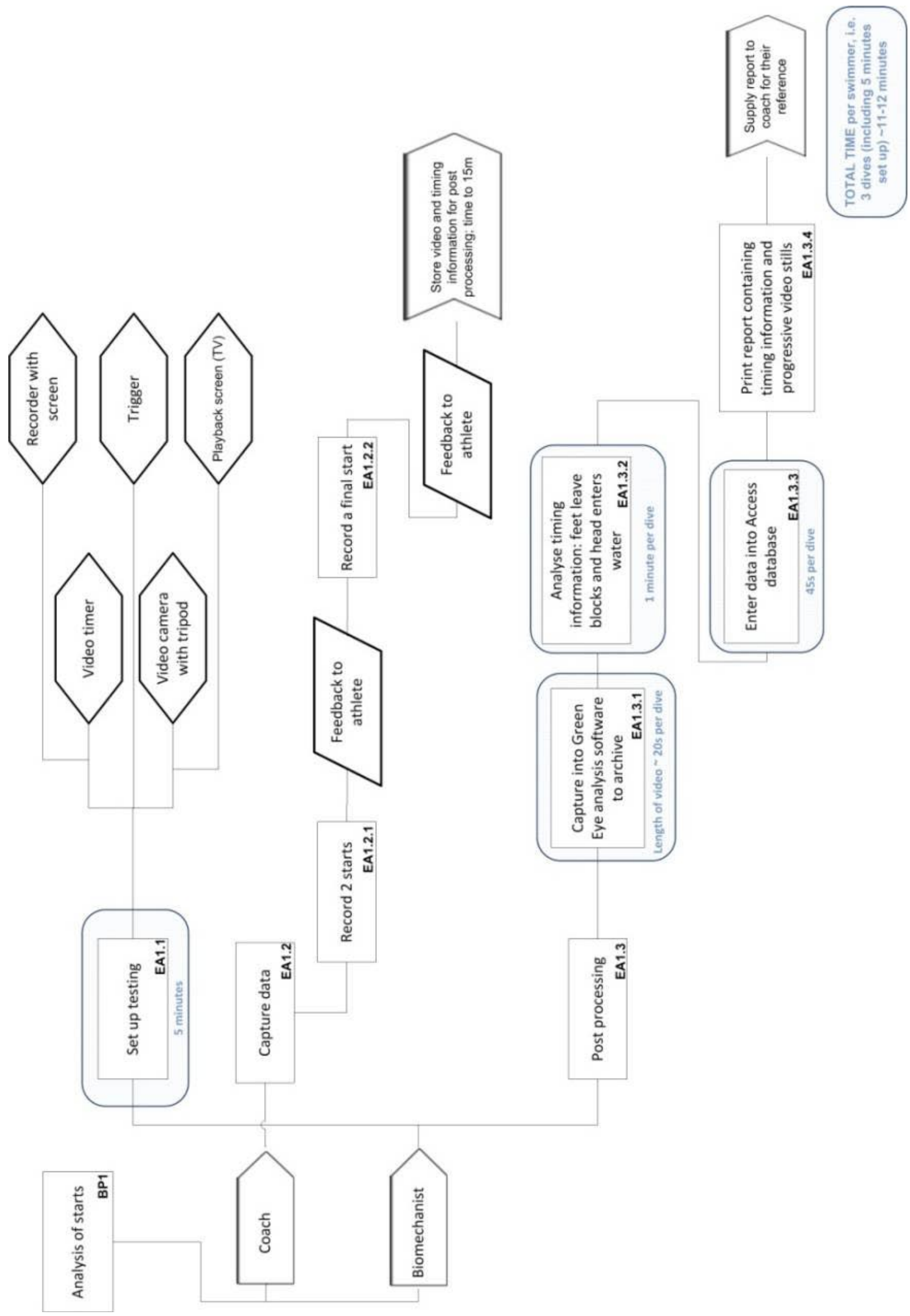


Figure 1-5: CIMOSA Interaction diagram for the Analysis of Starts

The current *Analysis of starts* process (i.e. BP1) integrates video recording with hand timing of events *IN SITU* and relies on limited analysis using manual digitisation techniques *POST ACTIVITIES* training. Results on the athletes "Time to 15m" performance coupled with subjective analysis of video is discussed during the session. Time to the feet leaving the blocks (i.e. Block Time: Table 1-1) and time to head entry

(EA1.3.2) are then measured post event and a report is supplied to the coach for their reference and feedback sessions after training. All videos are stored in a central Access database for archiving purposes along with a report on the athlete performance and training session structure for future reference.

The *AS-IS* process requires full time support from two users to enable analysis. Typical set up of a video camera with the appropriate trigger input and playback display takes approximately five minutes for one person to initiate. Recording of the starts is obviously performed in real-time. Post processing of dives involves the transfer of video data to the computer, analysis, parameter storage (i.e. data entry) and report production. The majority of time (and cost) in the current method is the result of EA1.3 (i.e. *Post processing*) and can be attributed to the use of the *manual* digitisation and data entry techniques employed. Set up testing, EA1.1, can also a major contributor if the facility doesn't have a permanent, fixed set up. In addition the stakeholders specified that any adopted system must portable such that it can be transported and used in different pools throughout the UK (for training) and the World (for events). Therefore, a permanent set up would not be appropriate for this application.

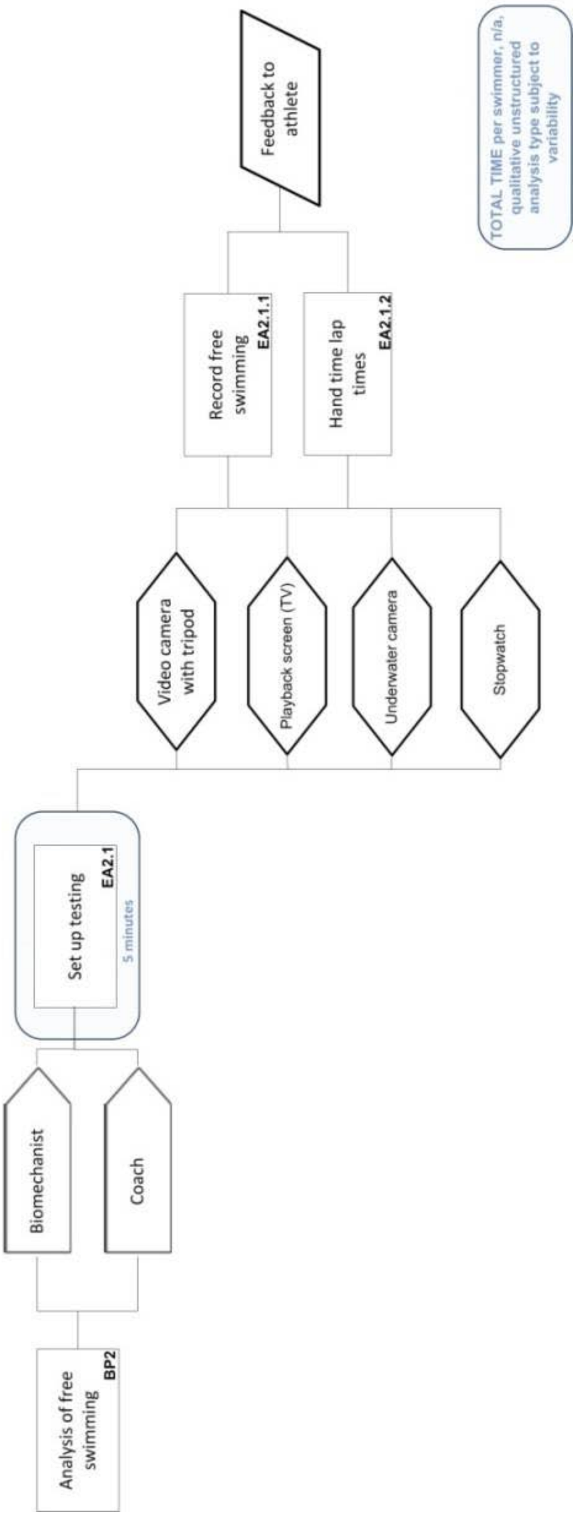


Figure 1-6: CIMOSA Interaction diagram for the Analysis of Free Swimming

Current processes employed for the *Analysis of free swimming* (BP2) are more primitive than those used for the *Analysis of starts* (BP1) and *Analysis of turns* (BP3) (compare Figure 1-6 with Figure 1-5 and Figure 1-7 respectively). There is currently no adopted protocol and no standard measurements taken to analyse the free swimming stage of the session. Video recording can be taken during the session and a viewing screen made available to re-watch swimming and provide verbal feedback as is appropriate. Hand timing is routinely performed by coaches to monitor the lap times of athletes. However, a single coach will often be monitoring up to 5-10 athletes in the same session and inaccuracies, lack of coverage and loss of data cannot be avoided.

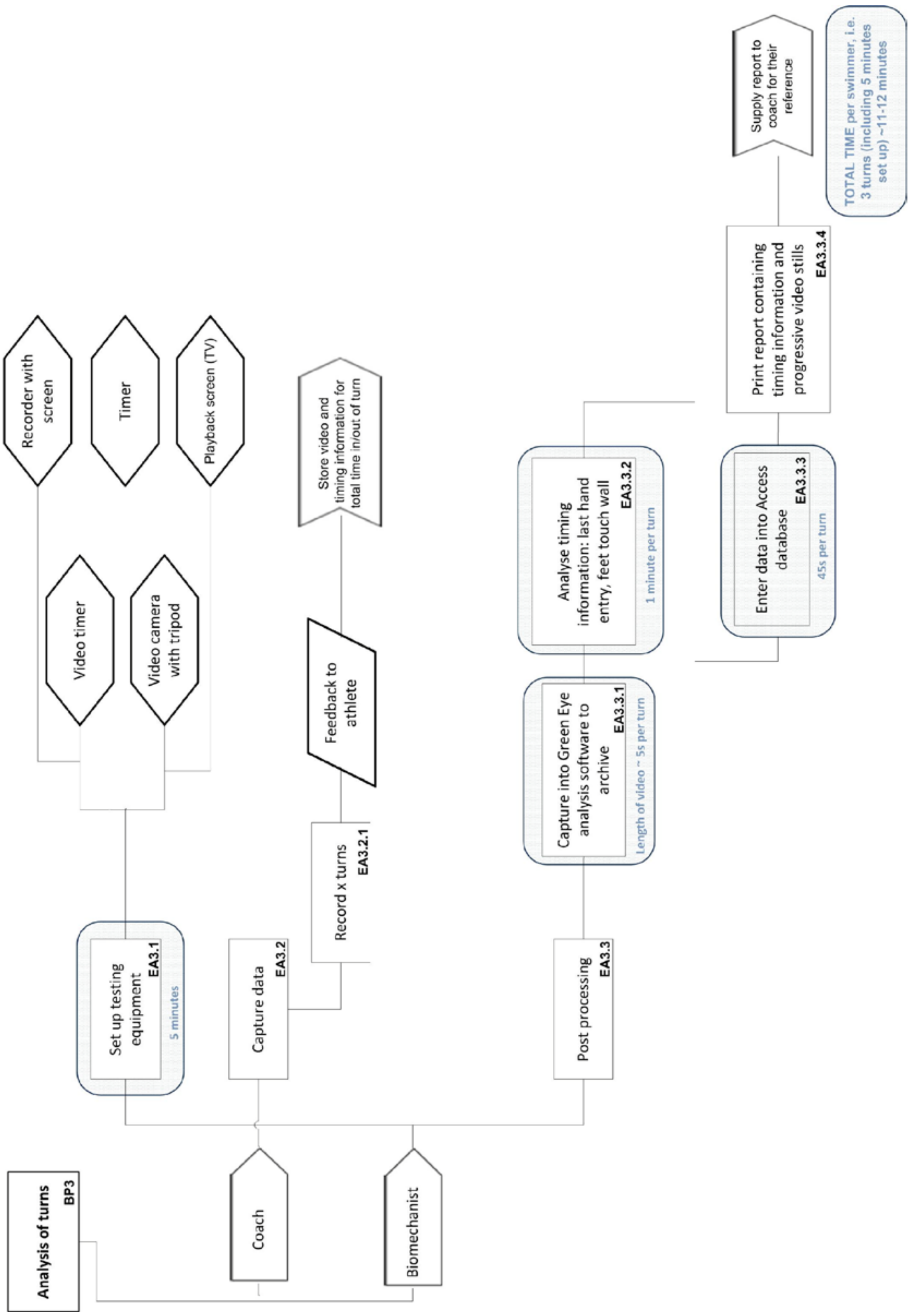


Figure 1-7: CIMOSA Interaction diagram for the Analysis of turns business process (BP3)

The procedure for the *Analysis of turns* (BP3) shares many elements with the *Analysis of starts* (BP1), the major difference being the use of an underwater rather than over water camera system. Time and costs are highest in the *Post processing* phase, (i.e. EA3.3), where manual digitisation and data entry create high demands on user input. At this phase measurements of the time of the *last stroke to wall timing* (see Table 1-1) and the time the feet touch the wall (i.e. the *time of wall contact*) are derived. Times and video are stored into the appropriate database and a report is given to the coach following the session.

Dividing the current processes into domain processes, business processes and enterprise activities enables the procedures used for the entire current performance analysis methods to be understood better. Currently the range of analysis routinely undertaken is limited, especially considering the range of requirements specified as vital for this system by the relevant stakeholders in Table 1. Current processes tend to have high resource utilisation in terms of time and labour intensity and hence cost. In both the starts and turns business processes, sub-processes BP1.3 and BP3.3 have been identified as key contributors to this cost. The research undertaken in this thesis has been targeted at streamlining these business processes while generating additional quantitative measurements of performance in line with the complete spectrum of requirements as specified by the user (see Table 1-2).

1.5 Stakeholder process requirements

Table 1-2: Stakeholder process requirements

No.	Requirement	Ranking
1.	Repeatable measures – i.e. comparisons can be drawn between the same swimmer on different days, different swimmers and swimmers in different locations	9
2.	Sport/skill specific measures	9
3.	Easy to understand results and feedback – i.e. direct measures of performance, confidence in techniques and how to interpret data in a meaningful way	8
4.	Real-time/In situ – results can be supplied during the session	8
5.	Easy to communicate useful feedback to athletes in a way that they understand and can respond to	8
6.	Suitable for multi-athlete analysis	8
7.	Low time cost and labour intensity to retrieve useable data	7
8.	Easy to use – can be set up and operated by one person	7
9.	Non invasive and non encumbering to the athlete while swimming	7
10.	Accessible – affordable, easy to get hold of, easy to apply in swimming	5
11.	Does not impact on ability to run session, e.g. minimal kit that does not encroach on space around pool, limiting coach mobility around a session	5

In addition to the measurement requirements provided in Table 1-1, swimming coaches and support staff were interviewed to ascertain their operational and non-functional needs (e.g. usability) for any solutions developed. The main requirements are listed in Table 1-2; along with the users' ranking of the importance of each statement (a high value indicates a high ranking). The degree of importance varied depending on the different stakeholders interviewed therefore the average is given in Table 1-2 as an indication of overall importance of each requirement to the swimming team.

Repeatability was marked as one of the most important parameters (Ranking 9). The necessity to produce repeatable measures from session to session would enable the ongoing monitoring of an individual athlete and to draw comparisons between multiple time-sequenced sessions and multiple athletes. For British Swimming repeatability was vital since they have athletes distributed across five primary Intensive Training Centres (ITC's) throughout the UK (i.e. Loughborough, Bath, Sterling, Swansea and Stockport). Any technologies adopted have to facilitate comparisons between athletes at different centres and allow support the movement of an athlete between different centres whilst receiving consistent complete and correct feedback.

Sport specificity was ranked alongside repeatability (Rank 9) as the most important feature of the system. Swimming is notoriously difficult to monitor due to the harsh environment presented by the water. In addition movements are complex and skills vary within each swim phase, i.e. start to free swimming to turns. Within each of these swim phases there are a number of subdivisions in terms of techniques which must also be considered (e.g. stroke rate, rotation, arm coordination, arm-leg coordination). The term "event specific" may be a more effective term. The technical nature and uniqueness of swimming mean that it was considered essential that technologies address performance specifically to provide most useful feedback depending on the individual swimmer, the event and the phase within the event.

The requirements that were considered to be of the next level of importance (i.e. Ranking 8) were that the system: (i) is *easy to understand* in terms of the results and feedback that are generated, (ii) it is *easy to communicate* useful feedback to athletes in a way that they understand and can respond to, (iii) results can be supplied in *real-time* during the session and (iv) suitable for *multi-athlete analysis*. For both support staff and coaches it is very important that results are easy to comprehend such that useful feedback may be derived from the additional data. There was a strong concern that new technologies may provide new technical data that would not be understood, i.e. the impact on performance would not be clear, and therefore would be difficult to assess the impact on current strategies and support the develop of alternatives. Similarly it was important that useful feedback could be given to athletes in a usable format. For example athletes are accustomed to watching video to supplement a coach's feedback as they can use the visual stimulus to help understand what is being explained. Summary statistics, colour coding and normalised graphs, supplemented with video, were suggested as acceptable feedback methods. These were favourable to the use of raw data, absolute values and the removal of all visual input. It was also important that this feedback would be available in a timely manner, ideally real-time. This would enable coaches to process data while the event was still at the front of their mind and therefore supply more detailed feedback to athletes, who, in turn would also be able to act more effectively on feedback.

Within each training session it is important for coaches to be able to monitor their entire squad simultaneously at certain times. Currently coaches monitor split times by running run up and down the poolside operating a multi-function stop watch. This process means that the coach cannot concentrate completely on the athlete performance and the measurements suffers from inherent user variability. A technology that enabled parameters, such as split times, to be monitored for a squad would relieve the coach and allow them to focus on the skill of coaching. This capability was considered a major benefit. In some situations this functionality may not be required or appropriate, for example, where start performance is analysed in a one to one environment, but where appropriate it should be integral to designs and development.

It was generally agreed that developed solutions must be *non-invasive and non-encumbering* to the swimmer (Ranking 7). The obvious reason for this was so that the swimmers technique and ability to swim would not be inhibited by using the technology. However the coaches stated that the swimmers would be willing to endure some disruption to their working environment, e.g. cabling, additional equipment, should it produce useful and usable information.

Ease of use was given a ranking of 7 predominantly by support staff, who would be the primary enablers of the technology, in terms of set up, operation, maintenance, data collection and analysis. It was specified that the equipment should be appropriate to be set up, operated and maintained by a single person who would be principally responsible for the implementation of the technologies used in testing (i.e. currently this would refer to vision systems). If multiple personnel are required to set up developed technology the uptake may be limited as there may not physically be enough people available to support the system.

The requirement to ensure efficient resource utilisation resulted in *Low time cost and labour intensity* to retrieve useable data to be considered of high importance to both coaches and support staff (Ranking 7). Currently vision techniques have been shown to be costly in terms of time and labour and produce limited analysis results post session. In addition these manual techniques also suffer from variability introduced by the reliance on human judgement. The processing time means that results cannot be fed back in a timely manner and therefore the effectiveness of feedback is reduced. A system which could reduce both time and labour intensity should enable more timely feedback and potentially increase the range of measurement parameters that can provide useful insight into performance enhancement.

The two lowest ranked (i.e. ranking 5) requirements were *Accessibility* and the *Impact on the ability to run a session*. Accessibility can be viewed from either stakeholder or researcher perspectives. Stakeholder concerns were with the cost and funding of development, whereas, researcher accessibility referred to the ease of accessing appropriate equipment and applying technologies in a swimming domain. For British Swimming, currently the cost would have to be integrated into budgets that were already secured for the research project. The impact on the ability to run a session is concerned with ensuring that the kit is minimally invasive from a coach's perspective and still allows them to manoeuvre around the pool to monitor performance and converse with athletes.

1.6 Summary

Two types of needs which must be satisfied to ensure successful outcomes, i.e. measurement requirements and process requirements have been described in this Chapter. The measurement requirements were defined by British Swimming to encompass certain measurement parameters that were desirable for providing more thorough feedback on performance, for example angle of entry, distance of entry and time to first stroke after the dive (see Table 1-1). Via interviewing, questionnaires and protocol analysis of end users, process needs were established. These needs define how the technologies should be developed to add most value to the user. The main considerations for these requirements were that systems developed should support specific, real-time, non invasive and distributed monitoring of athletes, with minimal time and operator input and minimal impact on how the coaches currently run their training sessions (see Table 1-2). In addition to this it was important that, as with current methods, summary data must be available to coaches in a format that they can understand and consequentially use to supply useful feedback either directly to the athlete or indirectly by using the information to adapt and specify future training strategies.

1.6.1 RQ1 Stakeholder Requirements

An overview of an elite athlete training system has been described to illustrate the context of research within this Thesis. The research presented in this chapter can be considered as part of the *Sensor Feedback* element of the control loop to enable more informed value judgment by coaches and support staff (see Figure 1-1). A number of measurement needs were specified by the end user, these were divided into the three phases of swimming: starts, free swimming and turns.

Evaluating existing methods of analysis allowed current measurement parameters to be identified and also the processes involved to achieve those measurements. It was found that manual vision analysis was the predominant method used, which required high levels of operator expertise, time costs and suffered inherent variability. It was also noted that only limited measurement parameters (6 out of a total desired 26: see Table 1-1) were currently derived.

Interviewing was undertaken with the end users, i.e. coaches, support staff and athletes, to determine a number of process needs and their priority within the system. Key themes were that developed technologies should be non-encumbering to the athlete, real-time, i.e. can be fed back within a session and measurements should be easy to understand and presented in such a way that coaches and athletes can apply effectively.

Chapter 2

2. LITERATURE REVIEW

2.1 Chapter Overview

Current research has been reviewed within this chapter, addressing literature for all relevant areas to work undertaken in the thesis. Firstly, the current state of the art in swimming research is evaluated for each phase of the swim, i.e. starts, free swimming and turns. The types of measurements taken and methods used to ascertain these measures are summarised. Further to this, supporting literature for the development of component technologies is discussed. This includes relevant literature relating to human motion analysis via automated vision techniques and the development of body sensor networks.

2.1.1 Research Questions (RQs)

<u>RQ1 Swimming research</u>

a. What are the current measurement parameters and methods used for the analysis of starts, free swimming and turn performance in swimming?

<u>RQ2 Body sensor networks</u>

a. What are the current technologies, implications and considerations associated with body sensor networks and their implementation?

RQ3 Automated vision analysis

a. What are the current technologies, implications and considerations associated with automated vision analysis techniques and their implementation?

2.1.2 Chapter Structure

The current state of the art in swimming research has been reviewed for starts, free swimming and turns. The ability of these methods to provide specific feedback on performance has been evaluated against the stakeholder requirements, specified in Chapter 1: Quantification of the Stakeholder Requirements. This evaluation refers to both measurement and process needs, i.e. what measurements are required and what methods are appropriate to achieve these measurements.

An overview of current research on body sensor networks has been carried out and several applications reviewed. Processes associated with implementing a body sensor network are discussed with reference to a swimming application.

Finally automated vision analysis for human motion tracking is explored. Typical processes, assumptions and methods have been summarised and their implications for application in a swimming environment assessed.

2.2 Current state of the art in swimming research

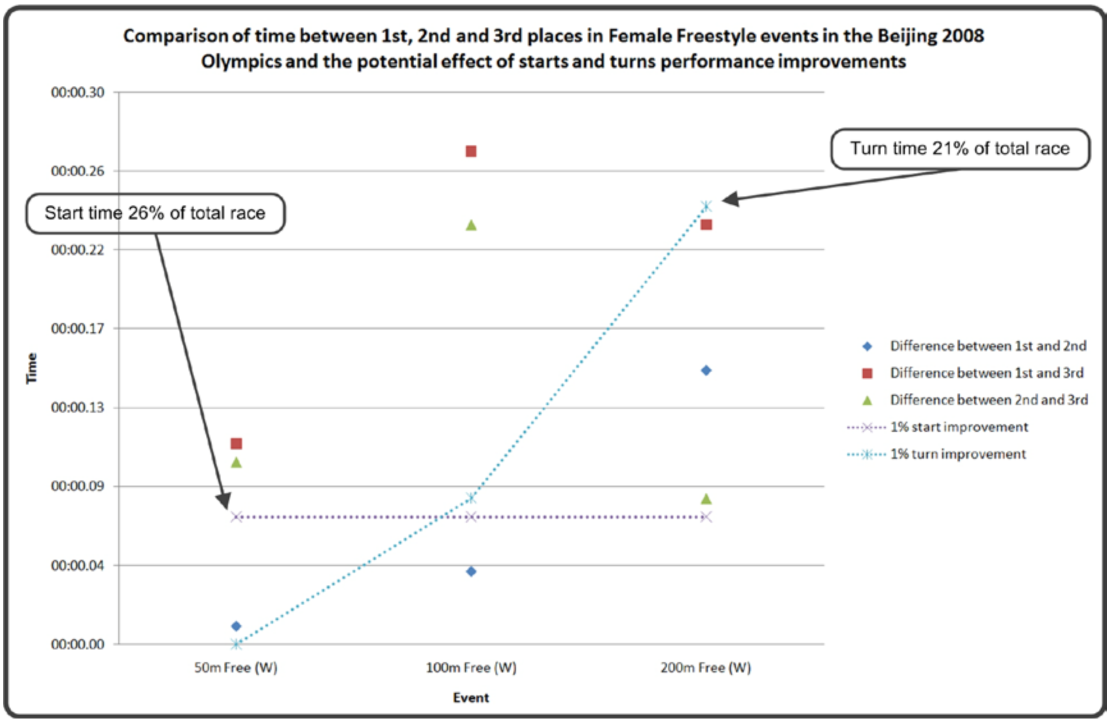


Figure 2-1: Analysis of start and turn contribution in Women's freestyle events, Beijing Olympics 2008

Swimming events can be broken into three elements that contribute to overall race time, i.e. the start, free swimming and turns. The contribution of each of these elements is event dependent, for example in a 50m event there are no turns, however, the start will contribute significantly. The contribution of the start was analysed for three events in the Beijing Olympics, Figure 2-1. The events analysed were the 50m, 100m and 200m freestyle women's races. For each of these races, start time was defined as the time the athlete took to reach 15m; an average for all athletes was calculated to give an indication of typical start time for this level of athlete.

A 1% improvement in the typical start time was plotted. The time difference in finishing times for the podium athletes was plotted to put the effect of an improved start time into context. For this example a 1% improvement in start time, i.e. 0.07s, would have altered the order of 1st and 2nd podium places for both the 50m and 100m events. For the 50m event the contribution of the start was 26% of total race time. This percentage degraded as the length of the race increased.

Similarly, the contribution of the turns has been considered for each of the races. Turn time was defined as the time from 5m into and 10m out of the wall. A 1% improvement in typical turn time was plotted. It was found that, for this example, a 1% turn improvement would affect the podium placing in the 100m event for 1st and 2nd places. More significantly it would alter the entire podium in the 200m event, where a 1% improvement equated to 0.24s. This time improvement was greater than the finishing time difference between each of the podium positions.

Unlike the start, the contribution of the turn was more significant with increasing race length. For this example, the contribution of the turn was 21% of total race time for the 200m event. For the events analysed the free swim contribution remained the most significant proportion, for 50m free swimming this accounts for 74% and for the 200m approximately 72%.

2.2.1 Swimming starts research

Swimming research for each of the start, free swimming and turns, has been reviewed respectively. A key aim was to establish what parameters were currently measured to indicate performance and what methods were used to obtain these measurements.
The block start can be broken into four key components, namely, the block phase, flight phase, underwater phase and break out. Within papers reviewed, summarised in Figure 2-2, measurements were taken pertaining to some or all of these phases to provide an analysis of starting performance.

During the block phase the most recurring measured parameter reported in the literature was the block time, typically reported as between 0.75s and 0.85s. Other less reported measurement parameters were concerned with velocities leaving the block and forces off the block. Of the papers that reported force off the block, a number suggested that maximum horizontal force was correlated to better start performance [Galbraith et al 2008, Mason et al 2007, Arellano et al 2005]. As force is related to a change in velocity over a time period, it can be assumed that horizontal force and/or impulse will have some influence on subsequent horizontal velocity leaving the block, and therefore, potentially affect overall performance.

The flight phase is defined as the time between the swimmer leaving the block and the time at which they enter the water. During this phase the most common measurement parameter reported in the literature was the flight time. It was noted that flight times reported were very similar for all papers reviewed, i.e. ~ 0.34s. This can be expected due to the predominant force acting on a swimmer in flight is gravity (9.81ms^{-2}) and given all swimmers projecting at a relatively flat angle, from a similar height, it would be expected that flight time would exhibit little variability from one swimmer to the next.

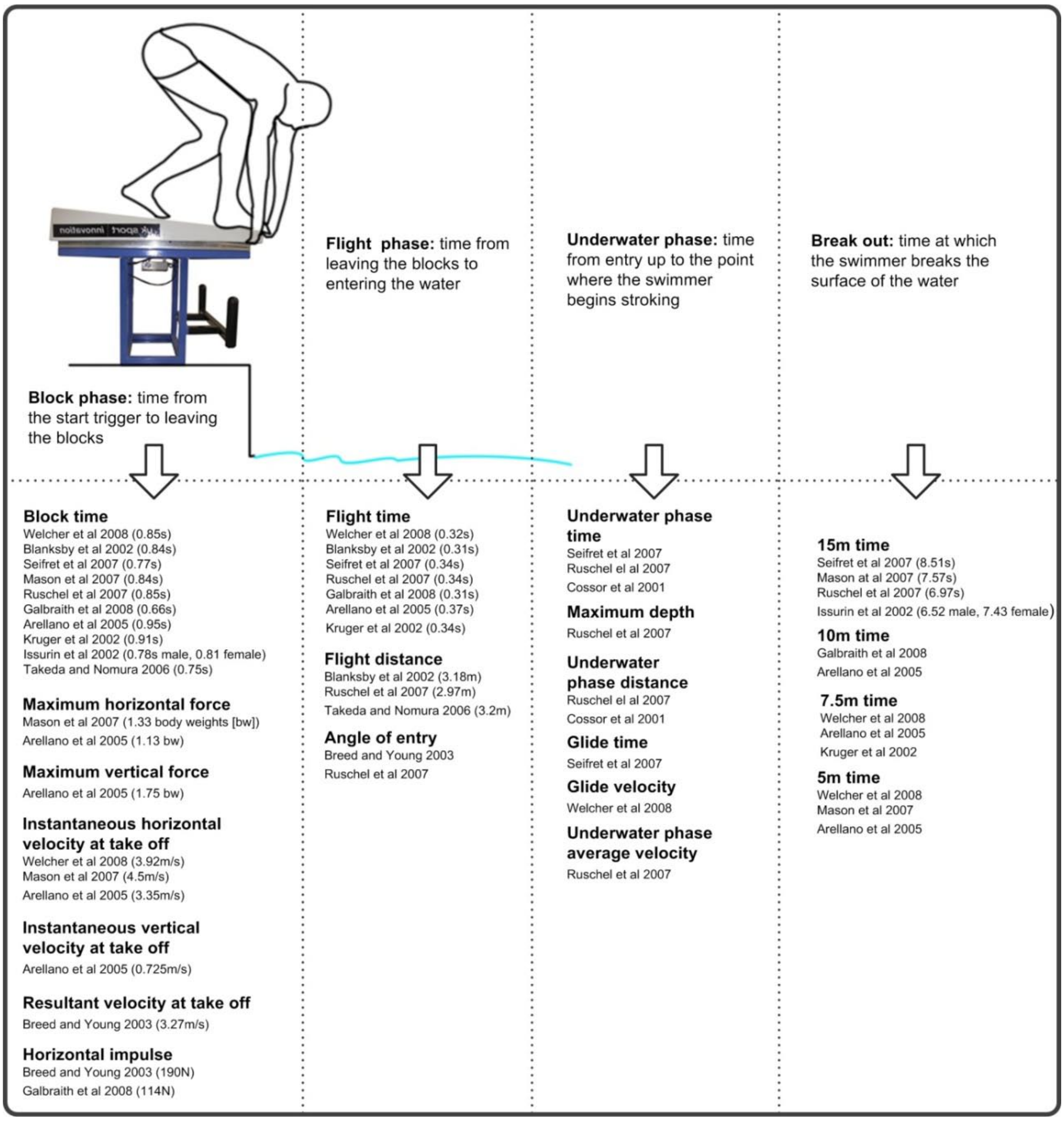


Figure 2-2: Review of swimming starts research

Flight distance and angle of entry were reported in few of the papers reviewed. Flight distance is considered an important performance variable as a swimmer can travel faster through air than through water [Breed and Young 2003], therefore, it is preferable that the swimmer travels as far as possible before entering the water. This sentiment was supported in papers by Cossor and Mason 2001, Ruschel 2007 and Pearson et al 1998, who reported that start time to 15m had been correlated to flight distance. Another recurring sentiment in papers reviewed, was that with all other things equal, the instantaneous horizontal velocity off the blocks would have the biggest effect on the distance the swimmer travels before entry [Breed and Young 2003, Welcher et al 2008, Mason et al 2007], therefore, a higher horizontal velocity at take off is preferential. However, it was also noted that although a critical component, horizontal velocity at take off cannot be used to assess start performance in isolation [Welcher et al 2008]. Mason 2007 reported that time on the blocks and horizontal velocity at take off were two parameters affecting start performance, and suggested that average acceleration would be a more useful performance measurement as it combines both parameters.

Angle of entry provides an indication of how the swimmer enters the water. In the two papers reviewed that reported angle of entry, little is discussed as to how the angle of entry affected overall starting performance [Breed and Young, 2003, Ruschel et al 2007]. It is speculated that the angle of entry affects the subsequent depth of the dive, which impacts the rest of the start phase. Ruschel et al 2007 suggested that higher angle of entry values corresponded to longer times to 15m.

The underwater phase has the largest impact on overall start time, as this is where the swimmer spends the greatest amount of time during the start phase, compared with block and flight phases [Mason et al 2007]. However, it is noted that the block and flight phases initiate the underwater phase, and therefore remain important [Mason et al 2007]. Measurements recorded regarding the underwater phase looked at time, depth, distance and velocity measurement parameters. The underwater phase encompasses the transition from water to air and finally the start of free swimming. There are two key elements within this phase; the glide, i.e. where the swimmer holds a fixed body position and then the phase prior to break out, where the swimmer may perform some movement before resuming the stroke, e.g. underwater kicking in freestyle events. Cossor and Mason 2001 reported that in the Sydney Olympics a negative correlation was found between underwater velocity and start time, i.e. time to 15m. This supports the need for swimmers to preserve their in-flight velocity through the transition into water, to maximise start performance.

Break out is the point at which the swimmer breaks the surface of the water and starts to stroke. Rather than report the distance or time of break out, papers tend to record the time taken for a swimmer to reach a predefined distance from the wall. These distances varied from 5m [Seifert et al 2007, Mason et al 2007, Ruschel et al 2007, Issurin et al 2002] to 15m [Welcher et al 2008, Mason et al 2007, Arellano et al 2005].

Welcher et al 2008 reported that given the number of research papers on swimming starts, there still seems to be little consensus on which parameters contribute most to overall swimming start performance. This sentiment is supported by the literature reviewed in this chapter, where no standardised sets of measurement parameters or methods were found for analysing the swimming start. Typically, for the papers reviewed, common measurement parameters were the block time, flight time and time to a given, non-standard, distance. In all cases, parameters were measured in one of two ways, most frequently, using manual video analysis techniques, and in the case of force measurements, using instrumented start platforms.

2.2.2 Free swimming research

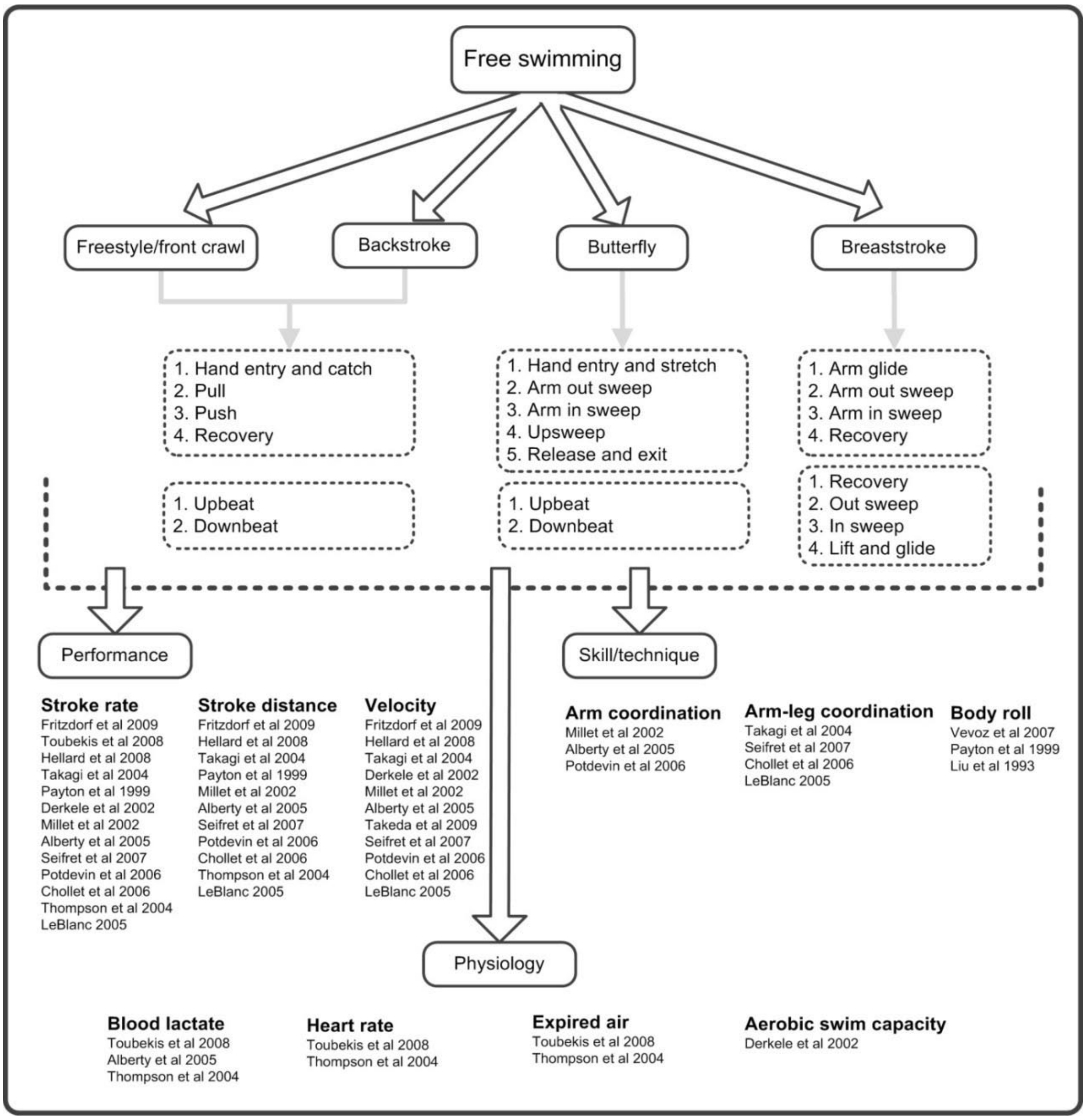


Figure 2-3: Review of free swimming research

Literature reviewed with reference to free swimming performance analysis was divided into the four major swimming strokes, freestyle, backstroke, butterfly and breaststroke, see Figure 2-3. Each stroke has cyclic phases associated with the arm and leg components of movement. Definitions of these phases varied to a degree in the literature reviewed, however, typical descriptions have been summarised.

Freestyle and backstroke share the same descriptors for arm and leg phases. The hand entry and catch is the point where the swimmer enters their hand into the water and gets a 'hold' of the water. The pull defines the first half of the stroke where the swimmer pulls their arm from a position stretched in front of their body to a medial point. The push describes the hand as it moves from the medial point towards the feet of the swimmer. The recovery is the action of the swimmers arm as it leaves the water and is returned to the starting point for re-entry. Leg phases are simply defined as an upbeat and downbeat, one describing the movement of the foot from a deeper to shallower position and vice versa. Similar descriptions are used for butterfly and breaststroke to describe the motion of the arms and legs. These definitions are important as they assist in the analysis of the different parts of the stroke; most importantly, perhaps, they are used in the analysis of coordination.

Contributors to free swimming performance were categorised into three major areas, performance, physiology and skill or technique. A number of papers have been reviewed that report research on each of these categories. All papers reviewed used vision analysis techniques to derive performance parameters. LeBlanc et al 2005 and Chollet et al 2004, supplement traditional vision analysis techniques with a tethered system to determine velocity of the swimmer.

Performance parameters dealt with gross measurements of movement such as stroke rate, stroke distance and velocity. It is accepted that relationships between said parameters give an indication of swimming performance. LeBlanc et al 2005 reported that within their study of breaststroke, increases in velocity were associated to an increase in stroke rate and a decrease in stroke duration, which supported similar findings by Chollet et al 2004. It was also noted that more competent swimmers performed a stroke characterised by a shorter glide phase and longer propulsive and recovery phases, than less accomplished counterparts at the same speed. Hellard et al 2008, reported that stroke rate, stroke length and stroke rate variability were influenced by the standard of swimmer. For example, it was noted that semi finalists in the Olympics demonstrated lower stroke rate variability than semi finalists in French national championships. These examples demonstrate how basic performance parameters may be applied to the monitoring and development of swimmers.

Skill or technique parameters addressed more technical aspects of swimming performance such as the coordination of swimming strokes. An index of coordination (IdC) was often used to describe a swimmers technique, referring to the coordination of the arm cycle in relation to the other arm, or in relation to the legs. For example in freestyle, the IdC deals with the arms only and there are three index types, namely catch-up, opposition and superposition. Catch-up is the term used when one arm completes the propulsive phase of a stroke before the other starts the propulsive phase of its stroke cycle. Opposition explains a point where one arm starts the propulsive phase of a stroke at the same time the other completes the propulsive phase of stroke cycle. Superposition is where the second arm starts the propulsive phase of the stroke cycle before the first has completed its propulsive phase. A study by Potdevin et al 2006, investigated whether arm coordination at different stroke rates differs with swimmer expertise. Distinguishing time gaps between the phases of the arm and legs has been used to monitor how a swimmer has adapted their stroke, for example, Chollet et al 2004, where stroke phases and timing of phases were used to evaluate flat breaststroke.

The relevance of physiological measurements within this project is limited due to the absence of any specification in the outlined stakeholder requirements. The most important thing to note for all papers reviewed that reported physiological parameters, was that all measurements were taken post swim, i.e. there was no capability for monitoring physiology in real-time. Heart rate systems are available that can monitor in real-time, [Hosand TMAQUA, 2010], although this technology was not applied in any of the reviewed literature. Blood, lactate and breathing parameters must be assessed post swim. Although not directly relevant to this project, it was considered that any developed solutions might need to be compatible with potential physiological measurement methods in the future.

2.2.3 Swim turn research

In the same manner as for the start and free swimming, it is conventional to divide the turn into phases. In swimming there are two types of turn, the tumble turn and the open turn. Tumble turns are used for both freestyle and backstroke events where the swimmer performs a forward roll as they approach to the wall and push off the wall with only their feet. The open turn is used in butterfly and breaststroke events where the swimmer touches both hands on the wall and then pushes off with their feet. The research reviewed was predominantly focused on the tumble turn technique, summarised in Figure 2-4. For this reason papers have been categorised into phases relevant for this type of turn, i.e. Approach, Rotation, Wall contact, Glide and Stroke Preparation, see Figure 2-4. Phases translate to the open turn with the exception of the rotation phase and the wall contact phase is divided into hand and foot contact as in Tourny-Chollet 2002.

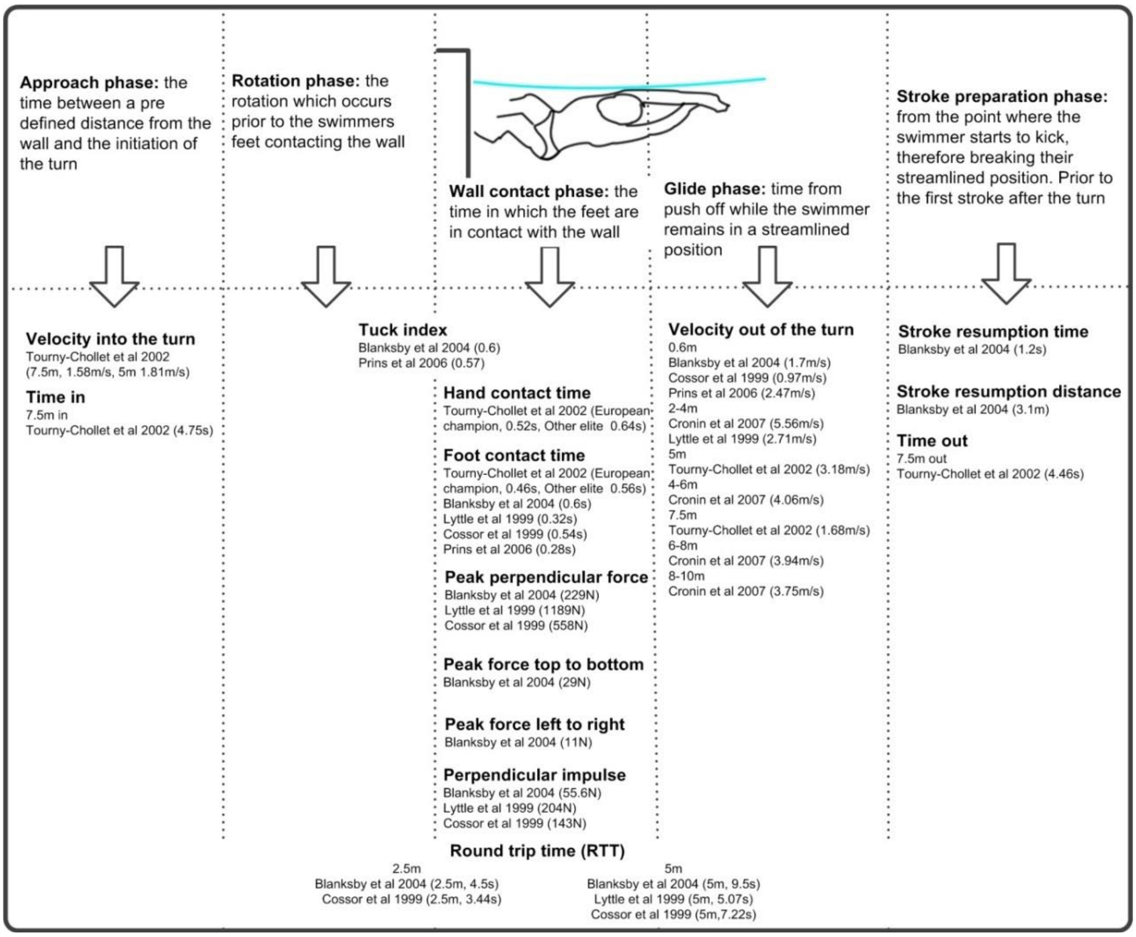


Figure 2-4: Summary of swimming turn research

The approach phase is defined as the time between a predefined distance from the wall or the last arm pull before the turn and the initiation of the turn, i.e. where the swimmer starts to rotate from a prone position. For Tourny-Chollet et al 2002, the distance from the wall used was 7.5m to determine the approach time. At 7.5m and 5m from the wall the velocity of the swimmer was recorded. No other papers reviewed directly dealt with the approach phase.

Little is reported about the rotation phase, which deals with the time during which the swimmer starts to rotate from a prone position to the point where their feet contact the wall. A tuck index, reported by Blanksby et al 2004 and Prins et al 2006, refers to the distance of the greater trochanter of the femur from the wall at foot contact divided by the standing height of the trochanter with straight legs. A higher tuck index implies the swimmer is contacting the wall with straighter legs. Blanksby et al 2004 reported that it may be beneficial for backstroke swimmers to turn with straighter legs, to reduce the distance the swimmer must travel in and out of the wall and reduce the resistance created when a swimmer compresses into a more bunched up position with a higher frontal area. Conversely Prins et al 2006 reported a negative correlation between tuck index and push off velocity, suggesting a more tucked position is better for turning. However, it is important to note that Blanksby et al 2004 used round trip time (RTT) to determine turn performance, whereas Prins et al 2006 used velocity out of the turn to determine performance. The swimmer's body position out of the turn will affect their ability to maintain their velocity off the wall and therefore it should be noted that a faster velocity off the wall may not result in the quickest turning time, if the swimmer is unable to maintain the velocity they have generated off the wall.

During the wall contact phase two types of measurements were reported, firstly wall contact time and secondly forces associated with this contact phase. For butterfly and breaststroke turns, contact times were divided into hand and foot components. Force measurements were facilitated by instrumenting the turning wall with force plate technology [Blanksby et al 2004, Lyttle et al 2004 and Cossor et al 1999]. Lyttle et al 1999 and Blanksby et al 2004 both reported that a higher peak force perpendicular to the wall resulted in better turning performance, however, neither reported similar correlations with perpendicular impulse. Prins et al reported a foot-plant index, which similarly to the tuck index, was a ratio of trochanter height but related to the depth of foot contact. It was reported that there was no significant relationship between foot plant index and push off velocity, though it should be noted that this is the only paper which discusses any aspect relating to the position of foot contact. Equally, none of the papers reviewed dealt with the orientation of the feet at contact, the area of foot contact or whether there was a greater force generated from one foot or the other.

The glide phase is the time after the swimmers feet have left the wall, where a streamlined position is assumed, up to the point where they prepare to recommence the stroke. Analysis of this phase is given by measuring velocities at predefined distances from the wall. In the literature reviewed, variability in protocols suggested there was no standard distance at which velocity was measured that best indicated turning performance. Velocities off the wall were higher than free swimming pace, which is typically just under $2ms^{-1}$ closer to the wall and degraded until free swimming was resumed. One outlier was a paper by Cronin et al 2007, which reported velocities of over 5.5m/s at 2-4m from the wall, diminishing to 3.75m/s at 8-10m from the wall.

At the latter distance from the wall it can be assumed that the swimmer will have returned to the stroke. At the paces recorded, this paper suggests that swimmers tested left the wall at velocities greater than they could typically achieve during the start and were free swimming at over 3.5m/s, both of which are unrealistic values and highly inconsistent with other papers. For this reason this paper was considered inaccurate and unreliable.

The stroke preparation phase is the time where the swimmer stops gliding and resumes free swimming. The time and distance of stroke resumption have been reported in literature by Blanksby et al 2004. Tourny-Chollet et al 2002 reported the time to 7.5m from the wall, a point at which the swimmer will have begun the stroke. Overall, turning performance was typically reviewed by considering the round trip time (RTT). This is the time from the swimmer passing a predetermined distance from the wall on approach, and returning to this distance from the wall after completing the turn. Papers reviewed reported on two distances, 2.5m and 5m RTT. Considering the papers reviewed here, it can be assumed that there is no standard technique that is considered most effective for analysing turning performance.

The number of papers pertaining specifically to swimming turning performance suggests that this is the least researched area of the three swimming phases, i.e. starts, free swimming and turns. Similarly to starts and free swimming, papers reviewed depended on manual vision analysis techniques to establish measurement parameters, with some testing supplemented with force plate analysis. It was concluded that relationships between contact time, forces and positioning on the wall must be better understood to generate future recommendations for turning performance.

2.2.4 Discussion: How current research satisfies stakeholder requirements

The reviewed literature was found to address a number, but not all, of the measurement requirements specified by British Swimming, as highlighted in bold type in Table 2-1. Manual vision analysis was a common method used in all papers reviewed. Additional technologies used were start blocks instrumented with force transducers, tethered systems for measuring velocity and turning walls instrumented with force transducers. These additional technologies allowed direct measurements to be taken that would not be possible using vision. The use of force plate technologies and tethered systems in the literature reviewed represented the exception in terms of testing methods and protocols, and were not systems implemented in day-to-day monitoring.

Table 2-1: Currently satisfied measurement requirements

	Simple	Compound
Starts	• Time from gun to first movement • **Block time** • **Angle of entry** • **Time to entry** • **Distance of entry** • Maximum depth • Time of first kick (relative to entry) • Break out distance • Break out time • First stroke timing	• **Velocity off blocks** • **Velocity of glide** • Velocity at break out
Free swimming	• **Stroke count** • **Distance per stroke** • Stroke duration • **Rotation during the stroke: longitudinal and vertical**	• **Stroke rate** • **Swimming velocity** • **Variations in velocity throughout a stroke cycle**
Turns	• Last stroke to wall timing • Rotation information • **Time of wall contact** • **Wall contact duration** • Depth profile • Break out distance • First stroke timing • Time of first kick	• **Velocity into/out of the turn, also glide, start of initial swimming**

The process requirements specified by stakeholders were summarised in Table 2-2. The compliance of current research to satisfy these process requirements was assessed. Colour coding has been used to distinguish needs that are entirely satisfied as green, and those which are satisfied to an extent as orange, see Table 2-3. Vision provides the least invasive method of data collection, which can be easily understood and analysed in real-time for subjective measurements. However, analysis that requires post processing cannot be supplied in real-time, but analysed post session. Repeatability was also highlighted as a need that cannot be completely satisfied using vision techniques. The reliance on human operator input and variability between operators introduces inherent uncertainty into the process. Two major shortcomings of vision were identified as the time and labour costs associated with manual analysis techniques, i.e. digitising, and the inability to monitor multiple athletes simultaneously. One paper by Naemi et al 2008, looked at the development of an automated vision system for analysis of the glide performance. Markers that were automatically tracked allowed real-time feedback on start performance. This example has currently only been applied in a limited capacity, i.e. to analyse the underwater phase, specifically the glide, after start entry and gliding phase after the push off from a turn.

Table 2-2: Process requirements defined by the user

No.	Requirement	Ranking
1.	Sport/skill specific measures	9
2.	Repeatable measures – i.e. comparisons can be drawn between the same swimmer on different days, different swimmers and swimmers in different locations	9
3.	Easy to understand results and feedback – i.e. direct measures of performance, confidence in techniques and how to interpret data in a meaningful way	8
4.	Real-time/In situ – results can be supplied during the session	8
5.	Easy to communicate useful feedback to athletes in a way that they understand and can respond to	8
6.	Suitable for multi-athlete analysis	8
7.	Low time cost and labour intensity to retrieve useable data	7
8.	Easy to use – can be set up and operated by one person	7
9.	Non invasive and non encumbering to the athlete while swimming	7
10.	Accessible – affordable, easy to get hold of, easy to apply in swimming	5
11.	Does not impact on ability to run session, e.g. minimal kit that does not encroach on space around pool, limiting coach mobility around a session	5

Table 2-3: Assessment of current technologies against process needs

Technology	1	2	3	4	5	6	7	8	9	10	11
Vision	🟢	🟢	🟢	🟢	🟢	🟠	🟠	🟢	🟢		
Tethered			🟢	🟢	🟢	🟢	🟢	🟢		🟢	
Force	🟢	🟠		🟠	🟢	🟢	🟢				

Tethered systems provided repeatable, real-time, easy to understand data concerning swimming performance, e.g. velocity. It was accepted that athletes and coaches were able to process the data presented to them, i.e. velocity information, however, in the absence of a complementary vision system it may be difficult for interpretation of the data to be achieved. For example, if a swimmer displays large fluctuations in their forward velocity it may be hard to distinguish at what point in the stroke the weakness is occurring without having concurrent vision data to supplement the velocity data, i.e. velocity is not useful as a standalone metric, but more an integrated component. There were, however, a number of needs that were not satisfied by tethered systems. Most importantly perhaps is the potential effect the physical attachment of a tether would have on the swimmer and subsequently their ability to perform normal swimming, i.e. the technology would be more invasive and encumbering than ideal. Another limitation was that the tethered system would limit lane use to a single swimmer, to ensure other swimmers are not at risk of becoming tangled in the tether. Tethered systems are also not standard pieces of equipment present for use at every poolside and therefore they are not freely accessible. Similarly to vision, tethered systems do not enable multi athlete analysis.

Force plate technologies, as with tethered systems, were considered successful in providing repeatable, real-time measurements that were sports specific. Typically it was considered that equipment would be reasonably unobtrusive, however, a badly designed solution may not have the same feel or characteristics that a swimmer is used to, which may prove problematic. The major drawback of using force plates was identified as the lack of knowledge and understanding regarding the data. Limited research studies were found that used force plate technologies, of which made some loose correlations between collected data and subsequent performance. Due to the minimal research using force plate technologies there is a gap in understanding how force generation impacts performance in the start and turns [Mason et al 2007, Arellano et al 2005, Blanksby et al 2004, Lyttle et al 1999, Cossor et al 1999.

It was concluded that current swimming analysis was heavily reliant on manual vision analysis techniques whose major failings were identified as measurement variability due to human judgement, non real-time quantitative feedback and high costs in terms of time and labour intensity. Alternative technologies were successful in providing additional measurements of performance, however, these were not useful in isolation and currently could be encumbering to the athlete. It was considered that enabling technologies developed should work towards automated, integrated processing components that maintained visual data to validate processes. The vision component is necessary to increase understanding of new types of data and supply the coach and athlete with an additional feedback stimulus that they are comfortable with interpreting and applying.

2.2.5 Automation vision analysis for human motion analysis

Technologies currently used for performance analysis of swimmers have been discussed. Video analysis was the predominant technique used to determine performance, either qualitatively or quantitatively. To establish quantitative measures of performance, vision data was manually digitised. Despite vision being the standard tool used for performance analysis there were key problems associated with these methods. Namely, these were resource intensive in terms of time and expertise, and the reliance on human judgement for analysis meant that measurements taken suffered from an inherent variability. To analyse a length of swimming data would minimally take the playback time of the video and be dependent on the number and type of measurements required that would further extend this analysis time. A trained member of personnel, to ensure reliability and a degree of repeatability of results, must perform the analysis. Despite these draw backs it was considered that vision would be an essential component in any solution developed. The use of a visual stimulus increases the ability of the user to explain and understand results and subsequently provide more informed feedback to athletes. It was considered that introducing automation to vision analysis processes would reduce the time and expertise resource in analysis while ensuring repeatable results.

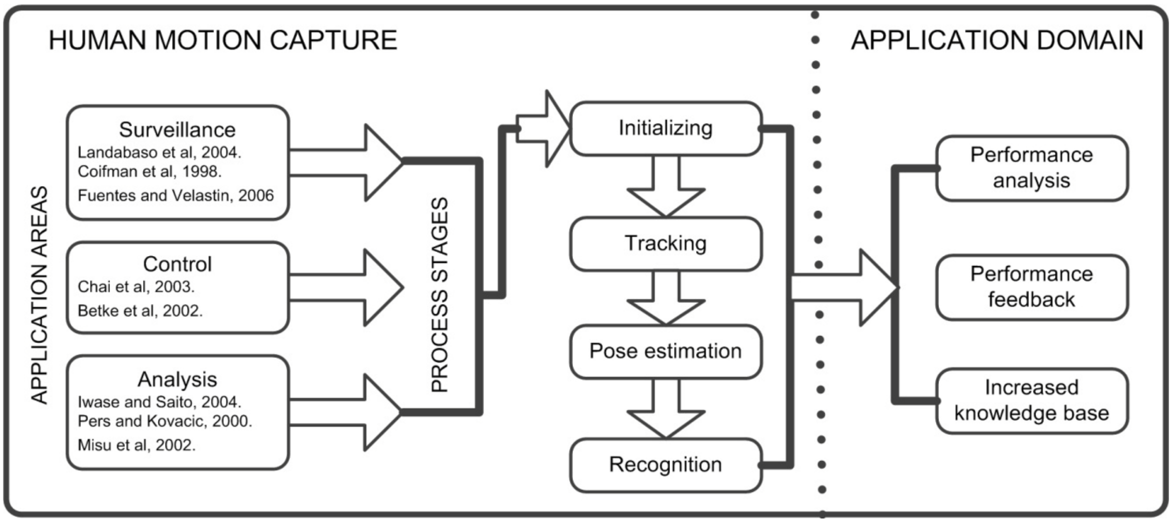


Figure 2-5: Stages of human motion capture

Human motion analysis using automated vision processes has been applied in a number of different domains, see Figure 2-6. Each system is built on a number of fundamental principles. Applications can be categorised into three subject areas, namely surveillance, control and analysis. Vision systems have been used within surveillance to monitor people, e.g. Fuentes and Velastin 2006 and Landabase et al 2004, and vehicles, e.g. Coifman et al 1998. Control refers to vision systems used to control something else, for example Chai et al 2003 discuss the use of vision to control facial expressions on a computer animation or Betke et al 2002 developed an on screen computer mouse controlled by the users' movements, intended for severely disabled subjects. Analysis applications are where data from the vision system is used to evaluate the activity being captured. For example, this has been seen in sporting situations where players have been tracked in handball [Pers and Kovavic 2002] and football [Iwase and Saito 2004, Misu et al 2002].

For each of the applications, four standard process stages were used to enable analysis. These phases were identified as: initialising, tracking, pose estimation and recognition. Initialising refers to actions that allow the system to be correctly set up. Actions at this stage varied depending on the application but typically include camera calibration, adjustment for scene characteristics and, where appropriate, model initialisation [Moeslund and Granum 2001].

The tracking phase relies on the ability to segment the area of interest (AOI). In human tracking this is the identification of the human figure/subject from within the background scene. Processes in this stage include segmentation of the image to isolate and track the AOI and then representation, which refers to the way in which the segmented figure is represented, for example using blobs, stick figures or silhouettes.

Pose estimation can be achieved with or without predefined models. In cases that use models, predefined expectations of pose and movement are used to improve tracking; this is possible where general movement is predictable. Alternatively model-free tracking is be used where no prior models or estimations are inputted into the system.
Recognition can either be by reconstruction or directly. Reconstruction involves the recreation of the image scene and subsequent recognition of what is occurring within it. Direct recognition is concerned with using the raw segmented representations, such as blobs, to recognise motion, without rebuilding the entire image.

A swimming analysis application would fall into the analysis area of human motion capture. The automated human motion system would be used to replace manual techniques that are currently used. This would reduce the resources required to perform analysis and would also provide reliable outputs that would not suffer from the inherent variability associated with manual techniques. This would allow any operator to perform analysis and obtain comparable results, whether they were skilled or not. Another advantage of using an automated system would be that results would be processed on a computer and therefore outputs could be automatically stored to a database, increasing the knowledge base for ongoing monitoring.

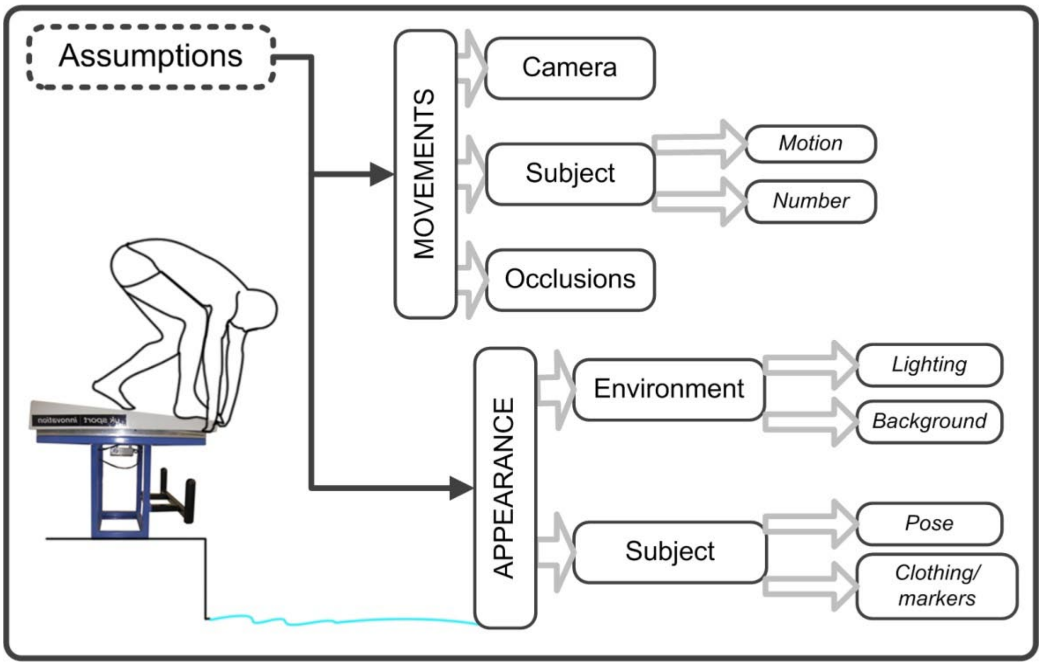


Figure 2-6: Typical assumptions made when applying automated vision for human motion analysis

Moeslund and Granum 2001 identified a number of assumptions that are typically made when implementing a vision-based human motion system, presented in Figure 2-6. It is important to note that the fulfilment of these assumptions will be unique for every application and that not all will hold for every situation. These assumptions were categorised as either movement assumptions, of the camera or subject or appearance assumptions relating to the environment or the subject. Each of these assumptions is discussed in relation to a swimming application.

Occlusion assumptions were included in the movement section, whereby it was assumed that the entire subject and motion would be visible throughout all images. This would not necessarily be the case in a swimming application using a single, or even multiple cameras. For example, during a swimming start the nearside limbs would occlude, at least in part, the far side of the body.

Additional assumptions were based on the camera and subject behaviour. It was assumed that the camera would be in a fixed position or would travel along a known path. The tracked subject was assumed to be moving in a single plane of motion and that movements would be smooth and continuous, i.e. would not display erratic behaviour. It was also assumed that only a single subject is present at any one time.

With regards to the appearance of the frame, typical assumptions included constant lighting, a stationary background and in some cases, such as chroma-keying, a uniform background was assumed [Yoo and Nixon, 2003]. These assumptions would not hold in a swimming pool environment where lighting and background characteristics would be difficult to control and water movement would create unavoidable reflection patterns that would prohibit the ability to employ a completely static background. It is possible that a Polaroid filter may be capable of removing reflections, however, the movement of the water would still rule out a stationary background.

Assumptions pertaining to the appearance of the subject include references to pose and specific markers [Campbell and Bobick, 1995, Goncalves et al 1998] or known features, such as clothing characteristics [Bharatkumar et al , 1994] . In some cases the initial pose of the subject is known, and compliance with this pose is required for initiation of the process, though not in all cases, i.e. those that do not employ model-based pose estimation. Clothing with specific characteristics, such as colour or markers, may also be used to assist the successful identification of features.

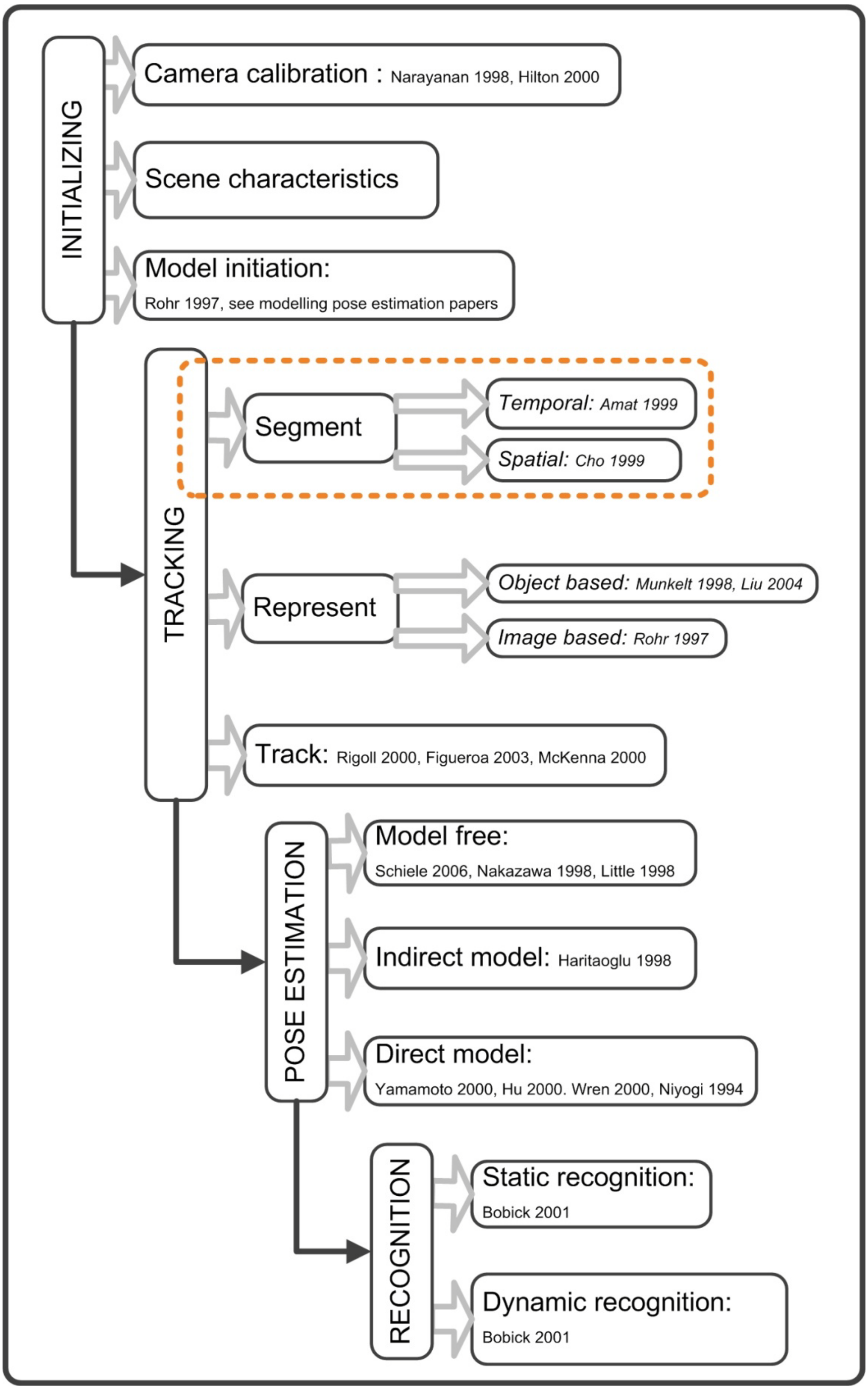


Figure 2-7: Phases of an automated vision system

The four process stages identified in Figure 2-7. Initialising a system involves actions such as camera calibration, as discussed in Narayanan et al , 1998 and Hilton et al, 2000], accounting for scene characteristics such as lighting and where relevant models are initialised [Rohr, 1997]. Tracking can be described in three phases, segmentation, representation and tracking. The ability to segment the AOI is fundamental to the success of the system. Segmentation can be performed by two means, temporally or spatially. Temporal segmentation describes methods which track the difference in pixels over time [Amat et al 1999], whereas spatial segmentation looks at pixel values, for example in research by Cho et al, 1997, where spatial segmentation is used to segment skin colour. Assumptions discussed previously will affect the methods and eventual success of segmentation.

The segmented area must them be represented, this can be achieved using object or image based methods. Object-based representation use such as silhouettes or blobs, to characterise tracked AOI's, for example in Liu et al 2004 and Munkelt et al 1998, where people are represented by silhouettes and points, respectively. Image-based representation methods use the pixels in the image, such as tracking edges or features [Rohr, et al 1997], to portray movement. Examples of tracking are described in Rigoll, et al 2000, Figueroa et al, 2003 and McKenna et al 2000.

Pose estimation can be performed using one of three methods, i.e. model free, indirect modelling or direct modelling. Model free methods assume no prior knowledge regarding the expected pose or movement of the tracked object, examples of which can be found in Little et al 1998, Schiele 2006 and Nakazawa et al 1998. Indirect methods use models to aid pose estimation, for example they may use look-up tables to guide the prediction of pose. An example of this is in Haritaoglu et al 1998, where ratios of body segments are used to better predict pose and track objects. Direct modelling uses a model that is updated throughout the tracking process, for example, Hu, et al 2000, Wren et al 2000, Yamamoto et al 2000 and Niyogi et al 1994.

Recognition of the object can be either static or dynamic. Static describes a method for recognising spatial information in a single frame, for example to define poses. An example of this is by Bobick et al, 2001, where gait is analysed by defining features within a frame such as the distance between the subjects head and foot, the distance between the head and the pelvis and the difference between the left and right foot. Dynamic methods analyse data temporally, i.e. movement between frames. Bobick et al 2001 used this to recognise human movement such as waving arms, sitting down and squatting. Recognition can also be achieved using reconstructive or direct methods, i.e.

by reconstructing the frame to understand the tracked object or by recognising motion based on tracking of low-level feature representation, such as in Polana and Nelson Considerations and implications of applying an automated vision system for the analysis of swimming have been discussed. A number of typical assumptions made in the implementation of automated vision systems were identified. It was found that a number of these assumptions did not hold true for a swimming application, highlighting the challenging environment that must be overcome to implement a successful automated vision system. For this reason it was considered that robust segmentation of the AOI would be the most important challenge to overcome in order to enable the automation of vision analysis.

In addition to vision analysis techniques alternative technologies have been discussed in literature. These include the development of swimmer worn sensor nodes that enable the collection of accelerometer data, which can be analysed to assess swimming performance. These technologies allow a greater resolution of measurement to be achieved, compared to vision techniques, and provide quantitative measurements of movement, rather than derived parameters.

2.3 Body sensor networks

Emerging technologies in swimming research have begun to address the shortcomings of current accepted methods of performance analysis. These systems look at the use of non-encumbering, swimmer worn 'nodes' to monitor performance, using sensors such as accelerometers. [Ohji et al 2003, 2005, James et al 2004, Davey et al 2008].

Table 2-4: Overview of accelerometry technologies in research and commercial applications

		Commercial		Research	
		Paper/product	Description	Paper/product	Description
Real-time (wireless)	One to one	• KinetiSense	• Wireless inertial sensing and EMG (electromyography). A number of nodes wired together in one system, e.g. to position on different parts of the body	• Tapia et al 2007 • Youngbum et al 2007 • Davey et al 2004 • Fong et al 2004	• Physical activity recognition (including sitting, walking, cycling and running) and heart rate • Monitoring of 'activities of daily living' (ADL) and ECG for heart rate. • MEM's unit with basic processing, e.g. Maximum, minimum, standard deviation. Building block for future applications. • Wireless motion sensing for sports science application, used to monitor hand movement while running.
	Network	• Toumaz sensium	• Physiological monitor, e.g. temperature, heart rate, ECG. Potential to add accelerometer. Up to 8 node network.	• Youngbum et al 2007	• Fall detection, with ZigBee wireless network
Data-logging		• Actigraph • Omron • Nokia step counter	• Activity monitor, primarily step counter/pedometer. • Pedometer • Pedometer	• Gopalai et al 2008 • Welk et al 2004 • Rodriguez et al 2005 • Wixted et al 2007 • Luinge et al 2005	• 2D human motion regeneration of bowling motion. Need more than an accelerometer, i.e. Other sensors, to assess 3D motion. • Reliability of accelerometer based activity monitors assessed. • GPS used to compliment accelerometer activity sensor. • Energy expenditure for walking a running using accelerometer. • Orientation of body segments using Kalman filter.
				SWIMMING	
				• James et al 2004 • Davey et al 2008 • Callaway et al 2009 • Ohji et al 2003 • Ohji 2006	• Traqua' development to assess swimming performance. • Validation of 'Traqua', accelerometer based swimming monitor. Video used for validation. Lap count, stroke rate, stroke count and stroke recognition compared. • Comparison of video and accelerometer analysis techniques in swimming. • Stroke phase discrimination in breaststroke, using acceleration of the wrist. Technique used as a stroke counter. • Discrimination of stroke phases using acceleration.

The use of accelerometers for monitoring human movement has emerged commercially for applications such as activity monitoring [e.g. Actigraph, Omron, Nokia Step Counter and KinetiSense] and health care [e.g. Toumaz Sensium]. Equally, accelerometers have been used in research for applications such as physical activity recognition [Tapia et al 2007], fall detection [Youngbum et al 2007], and predicting energy expenditure [Wixted et al 2007].

Current uses of accelerometry for monitoring of people have been divided in to real-time and data logging subsections and further into commercial and research applications, presented in Table 2-4. It was found that swimming specific applications grouped into a single category, namely data logging solutions within research. The literature presented validation trials for the use of accelerometers in swim specific analysis. It was reported that accelerometer data, mounted on the small of the back, could be analysed to derive lap count and timing to +/-1s in 90% of cases, stroke rate and stroke count to +/- 1 stroke for 90% of cases and stroke recognition for 95% of trials [Davey et al 2008]. Furthermore, Ohji et al 2003 found that acceleration traces from the wrist could be used to discriminate stroke phases, however, this was achieved by integrating synchronised video with the acceleration data.

Research to date has supplied confidence in the usefulness of accelerometer data for the performance analysis of swimming. Solutions have demonstrated that algorithms could be used to successfully monitor parameters such as stroke rate and duration, without the need for manual vision analysis techniques, which would be traditionally used. This means that analysis of multiple parameters could be completed in less than a second, rather than the minutes or tens of minutes associated with vision techniques. In addition to this, results had a greater reliability as consistent techniques were used to derive performance parameters that no longer relied on human judgement. Furthermore, it is believed that due to the increase in measurement resolution of sensors, such as accelerometers, compared with current vision data, more complex movements may be analysed.

The greatest shortcoming of current research is that the technologies developed do not possess a real-time capability and operate one-to-one, i.e. they cannot be networked. To achieve real-time analysis a move towards wireless technology would be necessary, where a network could be implemented, enabling multiple athletes to be monitored at concurrently.

2.4 Wireless Sensor Networks

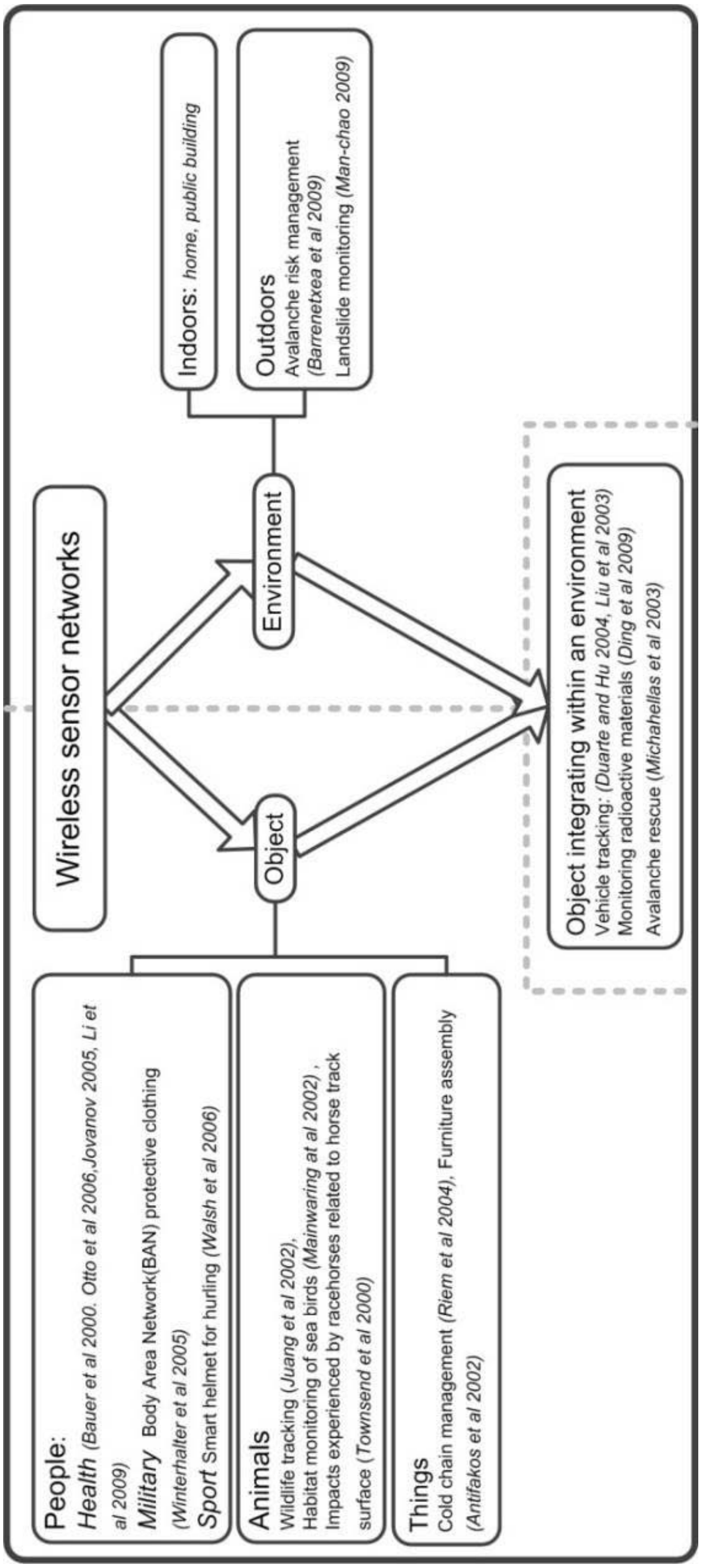


Figure 2-8: Wireless sensor network domains

Wireless Sensor Networks (WSN's) is an umbrella term for a range of technologies used for different applications. These enable distributed monitoring via sensors that communicate results and feedback wirelessly. There are three key application types for WSN's, namely, object, environment or an object integrating within and environment. These subdivisions can be seen in Figure 2-8 . WSN's to monitor objects may be used too for people, such as in healthcare [Bauer et al 2000, Otto et al 2006, Jovanov et at 2005, Liu et al 2009], military [Winterhalter et al 2005] or sports [Walsh et al 2006]. Also, objects may include animals, such as for wildlife tracking [Juang et al 2002], habitat monitoring [Mainwaring et al 2002] and things, such as cold chain management [Riem et al 2004] or furniture assembly [Antifakos et al 2002].

Environmental WSN's can be applied in indoor environments, such as in-home security, or heating control, and outdoor environments, such as in avalanche risk management [Barrenrtxea et al 2009] or landslide monitoring [Man-chao et al 2009]. Objects integrating within an environment WSN are concerned with monitoring how a person, animal or thing interacts with an environment. For example, in vehicle tracking [Duarte and Hu 2004, Liu et al 2003], monitoring radioactive materials [Ding et al 2009] or avalanche rescue [Michahellas et al 2003].

WSN's that monitor people, for example in sports and healthcare applications, often use body worn sensors that communicate to a local processing unit. This specific type of WSN has been termed a 'Body Sensor Network' (BSN) and is considered a separate platform type that has evolved from the WSN platform.

2.4.1 Body Sensor Networks

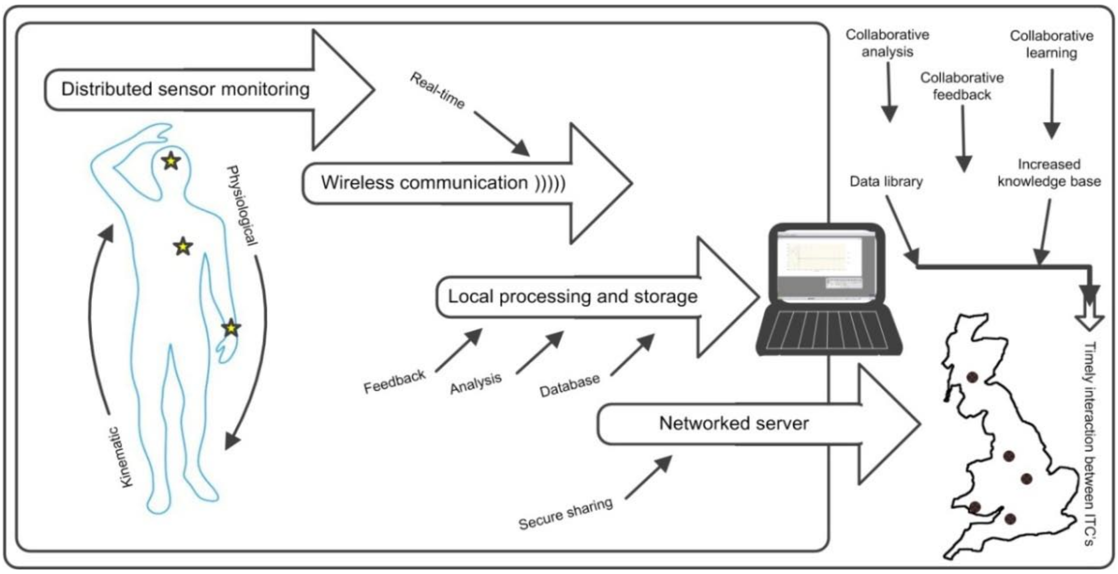


Figure 2-9: Body sensor network, component overview

A BSN has a number of standard components that are common throughout all applications. These have been summarised in Figure 2-9 as distributed sensor monitoring, wireless communication, local processing and storage and networked server. Distributed sensor monitoring can be achieved using implantable or wearable sensors that monitor the human body, either in a physiological or kinematic capacity. These sensors wirelessly communicate data to a local processing unit, for example a laptop or Personal Digital Assistant (PDA). Wireless communication allows real-time monitoring, which is essential for applications such as healthcare of a vulnerable patient. Typically the local processing unit stores sensor data into a database and enables analysis and feedback to be supplied to the monitored person. Alternatively this feedback can be directly relayed to external parties, e.g. in the case of healthcare this may be a doctor. This facilitates analysis of a patient's condition and feedback of results to be undertaken without the need for direct contact. For healthcare applications this also could also be used to flag emergency situations and enable action to be initiated. Equally it allows data to be shared remotely among external parties located in different geographical regions; this could be within a building, county, country or worldwide.

Within the context of this project it was believed that a swimmer-based BSN to monitor athlete performance would enable real-time data capture, analysis and feedback that could be shared among Intensive Training Centres (ITC's) across the country. This could facilitate the construction of a large data library that would increase the current knowledge base, i.e. where data would be normally noted on a piece of paper by hand and 'filed', this data could be stored over time and trends may be derived. Equally it was important to note that the structure within British Swimming is such that there is only one biomechanist, one strength and conditioning coach, one nutritionalist and one physiotherapist. This means that only one ITC could be serviced at any one time by each of these professionals. A networked server would enable constant monitoring of athletes across the country such that priority could be made to ensure these professionals were at the most appropriate location to best add value, and equally, where appropriate, feedback could be given to athletes remotely based on evaluation of shared data.

2.4.1.1 Challenges of implementing a BSN

Table 2-5: Technical challenges associated with implementing a body sensor network within a swimming environment. Table adapted from Yang, 2006

Features	Technical challenges (specific to swimming application)
Size	Needs to operate in a confined space, i.e. Small enough that the swimmer does not mind wearing it.
Power	Must be capable of recording a complete session, i.e. Up to 2 ½ hours before requiring recharging/replacement of batteries/power.
Cost	At the research and development minimal implications of cost.
Lifetime	Dependant on cost. If they are expensive then the lifetime must be longer than if they are manufactured inexpensively hence opening up the options for disposable devices, e.g. Potentially use for one session.
Wireless	Range, bandwidth, standards, protocols – Operation in a harsh environment, i.e. Submerged.
Network	How many swimmers, what is the bandwidth available, proximity
Sensors	Measurement types, specifications, size.
Electronics	Analogue/digital. Hardware/software.
Packaging	Waterproof, submersible, antenna operation underwater.

A number of technical challenges have been identified that are associated with the implementation of a BSN. The implications of these have been discussed with reference to a swimming based application in Table 2-5. Stakeholder requirements defined that the size of sensing units, or nodes, must be small enough that they can be worn without being encumbering to the swimmer. The nature of swimming is such that there is little opportunity to embed sensors into garments and little to mount sensors onto. For this reason the size and form of any developed solutions were identified as important to ensure comfort for the swimmer. Any discomfort or perceived performance detriment would not be acceptable for the final developed solution, as this would likely prevent uptake and use of the product. The largest component associated with a sensor node is the power supply and therefore a compromise between battery life and battery size would be required. It was expected that preliminary iterations would have a larger than ideal footprint due to the nature of development equipment, however, an eventual optimised size would be paramount to success.

The research and development of electronic devices attribute the biggest overall cost. Once a design has been consolidated and volumes are manufactured the cost per unit would be more significantly influenced by the research and development phase than the cost of materials and manufacture. The unit cost of solutions becomes more important once they are developed for commercial use, which is beyond the scope of this project.

The lifetime of developed solutions was not specified at this stage. If a low cost solution is developed it may be appropriate to consider units as disposable after a given period of usage. However, should costs associated with specialised microcontrollers, sensors and packaging increase the total unit price then a solution with a longer lifetime that reflects the additional cost, would be preferred.

Wireless communication was considered the most challenging feature in establishing a BSN for swimming. The water-air interface creates a challenging environment for wireless communications. Technologies such as acoustic transmission are successfully applied in open water, sea applications. These are, however, limited in bandwidth and assume an infinite body of water and therefore experience little, if any, noise from reflections. Overcoming this communications challenge was one of the biggest steps in enabling the establishment of a swimming sensor network.

The network capability of the final system would be influenced by the wireless communication solution. Aspects such as bandwidth, proximity and number of sensors would affect the maximum size of the network. Decisions regarding sensor types, sensor numbers, data rates and transmission rates need to be taken to achieve a compromise between functionality and network size. For example, for a typical squad size of eight athletes, given a node on each athlete, the maximum capacity of the system would have to be calculated such that the bandwidth would be effectively used but not exceeded for eight nodes.

Electronics are concerned with the hardware of the node. Decisions about the microcontroller, for example, would include whether to have an integrated transceiver or whether to interface to an external transceiver. The microcontroller and transceiver were considered the most influential parts of the electronics. These components would limit aspects such as, the number and types of sensors that could be interfaced, the bandwidth available for communications and the memory available for both programming functionality and storing data.

Packaging was an important consideration for the final developed solution. It was essential that packaging provided a waterproof enclosure for all of the components. During the development process it was preferred that packaging allowed easy access to components for reconfiguration, which would be a lower priority beyond the prototype phases.

2.3.2.2 Components of a BSN

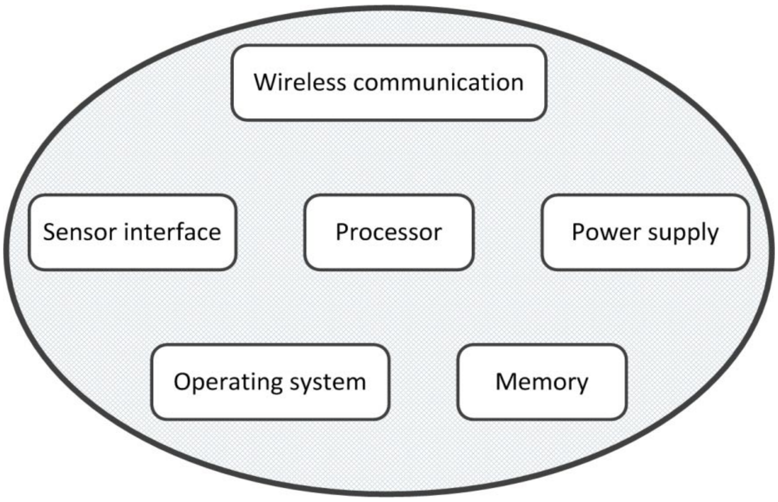


Figure 2-10: Components of a wireless node. Adapted from Yang, 2006.

A wireless node is built of six main components; the processor, power supply, memory, operating system, sensor interface and wireless communication, see Figure 2-10. The processor is the core component that interlinks all of the other components. Each of these components has been individually discussed with reference to a swimming system application.

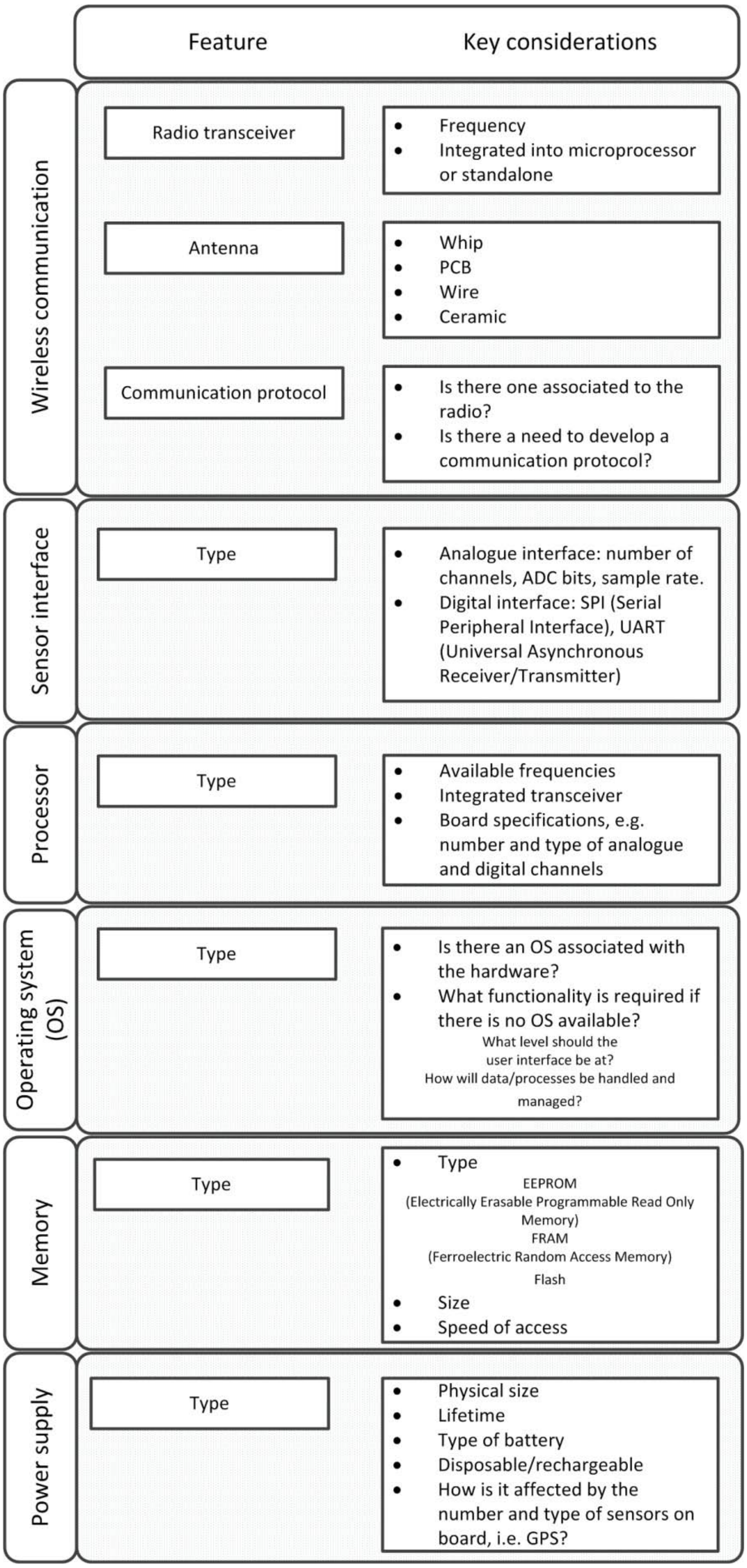


Figure 2-11: Considerations for wireless node design

Decisions pertaining to the six components, Figure 2-10, are reviewed in Figure 2-11 and considered in this section in further detail.

2.4.1.2 Wireless Communications: network topology

The wireless communications element has three key considerations; the radio transceiver, antenna and communication protocol. Decisions relating to the radio transceiver primarily relate to the frequency selection and whether to use an integrated or standalone radio transceiver. The antenna selection is constrained by elements driven by the frequency of the transmission. There are multiple antenna types that may be considered including a standard whip, typical for development, printed circuit board (PCB), wire and ceramic options. The final antenna must be designed to optimise transmission in terms of range, directionality and minimise data losses. It must also take into consideration its overall footprint and form given that a swimmer must wear it.

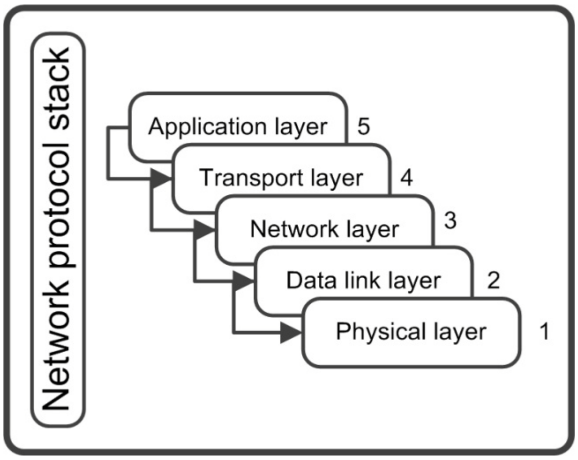


Figure 2-12: Network protocol stack layers

The network protocol stack may be supplied with the transceiver or may require development. Where applicable it should be designed to optimise efficient communications and minimise data losses, given a network of multiple nodes. A network protocol stack typically has five associated layers, see Figure 2-12. These layers link the physical components of the node hardware to high level programming used to control components and facilitate structured communications between a number of nodes.

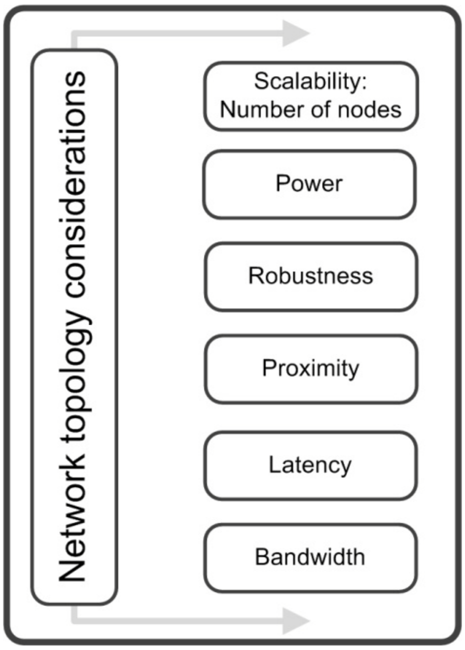
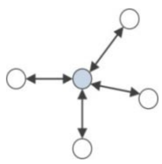


Figure 2-13: Network topology considerations

A networking capability was considered essential for any solutions developed to enable simultaneous multi athlete monitoring. Network topology would be selected based on a number of requirements. Typical considerations, summarised in Figure 2-13, are scalability, power consumption, robustness, proximity, latency and bandwidth.

For a swimmer-based application the number of nodes would depend on the measurement type, i.e. measuring the start, free swimming or turns, squad size and number of nodes per athlete. Starts and turns analysis tend to focus on individual athletes, whereas free swimming monitoring, e.g. of split times, may be required for an entire squad simultaneously.

Table 2-6: Point to point and star network topology descriptions

Topology	Diagram	Description	Advantages	Disadvantages
Point to point		A one to one link between devices	• Simple	• No scalability • Limited spatial coverage
Star		A number of nodes connected to a central node. Master-slave, all communication goes through the master	• Simple • Low power consumption of slaves • Easy to configure • Low latency and high bandwidth • Centralised • Scalable	• Dedicated central node • Limited spatial coverage • Inefficient slave to slave communications

Network topology describes the way in which communication between nodes is organised. In the literature reviewed relating to sensor nodes used in swimming, all applications have been developed on a point-to-point basis, using wired communications. Table 2-6 provides an overview of features associated to a point-to-point network. The move towards wireless technology would present the opportunity to create a network of nodes. The first iteration of this development would be to employ a star network, which supplies a basic master slave function between a network of nodes, see Table 2-6. Future developments may require increasing complexity of communications and therefore alternate topologies would be considered, e.g. that allowed inter-node communication or hopping of messages.

The power consumption of nodes was considered important due to the effect power requirements would have on its footprint. Ideally, to minimise size, the power consumption of the swimmer worn nodes would be low.

Robustness describes the reliability of communications, i.e. how well are messages being sent and received. It was considered essential that communications are highly robust to ensure minimal data losses. However, given the challenges of transmitting through an air-water interface, it was considered that robust communications may not always be achievable and therefore to minimise data losses, nodes must have available memory capacity for storing data as well as transmitting.

2.4.1.3 Wireless Communication: in water

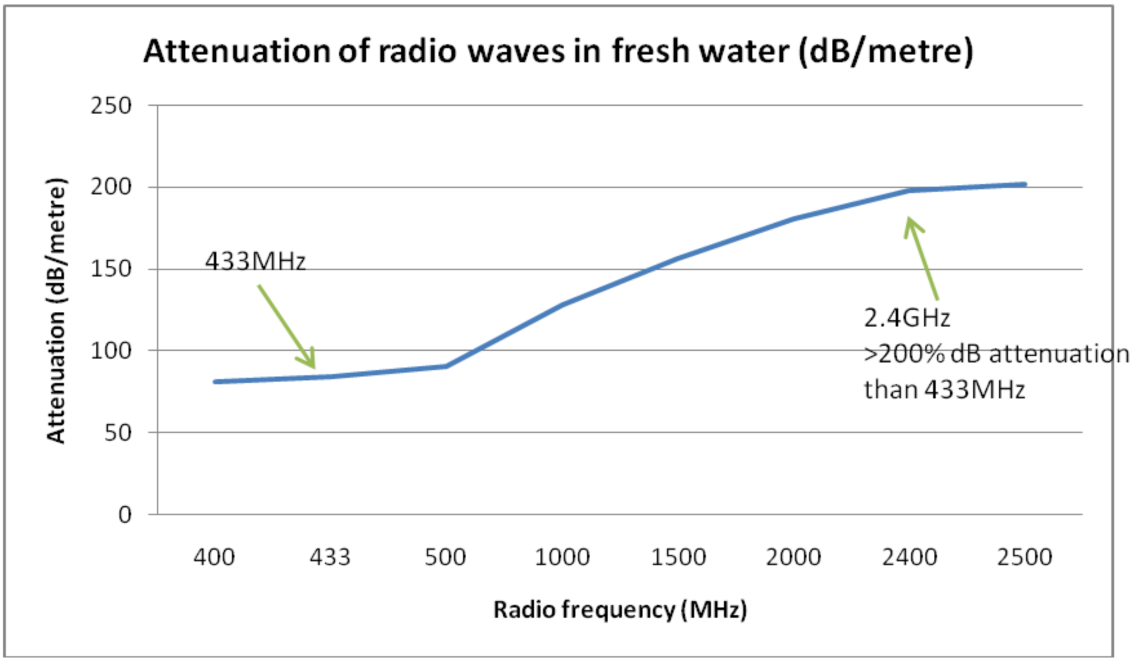


Figure 2-14: Attenuation of Radio waves in fresh water

The attenuation of radio waves in fresh water can be described by:

$$Attenuation\ (\alpha)\ in\ dBm = 0.0173\sqrt{f\sigma}$$

$$Where\ \ f = frequency\ (Hz)$$

$$\sigma = conductivity\ in\ mhos/metre$$

Given this equation, attenuation was plotted for frequencies from 400MHz to 2.5GHz, Figure 2-14. Radio waves at 2.4GHz attenuated more than 200% more than at 433MHz. This suggested a lower frequency would be attenuated less than a signal transmitted at a higher frequency when travelling through water. This assumed pool water follows a similar trend to fresh water.

2.4.2 Sensor Interface

The sensor interface, detailed in Figure 2-11, would be determined by the choice of microprocessor. The number and type of channel inputs was an important microcontroller feature as this would constrain the number and types of sensors that could be interfaced to the node. Sensor interfaces were either analogue or digital.

Sensor specifications, e.g. type, resolution and whether analogue/digital, would drive how the available inputs are used and the resolutions required of them.

2.4.3 Operating System

The operating system component associated with the node allows control and programming of the microprocessor and subsequently all of the peripheral components and functions on the board. The processor selection determines whether there is an operating system available or whether the chip must be programmed at the low level, i.e. whether functionality must be programmed at a pin level.

2.4.4 Memory

This may be supplied as part of the processor chip; alternatively there may be options to connect additional memory through one of the available interfaces. The type and size of memory would be important to ensure data can be stored and accessed as required by the system.

2.4.5 Power

The power supply for the wireless node was expected to be the most significant contributor to the overall footprint. Given that the form of the node was very important for a swimmer worn application, it was essential to minimise the footprint of the power supply while ensuring there was sufficient power supplied to each of the components. A compromise needed to be achieved between power availability and power-cell size to best satisfy the application.

2.5 Summary

2.5.1 RQ1 Current state of the art in swimming research

Current research pertaining to the performance analysis of starts, free swimming and turns has been reviewed. Manual vision analysis has been consistently used as a performance measurement technique. Other methods used for analysis included: starting blocks and turning walls instrumented with force transducers and tethered systems for measuring swimming velocity. The current limitations of research are such that a number of measurement and process stakeholder requirements, specified in the needs, are not currently satisfied. Manual vision analysis, the most common analysis technology, suffers from high time and expertise resource requirements. The reliance on human judgement reduces the reliability of results due to the inherent variability arising from either single user, (intra-person variability) or between measurements taken by different users (inter-person variability).

2.5.2 RQ2 Body sensor networks

The use of accelerometers for the analysis of swimming was identified as an emerging technology. Current applications of accelerometer-based analysis were discussed for both swimmer applications and alternative applications, such as activity monitoring. A review of body sensor networks has been carried out. Challenges, design considerations and implications of implementing a BSN for swimmer analysis have been presented.

2.5.3 RQ3 Automation vision analysis for human motion analysis

Automated vision systems for human motion analysis have been identified as an established area of research. Basic processes for successful implementation have been discussed and the implication of these processes evaluated within the context of a swimming application. A number of typical assumptions made in the implementation of automated vision systems have been identified. A number of these assumptions were not satisfied within the swimming environment, i.e. a swimming pool was identified as a challenging environment in which to implement automated vision techniques. It was concluded that to successfully apply an automated vision system, the ability to segment the swimmer, or feature pertaining to the swimmer, must be proven.

Chapter 3

3. DEVELOPMENT OF COMPONENT TECHNOLOGIES

3.1 Chapter Overview

Work presented in this chapter is concerned with the development of component technologies to enable performance analysis of starts, free swimming and turns. Each of the components was designed to minimise operator input in terms of time and expertise and maximise measurement output, i.e. satisfy as many of the stakeholder requirements as possible. Components were designed and validated in isolation but were conceived to work as an integrated system.

3.1.1 Research Questions (RQs)

RQ1 Automated Vision

a. What are the limitations of using current manual measurement techniques?
b. What processes are involved in the design and implementation of automated vision techniques in this application domain?

RQ2 Force Plate

a. What is required for the design and calibration of an instrumented starting platform?

RQ3 Wireless Node

a. What processes are involved in the design and implementation of a wireless sensor node?

b. What processes are used in the analysis of data obtained from wireless sensor technologies?

3.1.2 Chapter Structure

The variability of current vision analysis techniques, i.e. manual digitisation, was quantified using a study of dive angle measurement. Dive angle could then be used to validate any automated techniques developed. The principles behind automated vision systems are discussed pertaining to the development of a swimming specific system, in terms of components and processes. LED markers were designed to provide a marker system for use over and underwater.

The design and development of a start block instrumented with force transducers is detailed. Calibration of the block in three axes is detailed and results are discussed.

The design and development of a wireless sensor node is explained in terms of hardware selection, wireless communications and network protocol. Basic principles of feature extraction are outlined, specifically filter design and the use of time or frequency domain characteristics to analyse data.

3.2 Vision methods for automated vision analysis

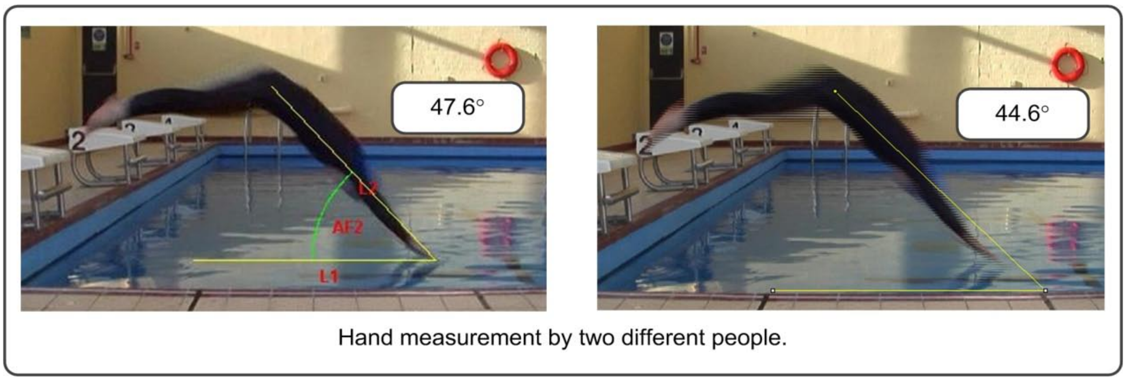


Figure 3-1: Hand measurement of dive angle by two different people

Current methods employ the use of vision analysis in two ways: subjective analyses and manual digitisation, both of which have inherent variability due to their reliance on human operator input and experience. This variability is highlighted by the variability in the measurement of the same dive ($\Delta\theta = 3^{o}$) by two different people of different levels of experience, Figure 3-1. Given that these methods are accepted as the state of the art in current use it was considered that this variability should be quantified in detail. Future tools could then be measured against this standard variation value.

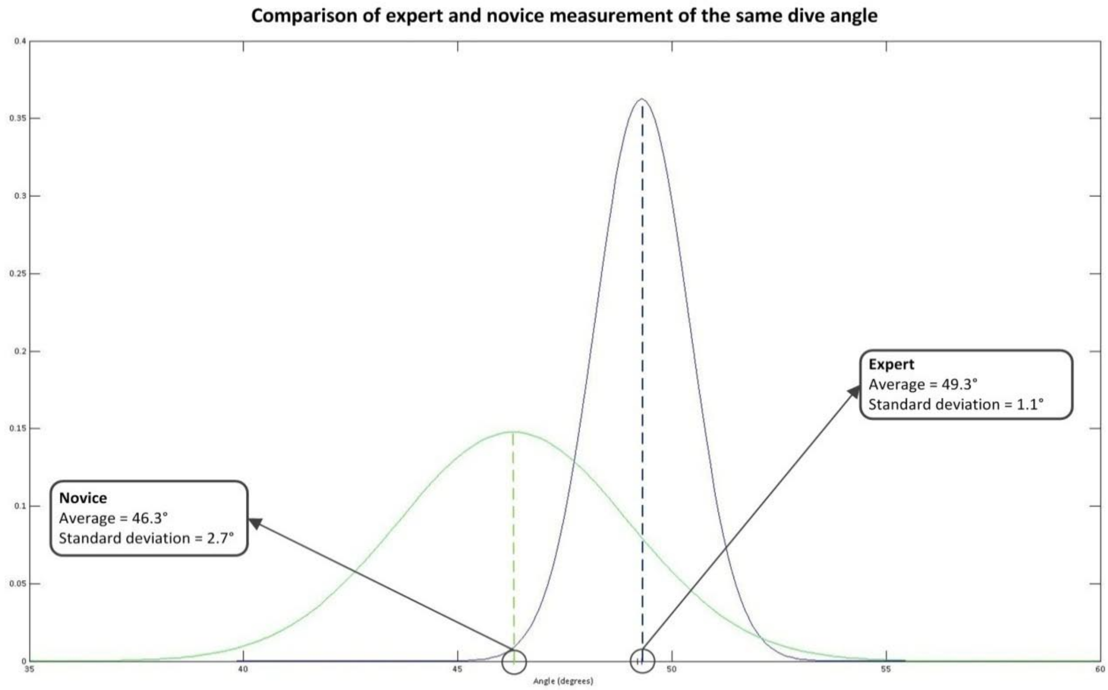


Figure 3-2: Distribution of hand measured variability for inter and intra person measurement

Dive angle is a performance measurement that is, among others, one of the desired requirements specified by the user (see Chapter 1: Quantification of Stakeholder Requirements, Table 1-1). Currently technologies available to enable this measurement are limited to manual digitisation of video. Manual methods suffer from two key limitations:

1. *intra* person variability, i.e. if a person measures the same angle on two different occasions how far will each value deviate.
2. *inter* person variability, i.e. if two different people measure the same thing how far will their values deviate.

To gather these data, two separate tests were undertaken, the results of which are plotted in Figure 3-2. Firstly the intra measurement variability of a single user was considered. Three subjects, who were from a technical background, were given an image of a swimmer as their fingers touched the water during the dive. They were asked to measure the angle of the swimmer's dive over a series of ten days. Separating measurement by this amount of time aimed to replicate typical current practise. Results showed that the standard deviation of a single user's measurements ranged from 0.8° - 1.4 ° (1 d.p.). On average the standard deviation of the three subjects' measurements was 1.1°.

The variability of multiple users was then addressed by asking ten subjects, from a technical background, to measure the angle of entry of a given dive. In this case the standard deviation of measurements was 2.8°, reflecting the influence of personal judgement on the consistency of measurement outcomes.

Using this study, the variability of manual measurement based on human judgement has been quantified. As a result, it can be concluded that when using hand measurement techniques, 68% of dives will fall within one standard deviation of the mean, i.e. ±1.1°, 95% within two and 99% within three (assuming measurements can be represented by a normal distribution , i.e. measurements are unbiased). This value gives an indication of acceptable performance for any systems and solutions developed. An automated method that is capable of generating analyses comparable to those achieved using manual methods and that can reduce operator input was the desired outcome of this work.

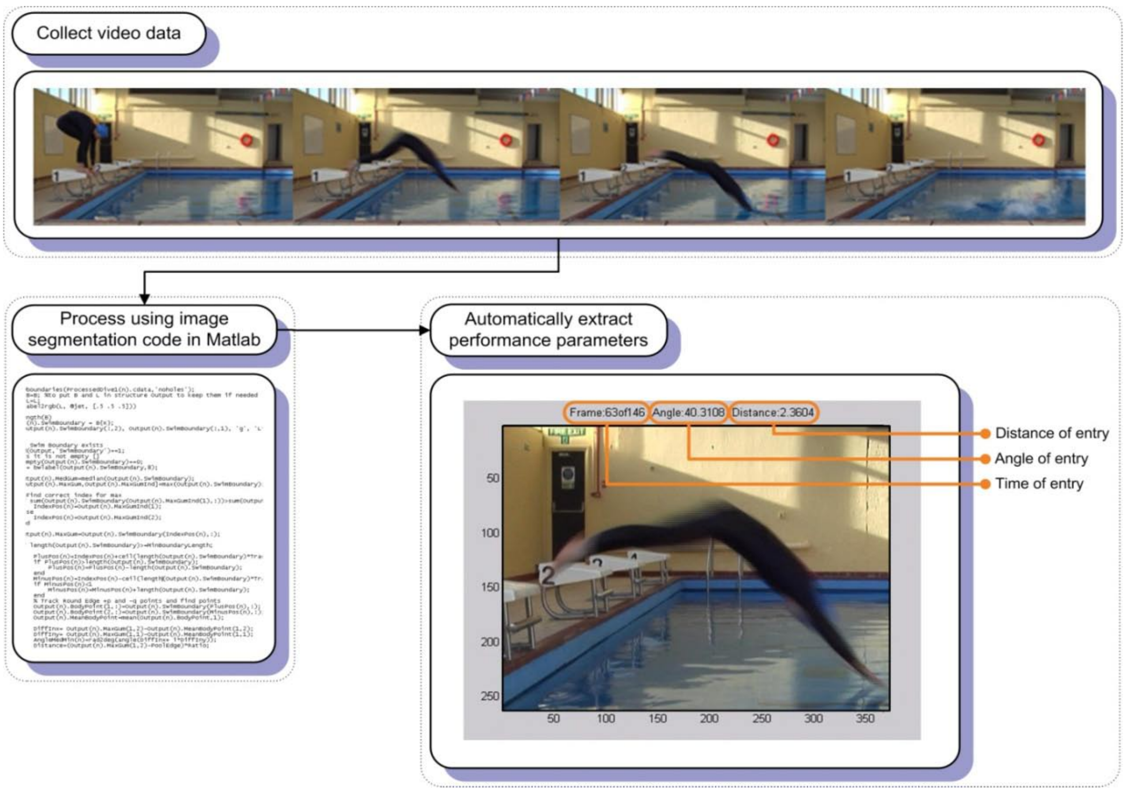


Figure 3-3: Overview of proposed image processing system

It was proposed that an automated image processing system be developed that will have the capacity to satisfy a number of the users' needs in a more efficient manner than current performance analysis methods. Fundamentally the system included a camera to capture video of the swimmer in the start, free swim or turning phase of their swim. This video is then processed on a computer using software algorithms developed to threshold the image and extract performance parameters about the swimmer (see Figure 3-3 and Chapter 2: Literature Review, Section 2.4). Temporal or spatial thresholding may be used to achieve these measurements, depending on the nature of the environment to which the image system is applied.

3.2.1 Image processing development components

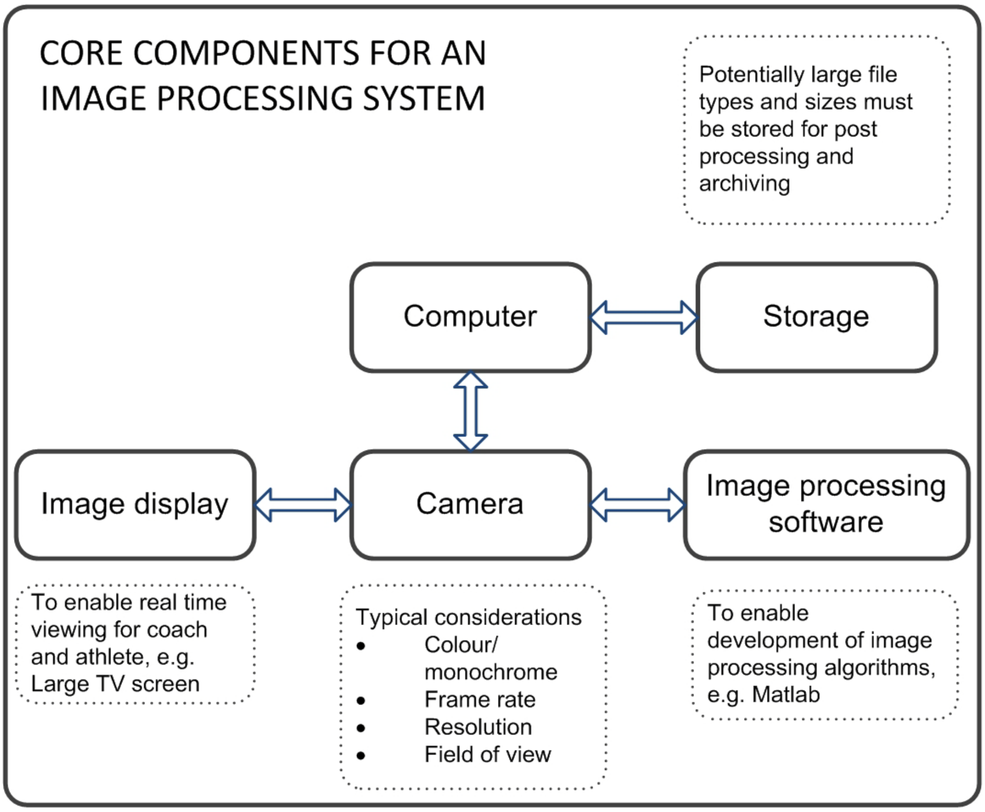


Figure 3-4: Core components of an automated image processing system

Image processing systems are built up from a set of core components [Acharya, T, 2005] that are tailored for the specific application, namely these are the *computer*, *storage*, *image display*, *camera* and *image processing software*, see Figure 3-4. Central to the system is the *camera*, since decisions made regarding this element impact directly on all other system components. Typical considerations for camera selection include colour or monochrome, frame rate, resolution and field of view. Within the swimming application there are a number of different requirements for camera specification, i.e. for starts, free swimming and turns.

There are three key driving factors for camera selection. Firstly, the functional aspects of use, e.g. for the start a relatively large field of view is required to allow the whole *start* to be viewed, ~7m x 4m, whereas, for a *turn* the area of interest is contained within a smaller area, ~ 5m x 1m. Similarly the function of the two cameras will differ as one will be required to operate underwater and the other above the water. The second driving factor is related to the stakeholder requirements. These drivers include real-time processing, cost and desired resolution of measurement (see Chapter 1: Quantification of Stakeholder Requirements, Table 2). Finally, the availability and capability of current technologies will ultimately impact on the final choice of camera. There will be a series of tradeoffs associated with balancing these needs to optimise the overall solution.

The *computer* serves as a link between hardware and software, facilitates storage and provides processing capabilities. The primary decision is whether to choose a desktop or laptop system. Given the swimming application, where portability is essential, a laptop provides a viable solution whereas a desktop would prove to be less fit for purpose. The choice of *computer* will inherently affect the size of *storage* available. A laptop will provide less memory space however, supplementary *storage* could be provided using external hard drives for archiving videos. The choice of camera will affect the amount of *storage* needed in the overall system, e.g. choosing a colour camera over a monochrome camera will increase each file size by a factor of three.

A *software* component is required to enable processing of the captured video for automated analysis of performance. There are a number of tools that can be used to develop software algorithms, (e.g. Matlab) which can then be embedded into the system, e.g. onto a real-time camera with embedded processing (e.g. Dalsa Boa Smart Camera [http://www.stemmer-imaging.co.uk/]) or into a PC located graphical user interface that can be accessed and operated by any person.

An *image display* is the final component associated with the overall system. This enables the operator and other users to view and re watch the activity. This is especially important in the given application, as coaches and athletes respond well to visual stimuli and rely on video sessions to feedback subjective analysis of performance, which is at the core of all analysis currently undertaken. For the operator an image display offers reassurance whereby a "by eye" check can be undertaken to ensure everything appears as expected.

Each of the components selected for the prototype system should aim to address the needs of the user and the needs of the application whilst complying with the current state of the art in the technologies available.

3.2.2 Vision analysis processes

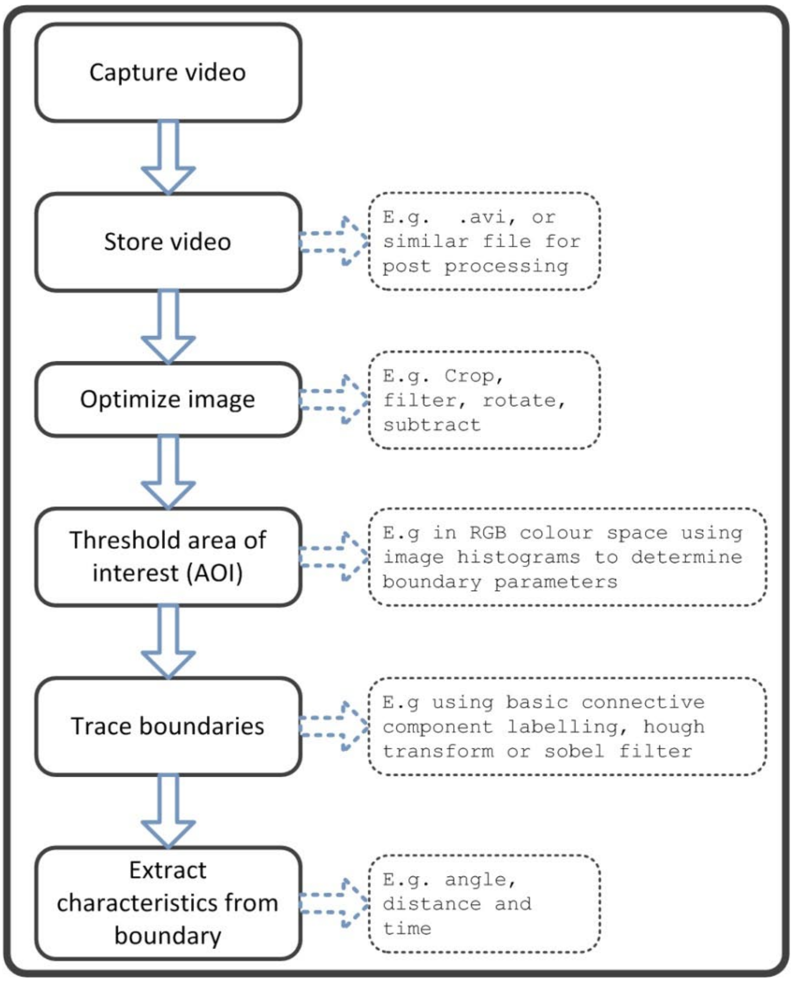


Figure 3-5: Processes for the development of image processing algorithms

To develop an image processing algorithm there are a number of standard functions that can be performed to ensure the best possible outcome, outlined in Figure 3-5. The first stage of the process is to *capture the video*. The *storage* of which will be determined by the camera choice which in turn will affect the storage requirements and file types.

Once the image is captured there are processes that can be undertaken to *optimise* the image for thresholding and feature extraction. These include image cropping, filtering to remove or minimise noise and subtraction of background images to try to eliminate unnecessary detail.

To *threshold* the resulting image, the Area Of Interest (AOI) must be identified. Ideally this AOI will have distinguishing characteristics which allow it to be identified as a feature within the image. The image can be separated into its individual colour channels which can be individually thresholded and recombined. The resultant binary image can then be used to provide measurement characteristics of the AOI by *tracing the boundary* and then *deriving parameters* from this boundary.

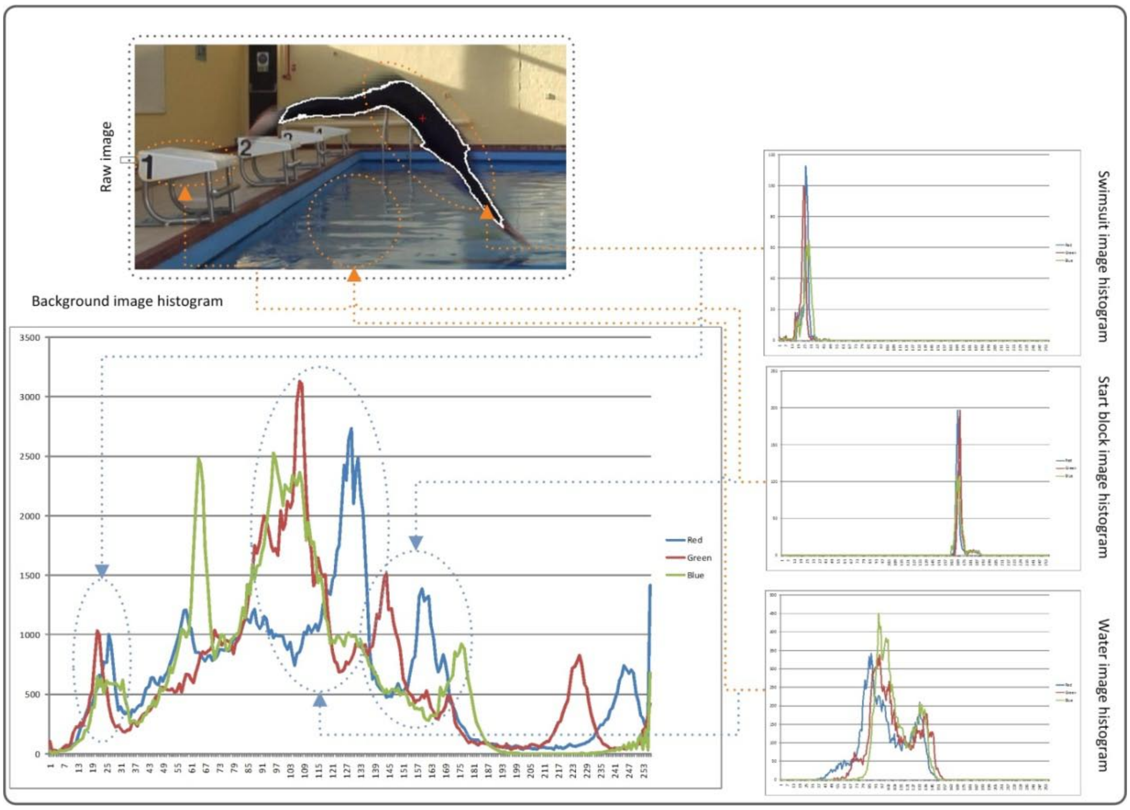


Figure 3-6: Using image histograms to determine feature pixel values

An image can be separated into its individual colour channels for thresholding, i.e. a colour image is made up of individual red, green and blue (RGB) images. Different *colour channel types* can be thresholded, for example, RGB and hue, saturation and value (HSV). RGB thresholding is typically good for colour images where the AOI can be distinguished by colour e.g. in skin thresholding. HSV is also often used for thresholding skin tone, for example in Cho et al, 1997. A discussion of the different spatial methods for skin segmentation can be found in Vezhnevets at al 2007.

Each of the separate colour channels contains information regarding the number of pixels in the image occurring at different intensities. The intensity range is on a scale of 0-255. In a black and white image 0 would represent the black pixels and 255 the white, with a range of grey scale between. Image histograms give a graphical representation of the tonal distribution within an image.

An image histogram supplies information about an image and gives an indication of whether a certain component of the image, e.g. a swimmer or specific marker feature, can be easily discriminated. In the example in Figure 3-6, three individual features in the image have been isolated namely; the swimsuit the swimmer is wearing, the start block and the water. Comparing the histogram for each of the features with the background histogram it becomes apparent where features can be clearly discriminated from the background and where they may be lost in the noise. The swimsuit in this example appears to create a clear feature within the background histogram and therefore it may be possible to isolate this feature from the background.
An image histogram of an AOI can also be used to determine appropriate threshold boundaries for each colour channel. By locating peaks in colour intensity and thresholding about these peaks for each of the channels allows the AOI to be isolated in colour space. Recombining the thresholded channels allows a binary image of the AOI to be generated. The success of this process is determined by the ability to distinguish the feature from the background characteristics.

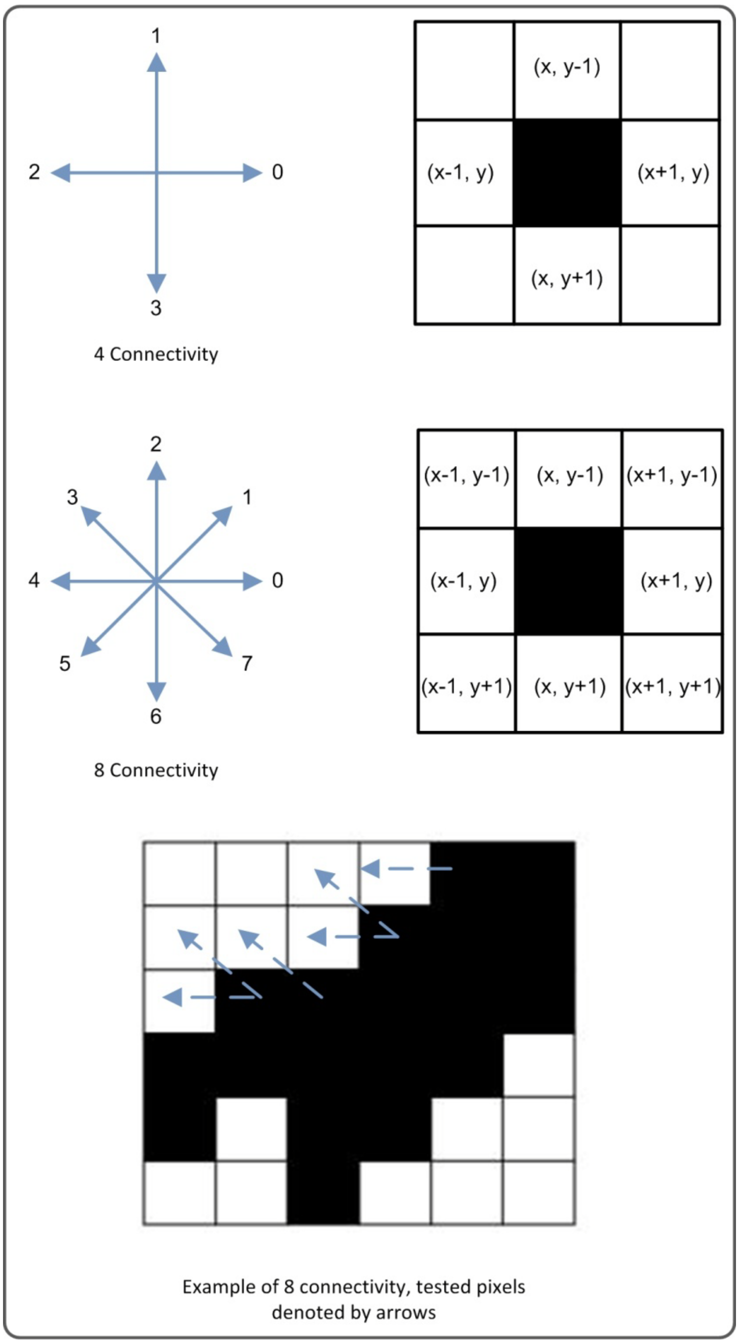


Figure 3-7: Boundary tracing using connective component algorithms

Boundary tracing follows the edge of a feature within a (typically) binary image. The boundary is determined by an algorithm designed to identify and locate pixels with the same value (see Figure 3-7). Once the edge has been detected measurements can be made with regards to the shape (i.e. extremes in x and y directions, centre of gravity, moments about axes) and size of the bounded area.

A typical connective component algorithm initially determines the starting pixel i.e. the top left pixel of the image and then searches to find first adjacent white pixel in a black image or vice versa. From this pixel the algorithm determines the values of the adjacent pixels in an anticlockwise direction. When a same value pixel is found the algorithm will step on and repeat the same process. There are two types of connectivity algorithm, a *4 connectivity* or *8 connectivity,* see Figure 3-7. In *4 connectivity* pixels in north, south, east and west adjacency are tested. In *8 connectivity* pixels in north west, south west, south east and north east will also be tested.

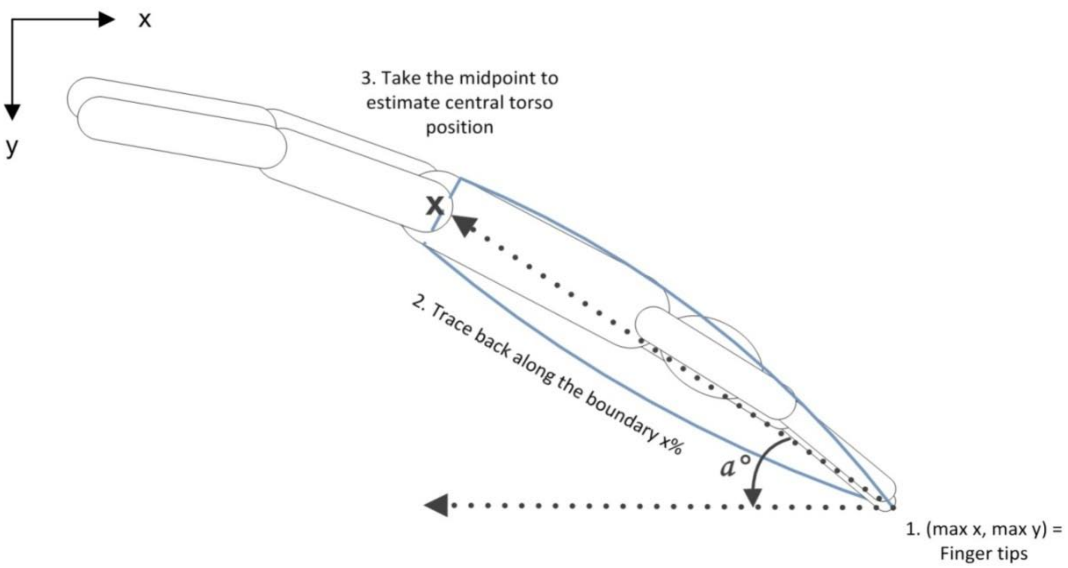


Figure 3-8: Using boundary tracing to derive angle of entry

Once the boundary of the feature has been traced, parameters may be derived from this boundary. An example of this can be used to calculate the dive angle of a swimmer (see Figure 3-8) assuming the boundary of the swimmers body can be established. This process involves estimating the fingertip point of the swimmer as the maximum point of the object, for a swimmer diving from left to right in the field of view. The boundary is then traced back by a given percentage in both positive and negative directions to estimate points either side of the hip. Taking the midpoint of these two point locations, the hip can be approximated on the image. A line can be "drawn" between the fingertips and hip point to give an indication of body angle. Given the assumption that the waterline is horizontal, the angle between the body and the water may be calculated.

Similar algorithms may be developed to derive other performance parameters (e.g. relative angles of body segments) relating to the same object. Using smaller positional markers on the swimmer's body may allow for more specific measurements to be taken to a better resolution.

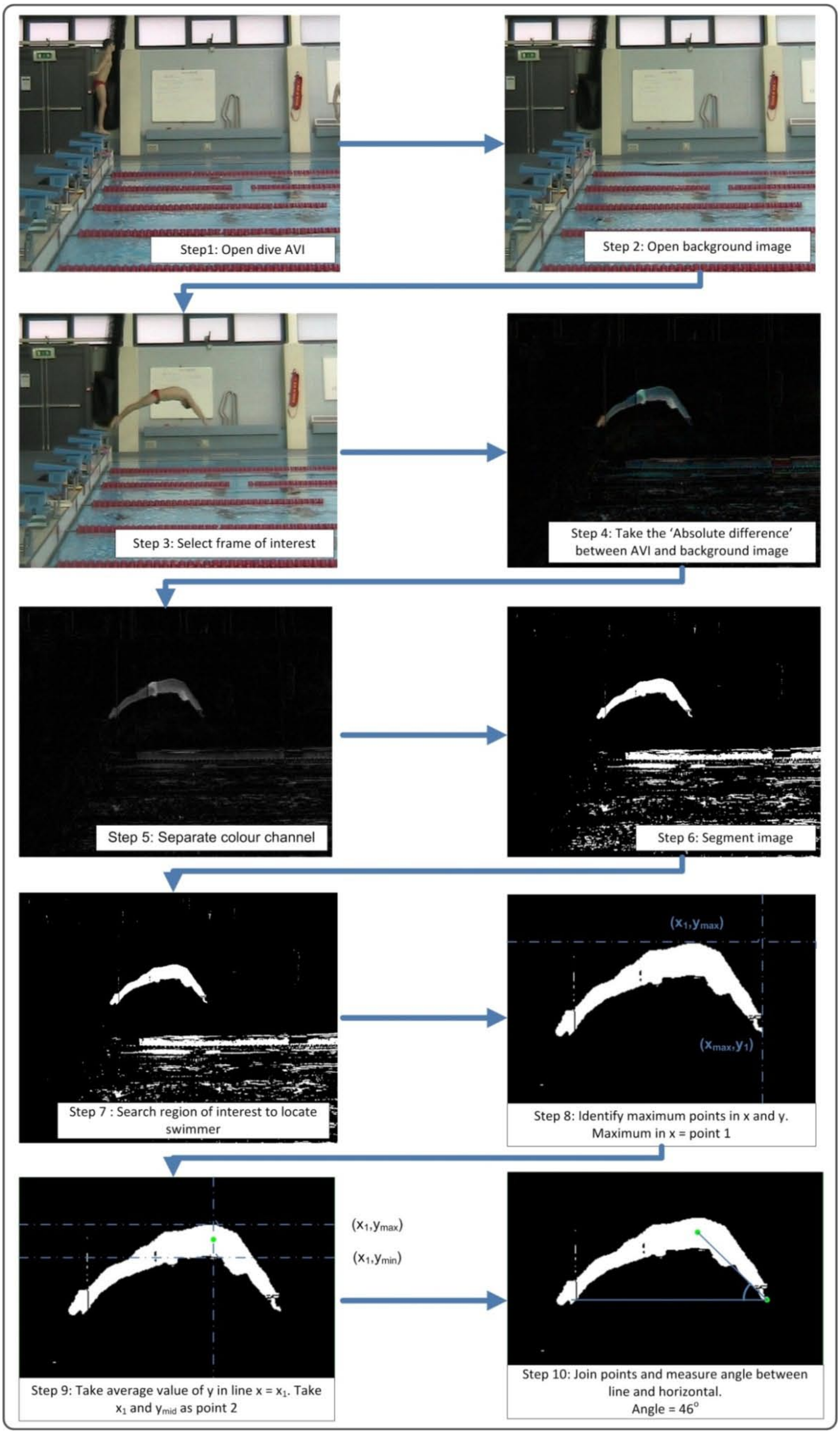


Figure 3-9: Process of applying a temporal segmentation algorithm for the analysis of the dive

The successful application of an automated image processing method for the analysis of starts is dependent on the ability of the algorithm to differentiate the swimmer from the background. It was initially conceived that it would be possible to discriminate the swimmer from the background because the swimmer is the only moving object within the field of view. The fundamental principle within this process is an "*absolute difference"* function whereby the background image is compared to each subsequent frame and only the difference is displayed in the processed image (see Figure 3-9). This type of thresholding is described as temporal segmentation. The *subtracted* image is then thresholded to give a binary image (in Figure 3-9 the swimmer is represented in white on a black background). By tracing the boundary of this white object parameters of interest could then be calculated, e.g. angle of entry.

The successful application of *temporal segmentation techniques* is limited by subtle variations in the background image (e.g. reflections off the surface of the water, movement of lane ropes, other individuals within the image and the inconsistency in lighting (see Chapter 4: Case Study – Starts, Section 4.2). To address these issues *spatial segmentation techniques* can be utilised including, for example, skin, garment and wearable marker thresholding. To enable successful spatial thresholding, the AOI must have distinguishable pixel characteristics. To enhance the signal to noise ratio, specific markers have been developed that could be used in both under and over water environments. These used a series of red LED's designed onto a wearable band to create a unique feature within the image.

The decision to use powered LED's rather than non light markers was made due to the problems incurred in testing whereby *shadowing* affected the consistency of a colour within a feature (see Chapter 4: Case Study – Starts, Section 4.2). Shadowing inconsistencies can be minimised (see Chapter 4: Case Study – Starts, Section 4.2.2.2) by using a distinguishable dark marker, i.e. a single coloured cover up swimsuit. For underwater applications, there are a number of sources of noise when using a dark marker, e.g. arising from the swimmer's suit, tiles and shadowed areas such as the underside of lane ropes. The other limitation of defining the swimmer's body as one "blob" is the difficulty in tracking specific landmarks would have to be predicted from a variable single boundary. For these reasons, combined with a reluctance by the end user to wear a full body suit in routine training lead to the development of less encumbering markers. It was also conceived that markers could result in a more usable solution whereby more specific analysis could be undertaken. In addition, a powered illuminated marker results in a more consistent feature that is not as sensitive to lighting changes within the background image.

Initial trials used simple waterproofed bicycle lights manufactured using two red LED's. Preliminary video analysis indicated that, although the LED's were clearly visible under the water, their directionality ($\Delta\theta$ = +/- 12.5°, see Figure 3-10(b)) limits their visibility within the field of view of the single fixed camera angle used in the trials. To overcome this problem it was decided that a prototype marker consisting of an array of LED's (i.e. a strip) should be implemented as a single marker.

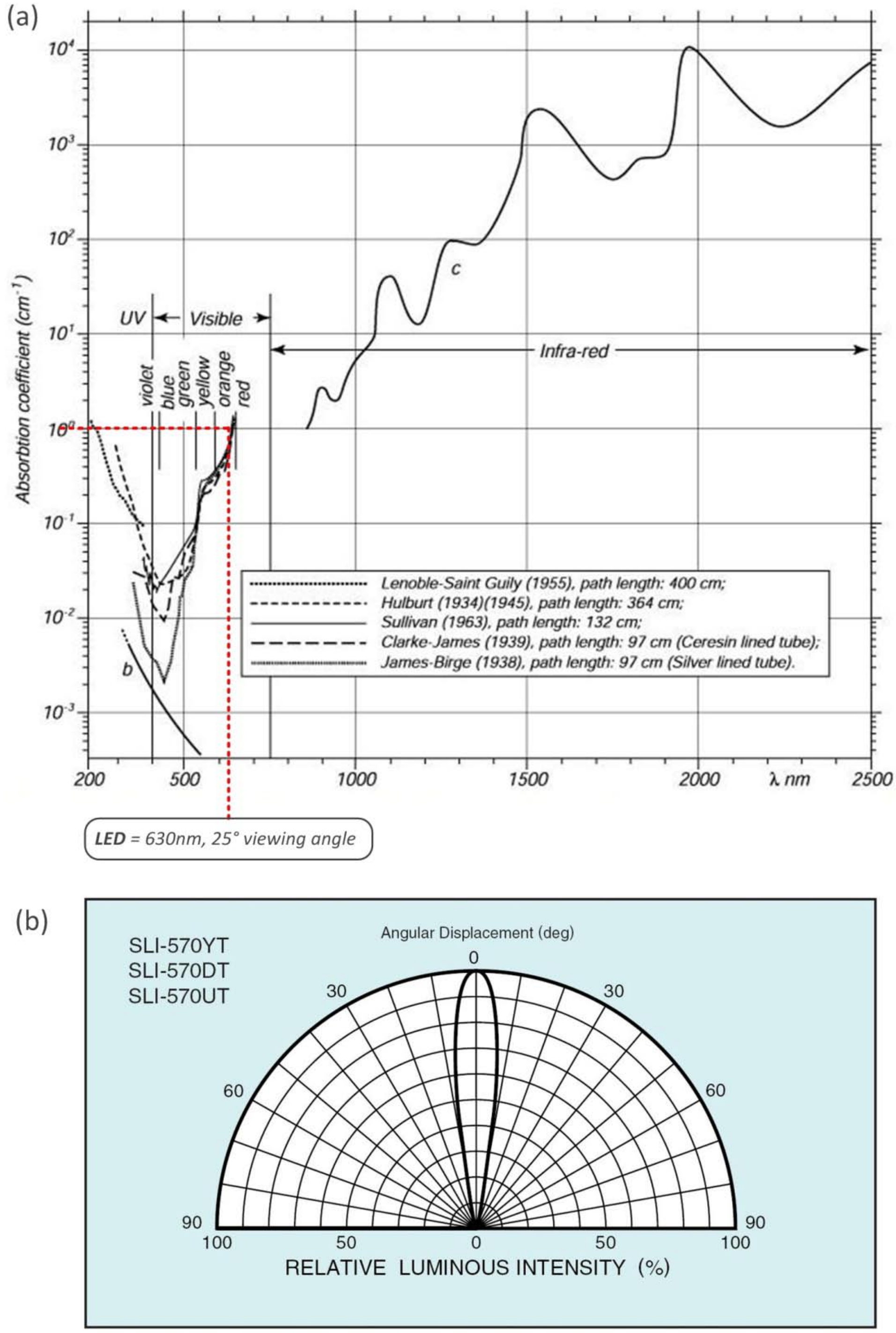


Figure 3-10: LED specification, - wavelength and viewing angle

A red LED was chosen for the marker, despite red light being the mostly highly attenuated colour in water, see Figure 10(a). Visible light at the blue/green end of the spectrum are the most prevalent colours within the background of the image i.e. the water. Therefore, it was hypothesised that a red LED of sufficient intensity would give the greatest potential for discrimination from the background. The chosen LED had a wavelength of 630 nm and a viewing angle of 25°.

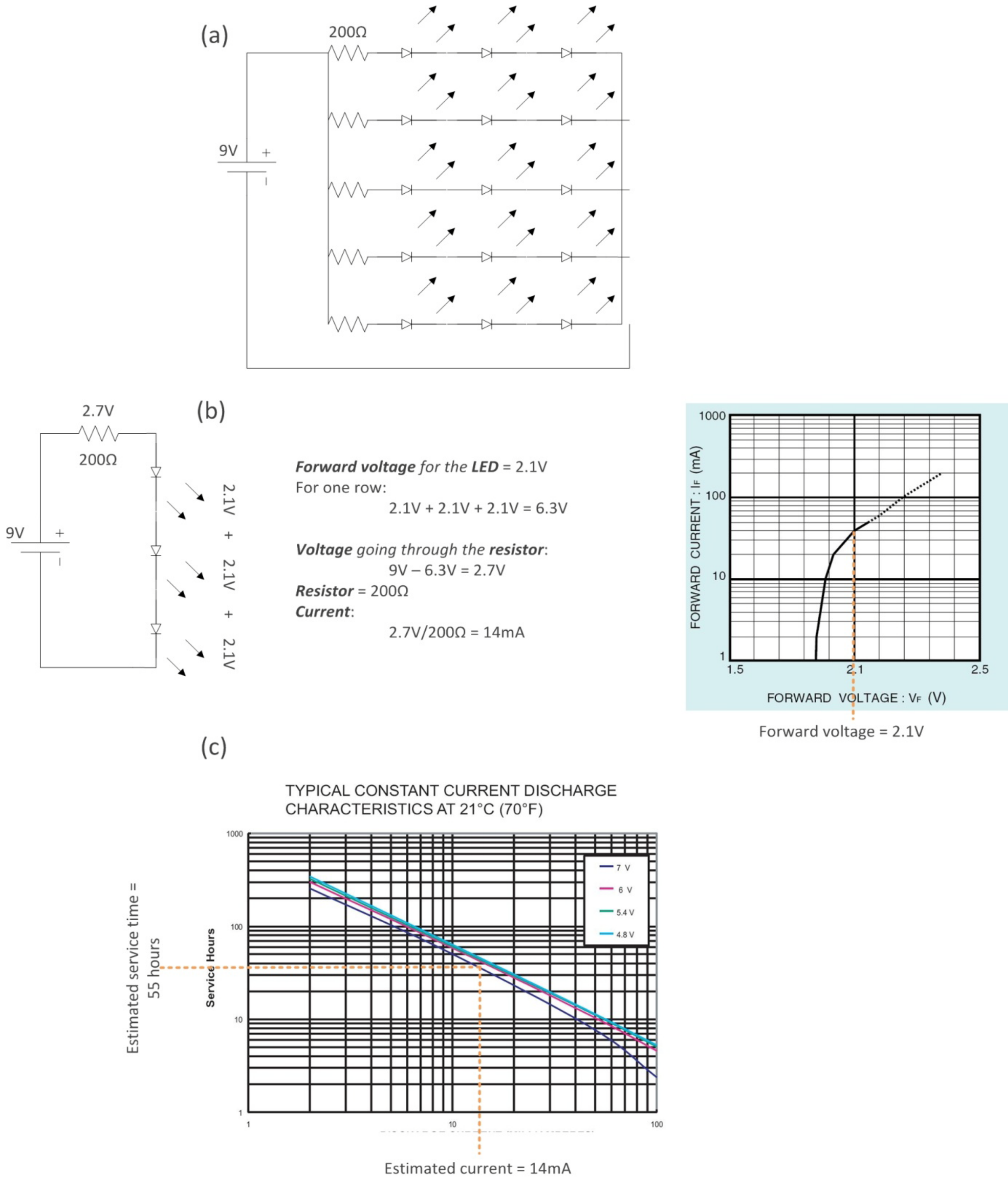


Figure 3-11: LED design - circuit diagram, voltage requirements and predicted battery life

The developed marker incorporates five rows of three LED's, i.e. 15 LED's see Figure 3-11(a). A 9 volt battery is used to power the marker to ensure the forward voltage requirements of the LED's (3 x 2.1V = 6.3V) were achieved (see Figure 3-11 (b)).

Since the current drawn for the desired LED intensity is 14mA, a service life of 55 hours per band is possible (Figure 3-11(c)). This is far in excess of the demands of a single swimming training session and in theory would support a number of sessions over a period of several weeks. The developed markers have been evaluated in each phase of swimming, i.e. starts, free swimming and turns (see Chapters 4, 5 and 6, Sections 4.2.2.3, 5.2.2 and 6.2).

3.3 Design and development of an instrumented starting platform

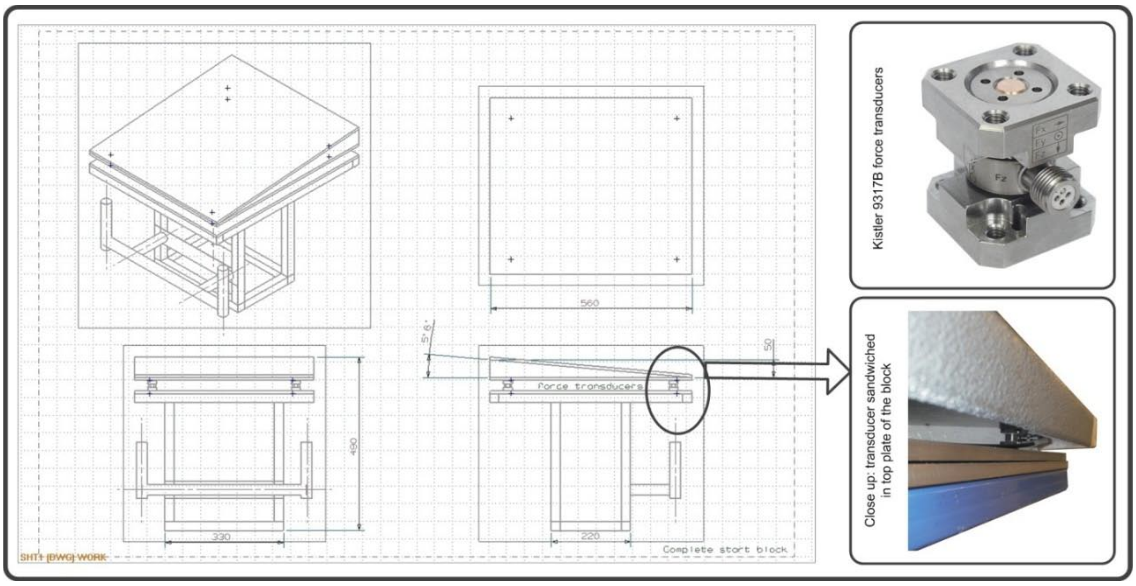


Figure 3-12: Instrumented start block design

An instrumented start block was designed of exact dimensions (plan area, height) and top plate angle (θ = 5°) to current blocks (i.e. preceding the latest OSB11 block with the integrated wedge, Omega, 2010 incorporating four force transducers sandwiched between the base construction and top plate, Figure 3-12. The four transducers (*9317B*, Kistler, 2010) were mounted towards the corners of the block to provide the maximum measurement area.

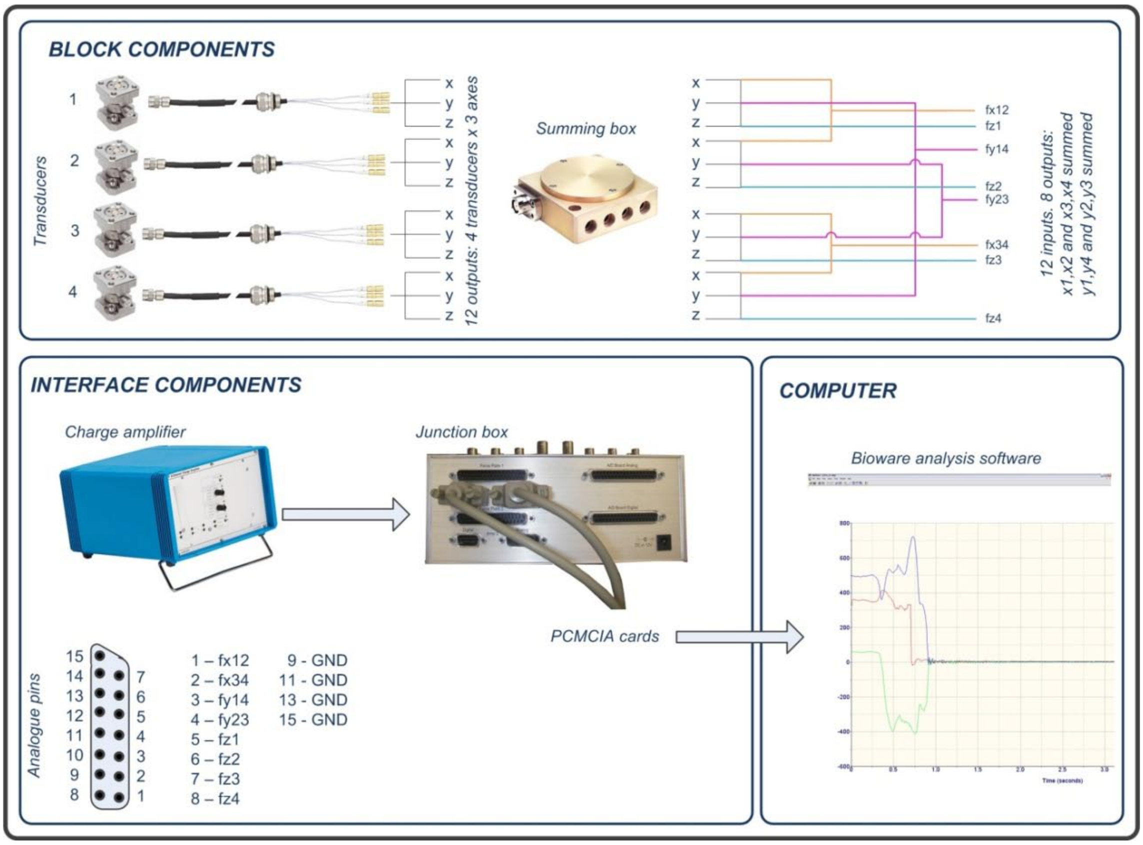
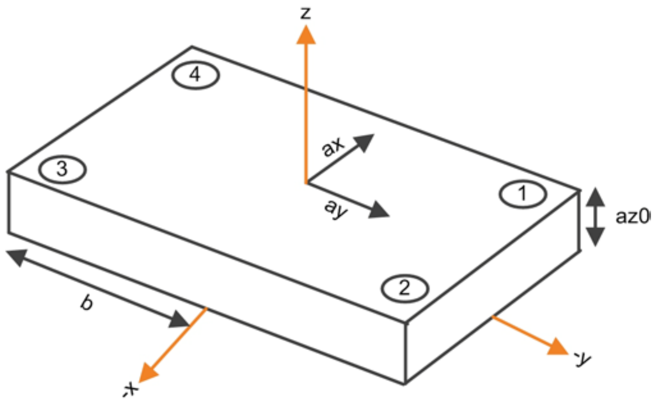


Figure 3-13: Components of the instrumented start block

The *block components* include the four transducers interfaced via a summing box mounted on the underside of the start block. Each of the four transducers measures force in three axes, output via three cables per transducer. At the summing box the 12 inputs, i.e. three axes of force for four transducers, are converted to eight by summing the x and y components into two pairs to support the fundamental force analysis provided by Kistler, e.g. fx1 and fx2 wires are soldered together becoming one output, fx12 (see Figure 3-13, Table 3-1 and following sections) The eight analogue outputs are then passed to the *interface components*, i.e. the charge amplifier, junction box and PCMCIA cards which convert the charges output by the force transducers into voltages and then digital representations via PCMCIA analogue to digital converters. The junction box enables additional channels such as an analogue or digital trigger to be integrated. The software used to capture and display the data was Bioware, a Kistler specific product which is interfaced to the PCMCIA cards via third party device drivers. The force data can be output from the Bioware software into a readable file type for further analysis.

Table 3-1: Measurements taken from the force plate, taken from Kistler data sheet, 2009

Parameter	Calculation	Description
Fx	= fx12 + fx34	Medio-lateral force
Fy	= fy14 + fy23	Anterior-posterior force
Fz	= fz1 + fz2 + fz3 + fz4	Vertical force
My	= b * (fz1 + fz2 – fz3 – fz4)	Plate moment about x axis
Mx	= a * (-fz1 + fz2 + fz3 – fz4)	Plate moment about y axis
ax	= -My / Fz	X coordinate of force application point (Centre of Pressure, CoP)
ay	= Mx/Fz	Y coordinate of force application point (CoP)



The parameters output from the Kistler force plate system (e.g. F_x, F_y, F_z) and details on how they are derived from the raw data are summarised in Table 3-1. These include raw forces and derived parameters such as centre of pressure (i.e. a_x and a_y). Force readings from the transducers are output as two channels of x and y force and four channels of z force. Combining these separate channels produced the overall readings for force in three axes. From these forces other parameters are derived, within the Bioware software. For example the moments of force My and Mx are used to determine the centre of pressure of the force on the top of the block. The centre of pressure provides an indication of how the swimmer moves their weight and force (back to front and left to right) throughout the dive.

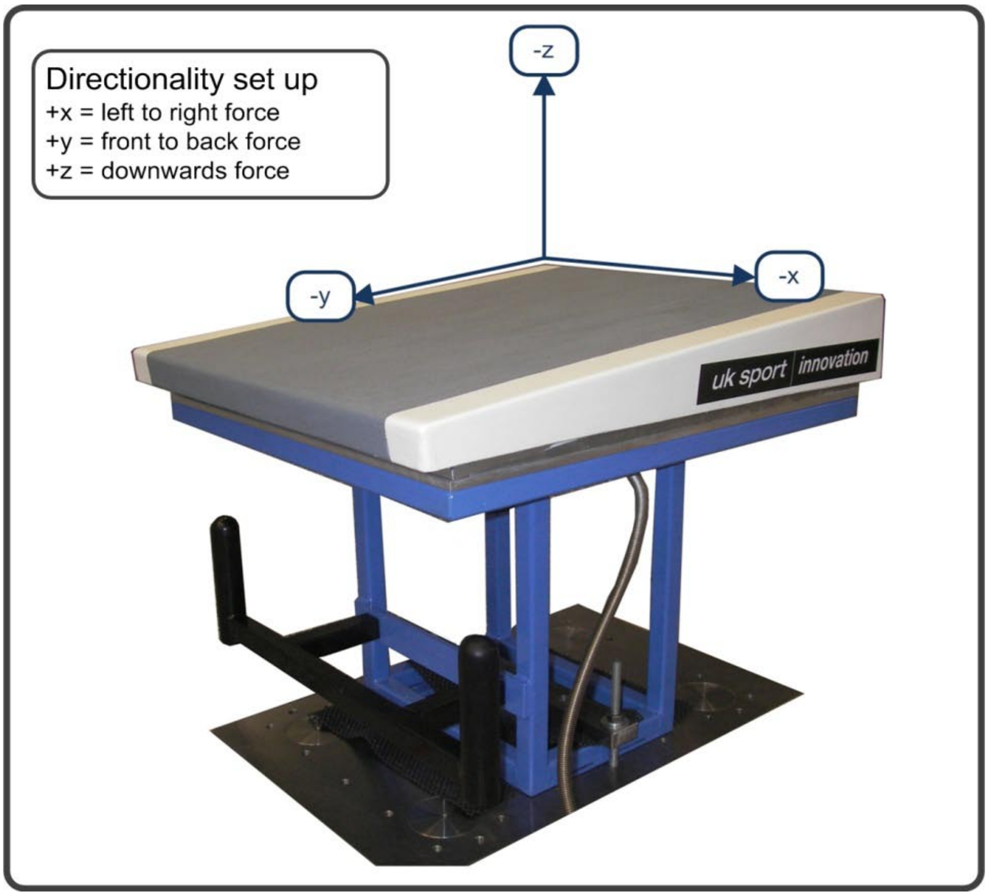


Figure 3-14: Axis orientation on the developed block

Transducers in the block were set up such that, x represented lateral (i.e. left to right) movement, y represented horizontal force (i.e. front to back) and z represented vertical force, see Figure 3-14. These were oriented such that movements in the directions left to right, front to back and top to bottom forces produced positive results.

3.3.1 Block calibration

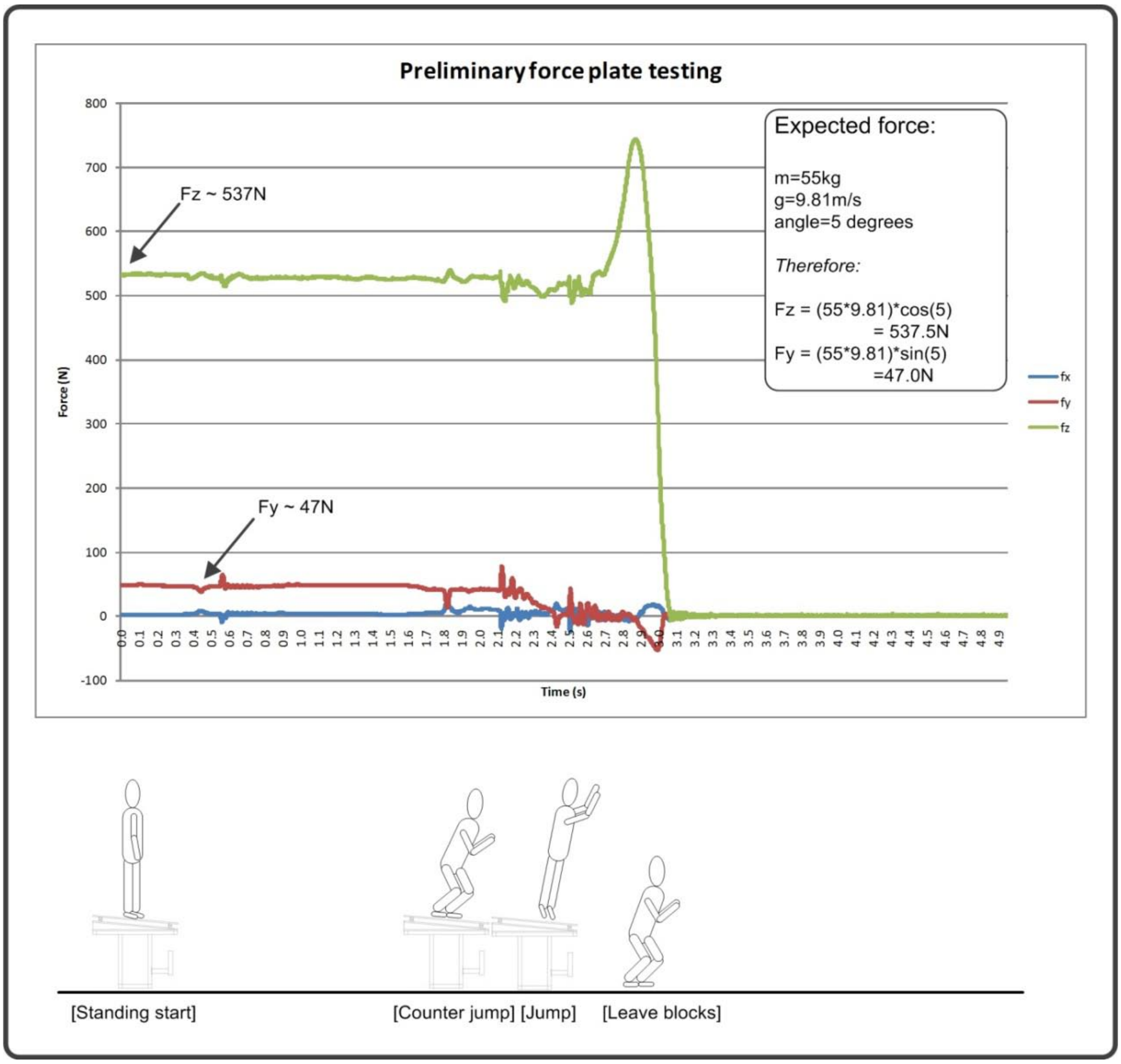


Figure 3-15: Preliminary test results using the force plate

Preliminary testing using the developed starting block included a subject of a known mass standing on the blocks and then jumping from it (see Figure 3-15). The block was physically attached to a separate floor mounted 3-axis force plate and data was collected from both force platforms during the trial. A comparison of the adapted start block and floor mounted plate showed they were both providing equivalent traces. Additionally the expected contribution in each axis was predicted given the mass of the subject (i.e. 55 kg) and the 5°angle of the block. The force profile produced was consistent with the predicted results (see Figure 3-15 for summary).

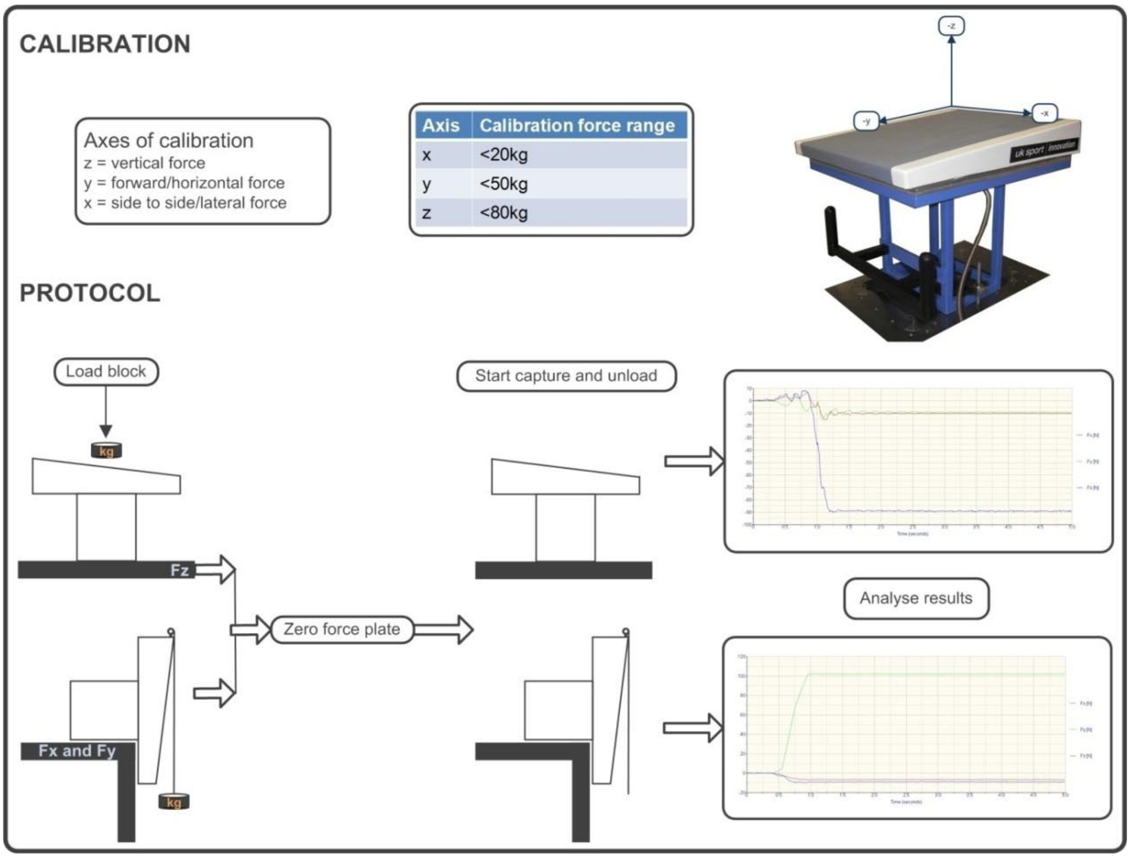


Figure 3-16: Calibration protocol for instrumented start block

The instrumented start block was also calibrated using known weights applied to a single axes, as detailed in Figure 3-16. The block was oriented for each specific axis using a digital spirit level (resolution <1 °) and fixed to ensure it was stable. I-bolts were screwed into holes drilled and tapped into the top plate, from which weights could be hung. Both the x and y axes were calibrated this way, with the z being calibrated by placing weights centrally onto the top plate. The procedure was that weights were applied to the block, the force plate was zeroed and then the weights were removed. This produced negative force profiles as the plate was unloaded.

The x, y and z axes were calibrated using 20kg, 50kg and 80kg masses respectively to determine the linearity of the performance of the block and load the block with forces representative of what the block may experience during a swimming start. It was expected that the x axis would experience forces significantly less than one body weight, whereas the y would experience higher forces and the z forces equal to or greater than body weight. For this reason the y and z axis were loaded with higher weights corresponding to approximately a small and large swimmers body weight respectively. Three measurements of each load were taken for each axis and averaged.

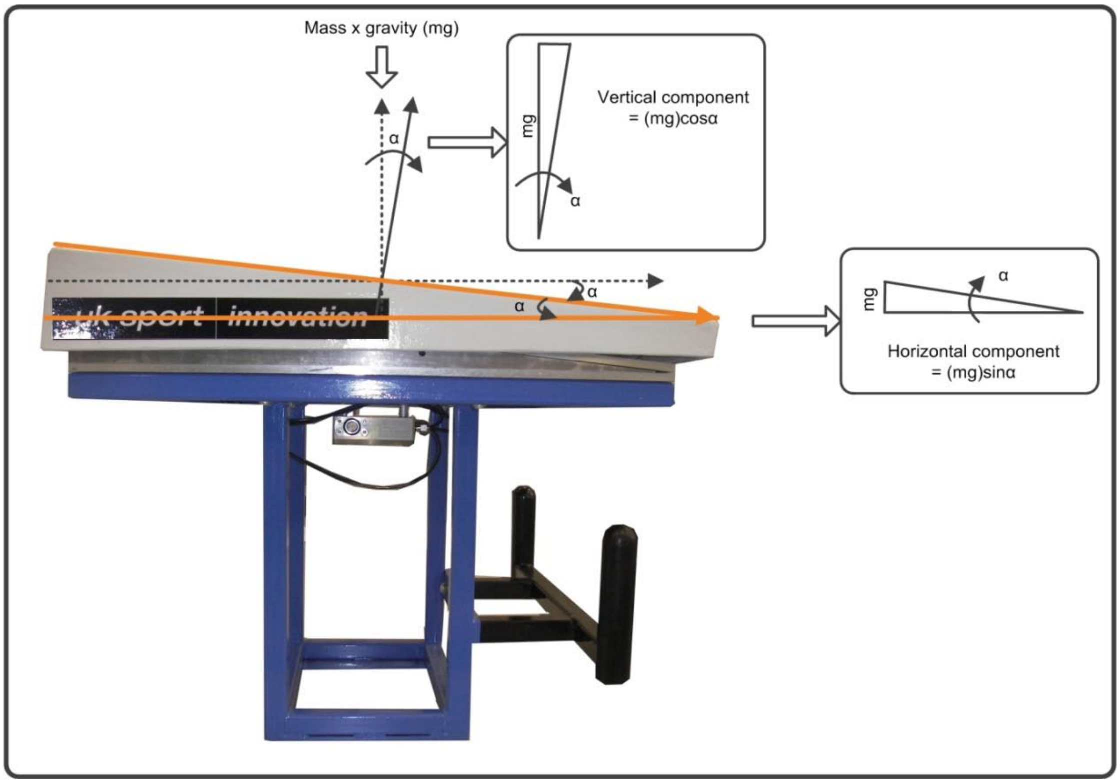


Figure 3-17: Calculating expected force readings using instrumented start block

Due to the 5° angle of the top plate of the block it was necessary to resolve the force in the y and z axes. Each of the axes would present a horizontal and vertical component when loaded, relative to the orientation of the block. For example in the vertical axis, z, the vertical component would be represented by (mg)cos(5) and the horizontal component would be (mg)sin(5), see Figure 3-17 where m is the mass and g the acceleration due to gravity (i.e. 9.81 ms^{-2}). Plots of measured force versus actual force are displayed in Figure 3-18(a)-(c).

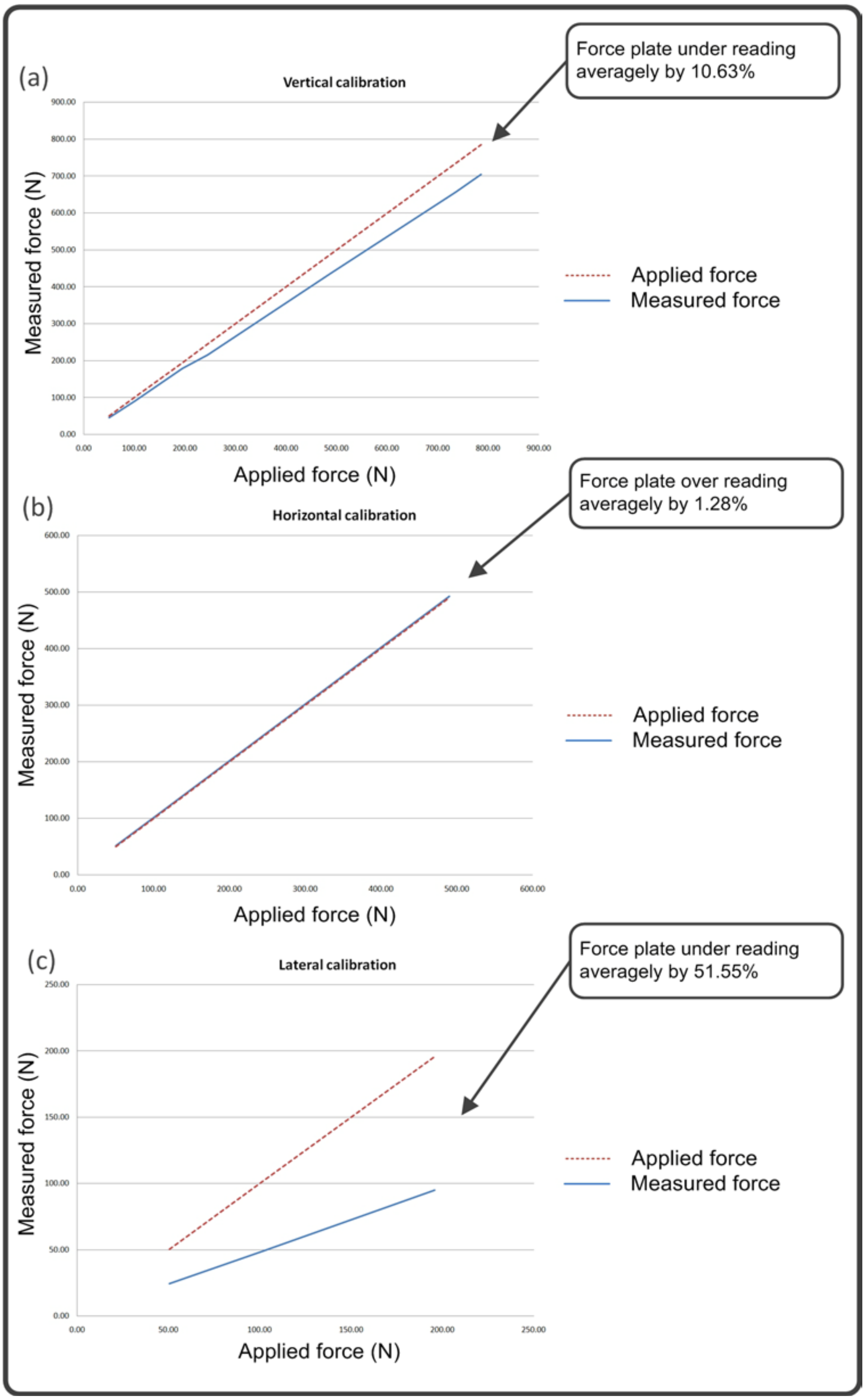


Figure 3-18: Results from calibration testing

In the z-axis, i.e. the *vertical* direction, it was found that on average the start block was measuring a force that was too low 10.6% for all weights tested up to 80kg (see Figure 3-18(a)). *Horizontally*, i.e. the y-axis, the start block was found on average to measure forces that were 1.28% larger than the expected value, see Figure 3-18(b).

Unfortunately the *lateral* calibration revealed a problem with the force plate. The reading was found to be lower than the expected value by 51.55% on average see Figure 3-18(c). This is the result of fx12 reading values close to zero, even when loaded. The primary axes of force generated in the swimming start are in the *horizontal* and *vertical* directions as they define with how much force the swimmer is generating forwards, i.e. out into the pool, and what angle of elevation is achieved. *Lateral* forces, from this point of view, are less important as it is preferable for the swimmer to generate force in a straight line in the forwards direction, rather than applying significant force side to side. Resolution of the errors on the lateral axis, x, have yet to be resolved despite significant effort from both Kistler and university staff.

3.4 Design and development of a wireless sensor node

The features required within wireless sensor systems that have to be developed for each specific application have been discussed in, Chapter 2: Literature Review. For example wireless communication considerations include frequency, bandwidth, network capability, antenna and radio transceiver selection.

Table 3-2: Technologies assessed as potential wireless communication solutions for swimming applications

Technology	Frequency	Data rates	Transmit power	Range in water	Comments
Bluetooth (IEEE 802.15.1)	2.4GHz	721kbps	4dBm (Class 2)	<10cm at <1cm depth (Class 2)	Very limited range and depth of transmission
UHF Ti CC1110	433MHz	250kbps	10dBm	35m at 25cm depth	Wireless protocol stack available for development (SimpliciTI), up to 8 analogue inputs and 21 general purpose digital inputs and data rates up to 250kbps.
Nordic NRF905	433MHz	50kbps	10dBm	25-30m at 1.5m depth	Limited on board functionality, only 4 ADC channels, relatively low data rates, no available wireless protocol for network purposes, limited support.
Ezurio power amplified bluetooth	2.4GHz	300kbps	18dBm	50m at 10cm depth	High sensitivity, high gain antenna used to provide better range. Only 2 analogue inputs. Supports audio.

A number of potential development technologies were tested and their transmission capabilities in water assessed, see Table 3-2. The lower, 433MHz, frequencies showed a greater penetration than the 2.4 GHz in water although the power amplified Bluetooth solution showed some capability, i.e. 10cm depth at 50m range. the *Ti CC1110* and the *Nordic NRF905*, were able to transmit data through the pool water (25cm and 1.5m depth at 35m and 30m range respectively). The class 2 *Bluetooth* radio had almost no capability to transmit through any depth of water. (Note: The power amplified *Bluetooth* system had a specially developed antenna designed to maximise range of transmission. In addition this board had only had two analogue inputs, severely limiting the choice of sensors that could be interfaced).

Of the two 433MHz solutions the *Ti CC1110* was chosen as it was capable of higher data rates, i.e. 250kbps rather than 50kbps, double the analogue inputs and supported a SimpliciTI protocol stack for the development of wireless network capabilities. The *Nordic* NRF905 was a more basic board with no support for network capability and therefore it would be necessary to develop the protocol stack "in house" to enable such functionality.

Table 3-3: Rates of movement in swimming

Feature	Maximum rates	Maximal rate
Stroking: One stroke (both arms) freestyle sprint	60/min average for 50m Men's freestyle	1 Hz
Kicking: One kick (one foot) freestyle sprint	360/min (6 beat kick given fastest stroke rate)	6 Hz
Velocity: Maximum velocity	At dive phase based on testing of 15 University squad of higher swimmers: distance of entry/flight time	<4m/s
Rotation: Tumble turn rotation– from start (last hand entry) to finish of rotation (return to prone position)	360°/1.5 second	240°/s
Rotation: Body roll – freestyle swimming	60°/stroke (one stroke taking 0.5 seconds)	60°/s

To determine the sensor requirements it was essential to understand the monitoring needs of the system, i.e. the fastest rates of gross movements in swimming which are observed in the men's 50m freestyle. *Stroking, kicking, velocities* and *rotation* rates have been determined, see Table 3-3. During this event, maximum stroking rates can reach one hertz, i.e. one full arm cycle (both left and right) per second. Typically when swimming freestyle either 2 beat, 4 beat or 6 beat *kicking* is employed. This means that for every arm pull the swimmer will kick 2, 4 or 6 times. In sprinting swimmers tend to favour the 6 beat technique. This equates to a maximal movement frequency of 6Hz. Nyquist theory suggests that sampling frequency must be at least twice the highest frequency that is being measured to ensure the signal is not lost, i.e. to pick out the swimmers kick it would be recommended to sample at least 12Hz. However, to allow more in depth analysis of pulses, a higher number of samples are needed. It was suggested that a minimum of five samples per movement would provide sufficient data to enable pulse analysis, i.e. for the kick this was 30Hz.

The fastest part of the swim is experienced during the start phase. Estimate of these *velocities* (v) and subsequent *accelerations* (a) were determined by analysing a number of dives performed by swimmers of a University squad or higher ability. Digitisation recorded maximal *velocities* at up to 4m/s equating to maximal accelerations of ~12m/s/s.

In free swimming the largest *rotations* are associated with the longitudinal roll (i.e. side to side throughout the stoking) in both freestyle and back stroke swimming. It has been reported (Liu et al 1993, Alberty et al, 2005) that maximal body roll in freestyle swimming is ~60°, for a single arm pull, i.e. half of a complete stroke. Given the maximal *stroking* rates in freestyle this equates to 60° rotation in 0.5 seconds, or 120°/s rotation.

In freestyle and backstroke events swimmers perform a tumble turn between each length. This involves the swimmer rotating 360° in both saggital and longitudinal planes (reference – see Chapter 6: Case Study – Turns, Figure 11). The time over which this rotation occurs is approximately 1.5 seconds, producing an overall *rotation* rate for the turn of 240°/s.

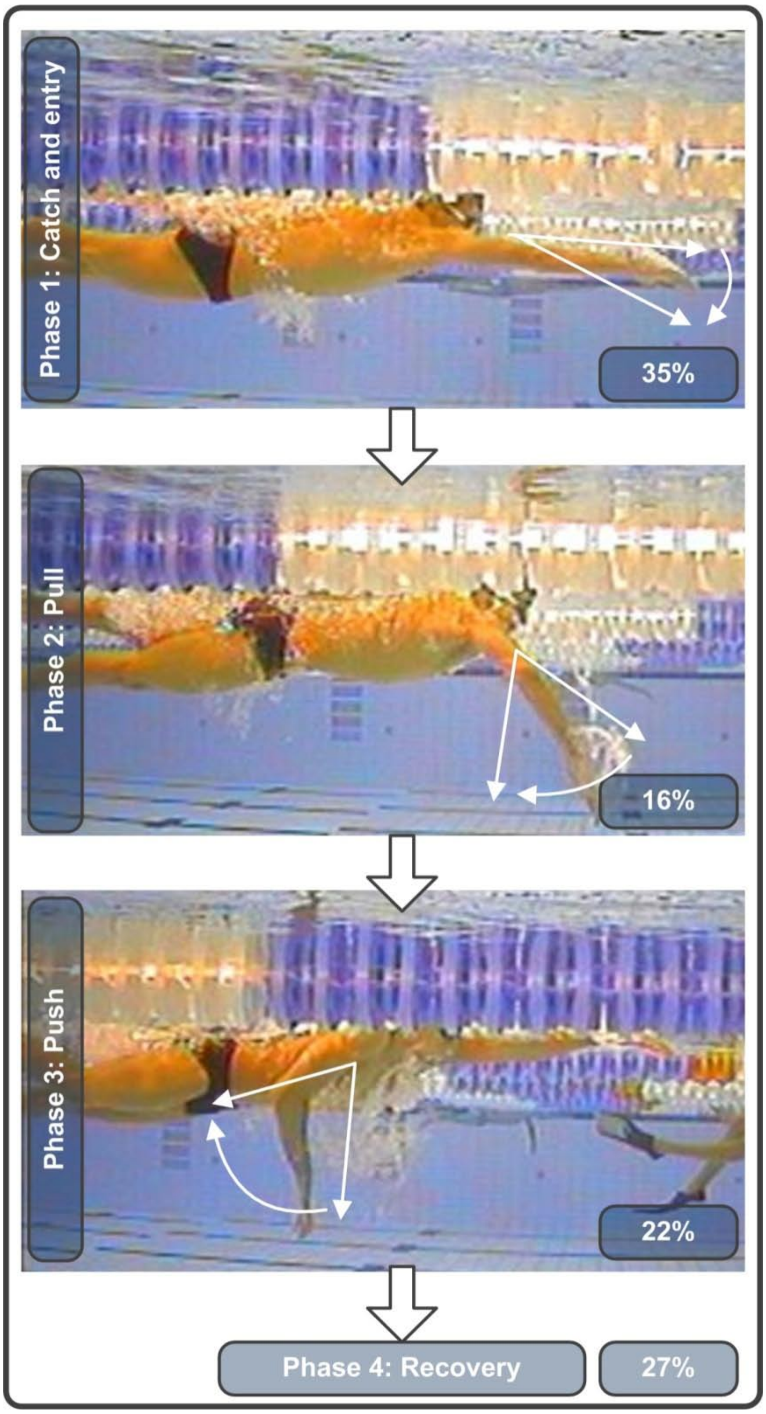


Figure 3-19: Phases of the freestyle swimming stroke

The freestyle arm pull can be divided into four key phases; *the catch and entry, the pull, the push* and the *recovery, see* Figure 3-19. It has been reported that these phases contribute to the total arm pull activity in the following timing ratios: 35%, 16%, 22% and 27% respectively (Liu, et al 1993).

The fastest phase is during the *pull* element of the stroke, only taking 16% of the total stroke time. Given that a typically stroke can take approximately 0.5s to complete, 16% is equal to 0.08s or 12.5Hz.

Table 3-4: Possible sensor types required for the different measurement variables

Measurement parameter	Possible sensor type	No. of channels required	Range of sensor (min)
Timing of events, e.g. Stroke rates, time to first stroke after turn	Accelerometer (1,2 or 3 axis)	1-3	+/-2g
Rotation information	Gyroscope (1-2 axis -rate of change of angle) **or** Inclinometer / magnetometer (1 axis angle)	1-2 gyroscope 1 inclinometer	+/- 300°/s (gyro)
Velocities	Accelerometer integrated with gyroscope/inclinometer	1-3 accelerometer 1-2 gyroscope	As above
Depth	Depth sensor Pressure transducer	1	Up to 2m (University pool)

To select the most appropriate hardware solution for the wireless node, the types of sensors, their specifications and interfacing requirements were considered, see Table 3-4. Note: the major requirements for sensor data include *timing* of swimming characteristics from laps to strokes, rotation information in free swimming and turns, velocities and depth profiling.

Acceleration data had been proven to provide information regarding stroking and timing information in swimming [Ohji et al 2003, 2006, Davey et al 2008, James et al, 2004]. The number of axes required and range and sensitivity of the sensors are key considerations when specifying both accelerometer and gyroscope (i.e. velocity of rotation) sensors. Given that maximal gross accelerations during the swimming start were measured at less than 12m/s/s it was decided that a sensor capable of measuring +/-2g would supply a large enough range to monitor swimming. Given the three dimensional nature of the swimming action a three axis accelerometer would be required using three channels of ADC input.

Gyroscopes are available with either 1, 2 or 3 axis / axes solutions [IDG-300, Analog Adxrs150, St Microelectronics: LPY430AL]. Since the tumble turn presents the highest *rotation* rates of up to 240°/s a minimum range of +/- 300°/s was selected to ensure the sensor would not saturate. A 2 axis solution was preferred due to the rotations and twists about orthogonal axes evident in typical swimming turns.

A *depth* sensor would be required to work in depths of up to 2m. It was considered that 2cm resolution (i.e. 1.0 % of maximum) or better would supply adequate detail regarding the depth profile of the swimmer.

Table 3-5: Components specified for development sensor node

Component	Specification
Microprocessor	Texas Instruments CC1110
Sensor interface	10bit ADC, using 5 out of 8 channels (3 axis acceleration, 2 axis gyroscope)
Wireless communications	433MHz, wireless protocol from adapted SimpliciTI Texas Instruments protocol
Power supply	9V battery
Memory	On board EEPROM (32kbits) for programming, additional FRAM (32kbytes) for buffer
Operating system	Non supplied with the chip
Antenna	¼ length whip

The components selected for the wireless sensor node are summarised in Table 3-5. The *microprocessor* selected was the Texas Instruments CC1110 with integrated transceiver. The chip is supplied with an 8 channel, 10bit ADC used to interface to the selected *sensors*, i.e. a three axis accelerometer (ADXL330) and a dual axis gyroscope (IDG300). The *wireless transceiver* operates at 433MHz and used the SimpliciTI wireless protocol for network development.

The board was supplied with power requirements for a standard 9 V battery. The *antenna* supplied with the development environment was a ¼ length whip (i.e.14 cm), which was used for the initial prototyping. Both the *power* and *antenna* solutions detailed above were adopted for prototype evaluation. The intention was to develop more specific and practical solutions once the efficacy of the system was proven.

Thirty-two kilobits of EEPROM *memory* onboard the CC1110 was used for programming and a further 32kbytes of FRAM were connected to allow storage buffers for data. No *operating system* [e.g Tiny OS, http://www.tinyos.net/ , Contiki, http://www.sics.se/contiki/] is supplied with the system, and therefore development of code was carried out in C low level using a Keil µVision 3Compiler[www.keil.com].

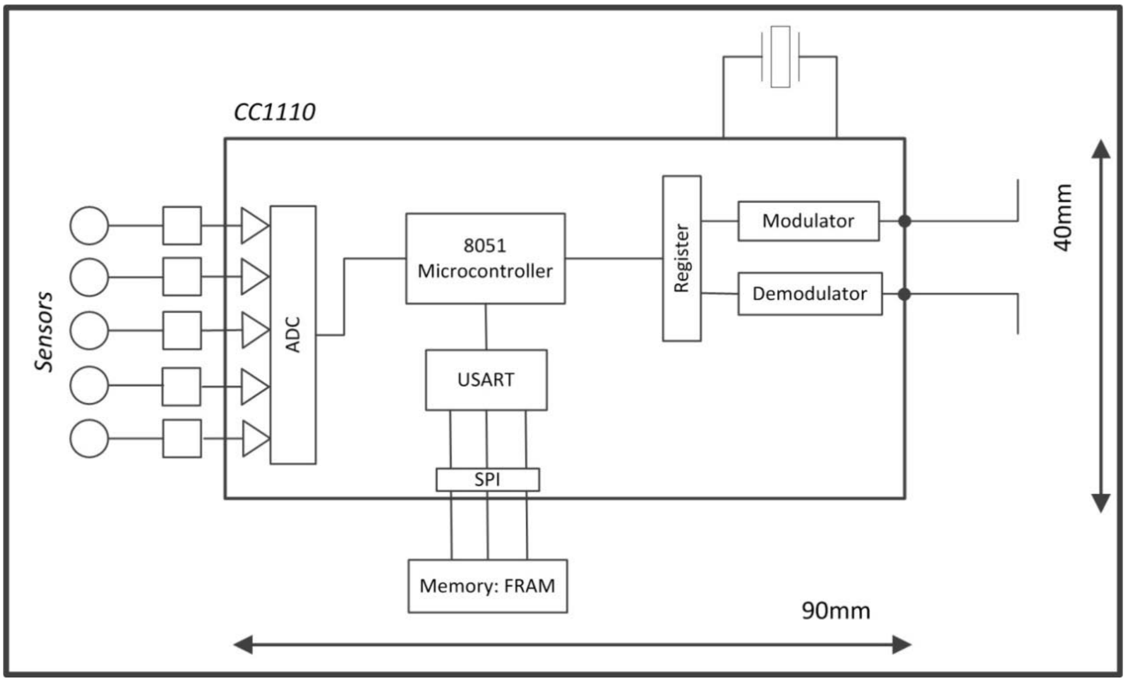


Figure 3-20: Developed board layout

The CC1110 development kits are such that the boards have large footprints that were not ideal for a swimmer worn application. For this reason a smaller solution was designed to reduce the footprint, by eliminating non-essential components and integrating the sensors into the board design rather than attaching them via break-out boards. The board was designed to include only the *microcontroller* including its onboard *ADC* with associated *sensors*, *digital interface* to enable the connection of additional *memory*, the *crystal oscillator*, *radio* components and *power* solution, see Figure 3-20. This resulted in a board with a much smaller footprint, i.e. 90mm x 40mm, rather than 1250mm x 1250mm.

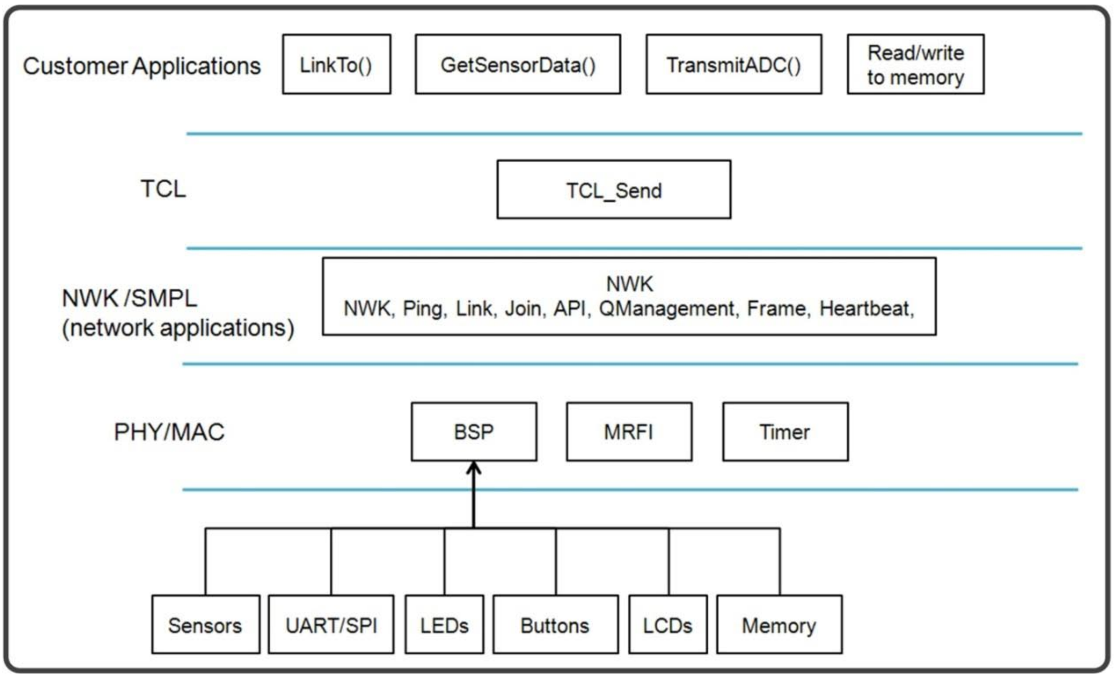


Figure 3-21: Adapted SimpliciTI protocol stack for the swimming application

A custom protocol stack has been derived from the Texas Instruments SimpliciTI stack [http://focus.ti.com/docs/toolsw/folders/print/simpliciti.html]. The SimpliciTI stack enables network communications on 433MHz and relatively easy adaption of the protocol for specific applications as compared with other standards such as IEEE 802.15.4 [http://www.ieee802.org/15/pub/TG4.html]. The layers adopted were the *physical/ medium access control layers (PHY/MAC)*, the *network /simple message passing library layers (NWK/SMPL)*, the *Transport Control Layer* (*TCL*) and finally the *customer application layer,* see Figure 3-21. The physical layer is board specific and includes the Board Support Package (BSP), Minimum Radio Frequency Interface (MRFI) and the timer. This layer talks to and controls the hardware components of the board. The timer is included in the microcontroller and provides counter functionality.

The network layer configures, establishes and manages network connections between nodes. The TCL layer functions to ensure that messages a reliably sent and checks that packages are not lost. It is necessary to have this layer when using the *external memory* buffer. It provides a two-way handshake that verifies communication between the base station and wireless node. The customer application layer is concerned with specific actions for the application. In the case of a swimmer worn node this includes actions such as adding a swimmer to a session, displaying data to the coach and processing data to derive performance parameters.

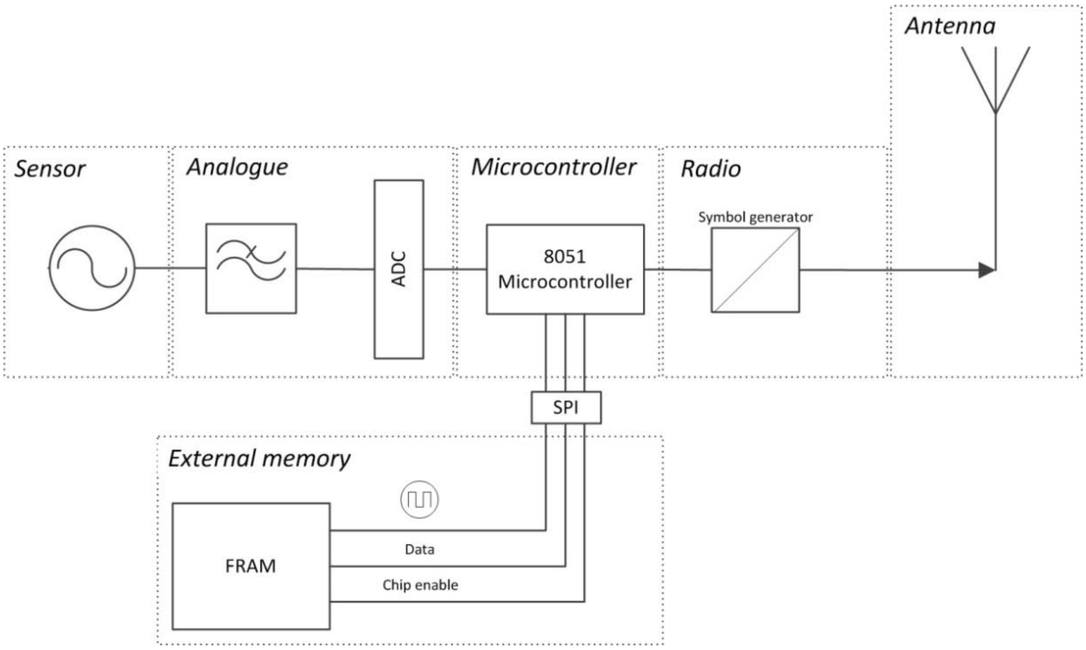


Figure 3-22: Block diagram of data flow in the system

The flow of data within the monitoring node is described using the block diagram of Figure 3-22. Data collected by the *sensors* is converted by the *analogue to digital converter* (ADC) where it can be read by the *microcontroller*. *FRAM* was interfaced to the microcontroller via the *serial peripheral interface* (SPI) allowing the digital data to be stored into the buffer before transmission. Data from the buffer was passed to the *radio* via the symbol generator where it is modulated using Gaussian Frequency Shift Keying (GFSK). The transmitted data is received by a base station node and stored via serial communications into the PC.

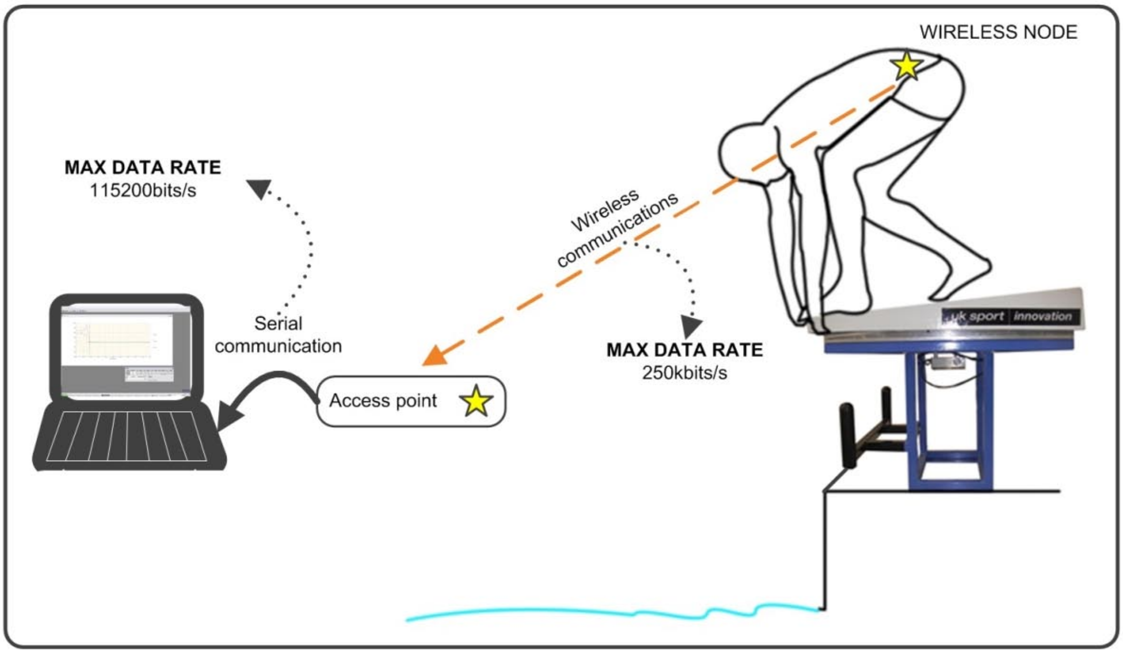


Figure 3-23: Overview of developed system

An overview of the capabilities of the *node*, *communications* and *base station* is presented in Figure 3-23. The designed *node* utilised five of the eight analogue inputs integrating a three axis accelerometer and a two axis gyroscope. Each channel is sampled at 50Hz at 10bit resolution. Wireless *communications* at 433MHz are used to transmit data to the base station. The maximum capacity of the wireless transfer is 250kbits/s. The *base station* has a physical link to the PC via an RS232 connection configured to 115200bit/s.

Preamble	Sync	Length	Misc	DSTADDR	SRCADDR	Port	Device Info	TractID	App Payload	FCS
2	1	1	Null	4	4	1	1	1	n = Up to 50	2

SimpliciTI Packet Frame

MRFI (Radio) Frame

MRFI/Network Header | Payload

Packet Element (Maximum values)	Size in Bytes
SimpliciTI Packet Frame	17 + 50 = 67
MRFI Frame	12 + 50 = 62
MRFI Header	9
MRFI Payload	3 + 50 = 53
Network Header	3
Application Payload	n = 50

Packet Element (current values)	Size in Bytes
SimpliciTI Packet Frame	17 + 45 = 62
MRFI Frame	12 + 45 = 57
MRFI/Network Header	12
MRFI Payload	45
Application Payload	n = 45

Figure 3-24:Packet structure for SimpliciTI protocol

To transmit data using the adapted SimpliciTI protocol a formalised data structure must be used, see Figure 3-24. To set up the transmission, 62 bytes of information are included in the message structure although not all of these are utilised for the radio transmission, i.e. only 57 of the 62 bytes are required as detailed in Table 3-8. The complete message structure included a *PREAMBLE*, *SYNC* and *frame check sequence* (*FCS*). The first three bytes serve to synchronise the radio with the *FCS* used to complete the message and give an indication of the quality of the message. The *LENGTH* byte indicated the number of remaining bytes included in the message. *MISC* bytes are radio dependant and may be required for future IEEE support, currently there are no bytes used. The *destination* and *source addresses (DSTADDR and SRCADDR)* specify where the message is being sent from and where it is being delivered to. The *port number (PORT)* defines where in the destination address the message should be sent. *Device information (DEVICE INFO)* explains the type of node and its behaviour, e.g. always on, always off and polling. The *transaction ID (TRACTID)* is an incrementing counter relating to the number of the transaction. This can be used to prevent messages being received twice or to indicate where packets may have been lost.

The *application payload (APP PAYLOAD)* is the sensor data being transmitted. The capacity of the developed protocol was a maximum payload of 50 bytes. All other parts of the message can be considered as overhead values that cannot be changed without using an alternate protocol, i.e. the application payload is the only part of the message structure than can be adapted for the specific application. It is preferable to maximise the payload content to minimise the ratio of overhead to payload size and therefore increase the efficiency of the transmission.

Value	No. of bits
x acceleration	10
y acceleration	10
z acceleration	10
φ rotation	10
α rotation	10
Count	16
TOTAL	**66**

No. Of bytes required for each packet	9 (72 bits)
No. Of packets sent in each transmit	5
Total payload (bytes)	45

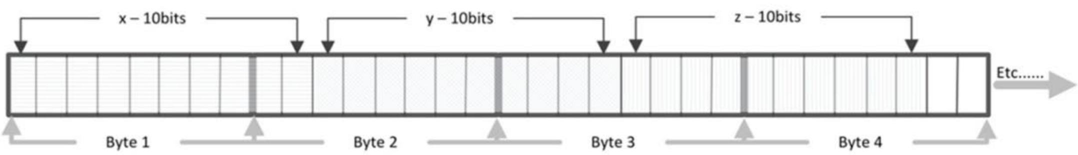


Figure 3-25: Message structure for swimming data

For the prototype application a payload size of 45 bytes was used, see Figure 3-25. This was constructed of readings from five sensors; x, y and z acceleration, φ and α rotation and a counter. All sensor data is recorded at 10 bit resolution with the counter resolution being 16 bit. This totals 66 bits per readings. To optimise the use of the payload five readings were transmitted in each packet and structured such that they filled each byte in a sequence, see Figure 3-26 and discussion below.

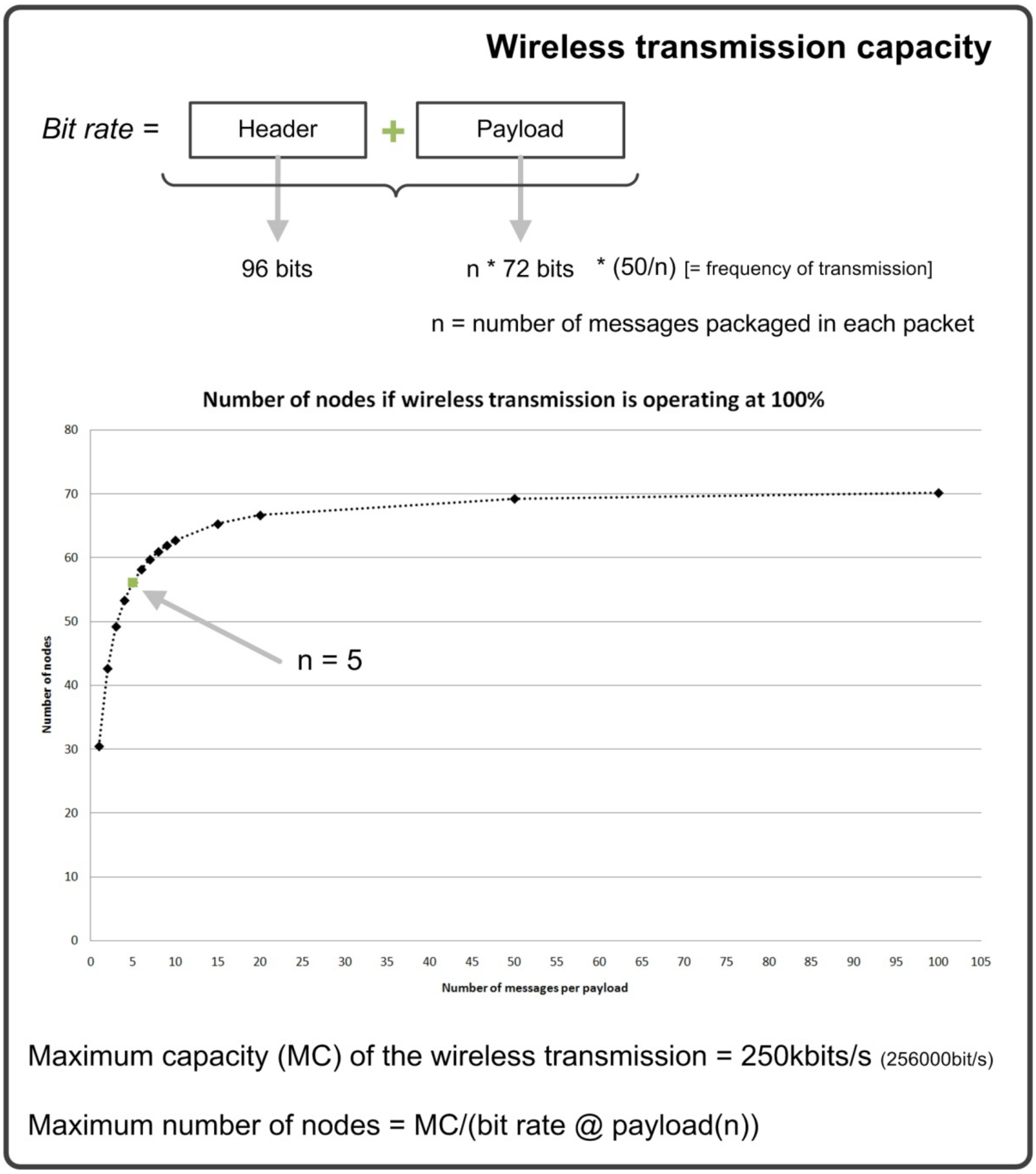


Figure 3-26: Wireless transmission capacity

The maximum capability of the wireless transmission has been considered with reference to optimising message structure. The bit rate capacity of the wireless transmission was 250kbit/s, i.e. 256000bits/s. The message overhead, associated with the wireless protocol, was 96bits, therefore the total message size totalled 96bits plus the payload. For a single message, i.e. one reading from each of the five sensors plus the counter, 72bits were required to package the data. By combining the header, payload and frequency of transmission, the theoretical maximum capacity of the system was calculated, a sampling rate of 50Hz .was assumed.

It was calculated that given the transmission of just one reading in each packet of data, that the maximum number of nodes available on the network would be ~30. For 100 readings per packet this number increased to ~70 nodes. Increasing the overall packet size increases the maximum number of nodes that can operate on the network. This relationship is not linear and is shown to diminish significantly, see Figure 3-26. For example, packaging five messages, rather than sending a single message, increases the capacity of the system from 30 to 56, i.e. an 84% increase. However, the difference between sending five or ten messages in each packet is only 11% and the difference between 10 to 50 messages a further 10%.

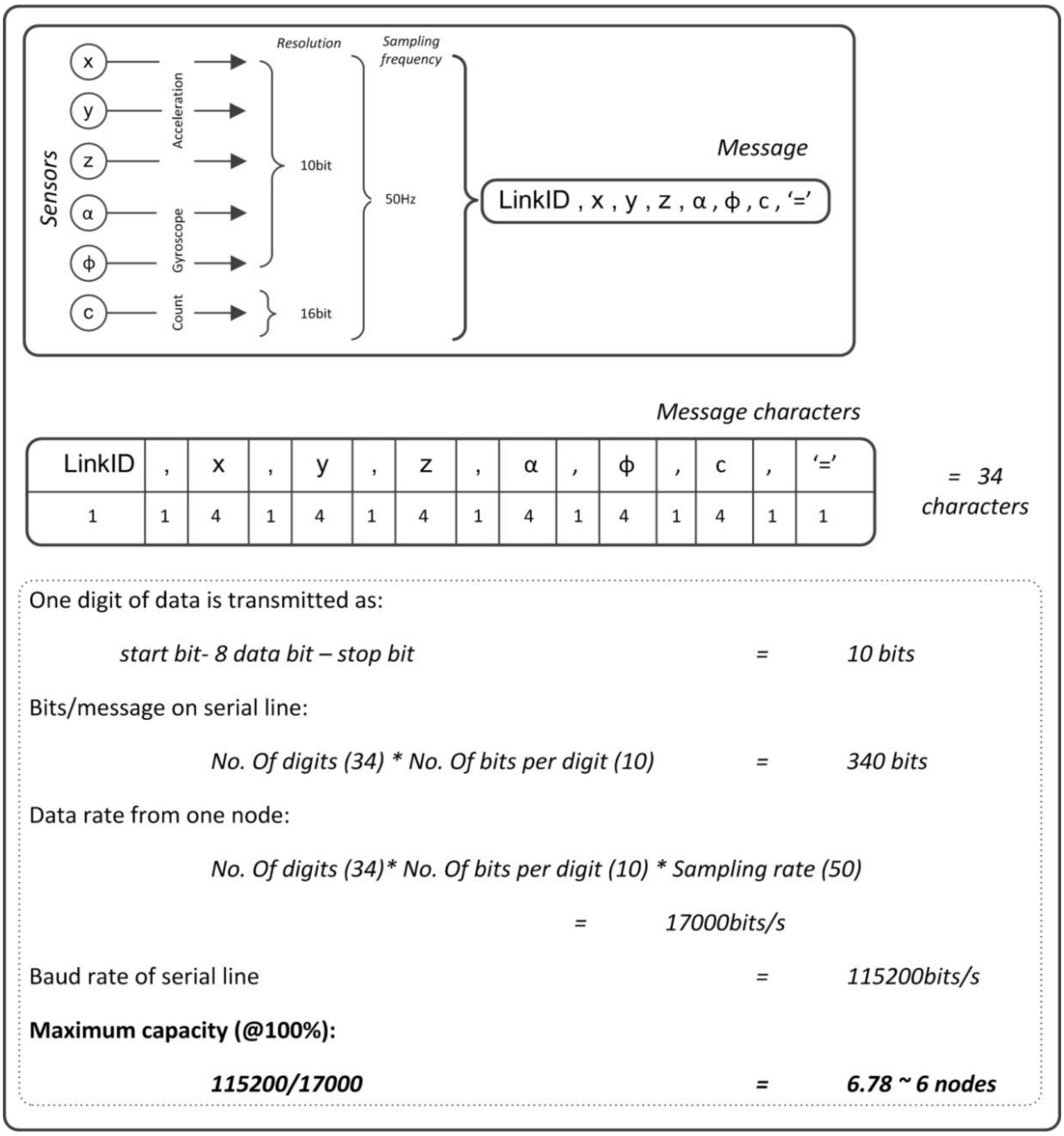


Figure 23: Transmission structure of data between the access point and the PC

The structure of the serial messages between the access point and the PC and theoretical capacity of the current system is presented in Figure 3-27. Six parameters are transmitted from each node; three axes of acceleration, two axes of gyroscope and a

counter, which allowed sequential stamping of messages such that failed sending could be identified, i.e. if messages marked 1, 2, 3, 4, 7 were received it could be noted that 5 and 6 were missing. Sensor data are sampled at a 10 bit resolution whereas the counter has 16 bit resolution. The structure of data transmitted down the serial line is built up of 34 characters (see Figure 3-27). Each message is initiated with a link ID (i.e. the unique identifier of the node), followed by the raw data and terminated with a stop bit. A comma, separates the data values. Using an ADC with a 10 bit resolution implies that the maximum digital ranges of the sensors are limited to 0-1024, i.e. 2^{10}. One way of encoding this is to utilise four characters (i.e. 4 x 8bits) for each of these readings. Similarly the 16 bit counter had a maximum value of 65536, i.e. five characters of data.
Each character of data comprises a start bit, eight bits of data and a stop bit, i.e. a total of 10 bits. The data rate from each node Nb:
(number of characters) x (number of bits per character) x (sampling rate) = 17000bits/s.

Given the baud rate of the serial line, 115200bits/s this would theoretically allow the data from six nodes to be communicated in real-time before the system was saturated. The serial line interface to PC is hence the main bottleneck in the current system in terms of the real-time maximum data rate capacity. (Note: if PC communications were supported via USB hardware and protocols then a data rates could increase from 115200bits/s to 480Mbits/s, i.e. by over 4000%.

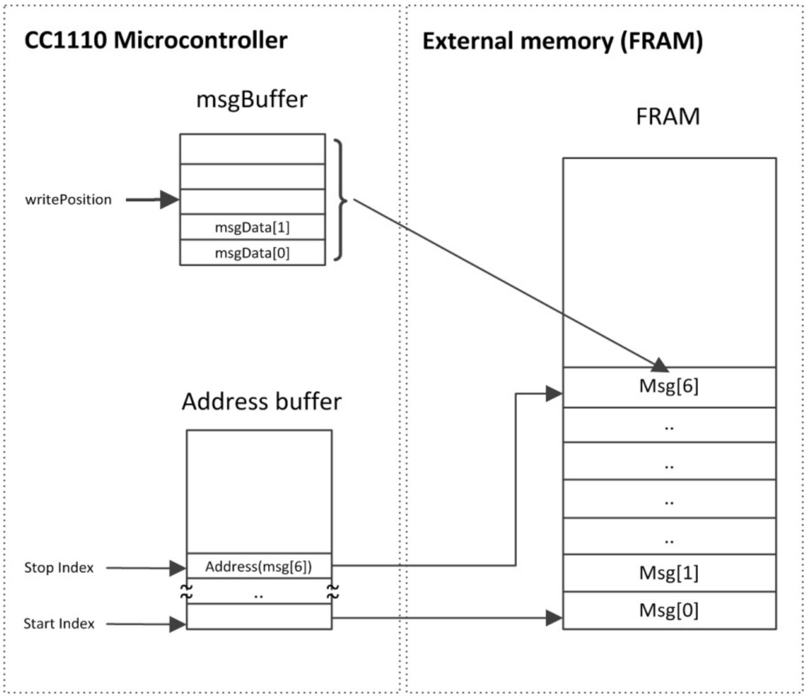


Figure 3-27: Message buffer structure

A data buffer has been developed for the system, (see Figure 3-27), using external FRAM memory, to minimise the effect of possible data losses via communication losses when a node may be too deep under water to transmit real-time data successfully. Data from the sensors, captured at 50Hz, is hence transferred from the *CC1110 microcontroller* into a *msgbuffer*. Five data readings are collected into the on chip *msgbuffer* before being stored into the *external memory (FRAM)*. An *address buffer* in the internal memory is used to "point" to the location of the data in the *external memory buffer*.

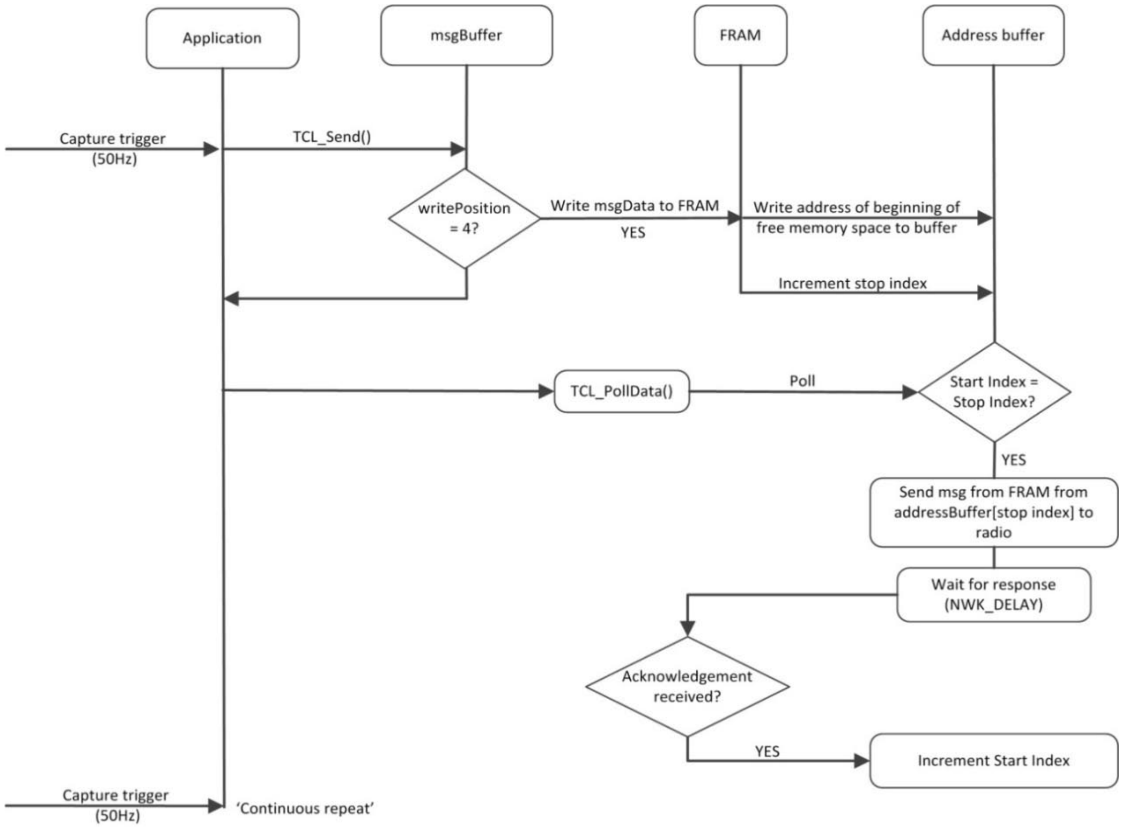
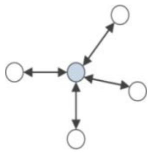
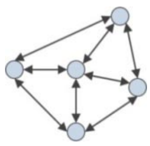
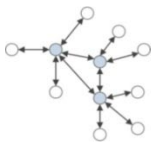
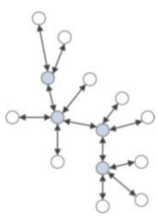


Figure 3-28: Movement of data into and out of the message buffer

The movement of data into and out of the *msgbuffer* and *external memory* stores has been described using a flow diagram in Figure 3-28. From the *external memory* the message is sent to the *radio* and waits for an acknowledge signal from the receiving node before transmission. If an acknowledge is not received the packet remains in the *external memory* that is augmented with subsequent packets until transmission is possible. With each packet stored into the memory the *address buffer* stop index is incremented.

Table 3-6: Overview of network topologies

Topology	Diagram	Description	Advantages	Disadvantages
Point to point		A one to one link between devices	• Simple	• No scalability • Limited spatial coverage
Star		A number of nodes connected to a central node. Master-slave, all communication goes through the master	• Simple • Low power consumption of slaves • Easy to configure • Low latency and high bandwidth • Centralised	• Dedicated central node • Limited spatial coverage • Low scalability • Inefficient slave to slave communications
Mesh		Any device can communicate with any other device that is within range. Can use multi hop to communicate with devices out of range	• Peer to peer communicatio n • Scalable • Low/medium complexity • Large spatial coverage • Power consumption can be balanced among nodes	• High latency and low bandwidth • Routing complexity • Nodes must have same basic functions, i.e. may require excessive functionality for purpose
Star mesh		Connects a mesh network with one/a number of star networks.	• Low/medium complexity • Low latency and high bandwidth • High reliability possible • Large spatial coverage • Scalable • Power consumption can be balanced among master nodes	• High complexity • High latency and low bandwidth for multi hop communications
Cluster tree		Multi hop network where there is only a single path between two devices. The first device becomes the root of the tree. Other devices join as 'child'/'leaf' devices.	• Large spatial coverage • Scalable – many nodes possible • Medium complexity • Low power consumption of leaf nodes	• Root of tree is bottleneck to scalability • Low reliability • High latency and low bandwidth • Nodes must have same basic functions, i.e. may require excessive functionality for purpose

There are a number of physical topologies available when developing wireless networks, see Table 3-6 [Yang, 2006, Holger, 2005]. The requirements of the system determine the most appropriate topology. The simplest topology is a *point to point* structure where a single node can communicate with another single node. To enable communication between multiple nodes more complex topologies must be established.

A *star* network connects a number of nodes via a central master node. While still relatively simple this enables communications between multiple nodes. A major advantage of this topology is the low power consumption of slave nodes. This would be preferable to minimise the footprint of swimmer worn nodes.

Mesh networks allow direct communication between any of the nodes. Power in a mesh network is distributed across the nodes. Latency is high and bandwidths are lower due to the additional complexity of the network. *Mesh* networks are capable of multi hop communications, which allow a larger spatial coverage.

A *star-mesh* network connects a mesh network with one or a number of *star* networks. Multi-hop communications are possible but have a high latency and low bandwidths. The use of the connecting star network enables low latencies and high bandwidths. The combination of both topologies facilitates a higher spatial coverage than just using a star topology.

Cluster tree is a multi-hop network whereby there is only a single path between any two nodes. Devices join the network as child devices, the first node being the ”parent” node. This type of topology allows large spatial coverage and is scalable. The leaf devices that connect to the root of the tree have low power consumption. Limitations include high latency and low bandwidths. Equally nodes must have the same basic function, which means that nodes may have excessive functionality for their intended purpose.

Table 3-7: Review of fulfilment of stakeholder requirements against features for different network topologies

Requirements	Low latency	High bandwidth	Spatial coverage over 65m	Low power consumption of swimmer worn node	Scale to ~6 nodes (i.e. Theoretical maximum of the current system)
Point to point	•	•	•		
Star	•	•	•	•	•
Mesh			•		•
Star mesh	•	•	•		•
Cluster tree			•	•	•

Requirements for the swimmer system have been compared with the features of the different network topologies in Table 3-7. Key requirements for the swimming monitoring application are defined as *low latency, high bandwidth, spatial coverage* at least 65m, *low power consumption* of swimmer worn nodes to minimise their *size* and a minimum of *six node capability*.

Low latency ensures quick communications, which is essential for the real-time nature of the system. *High bandwidth* is preferable as it facilitates the scalable nature of the design, i.e. if more sensors or more nodes are required then the network capability will be able to cope with these additional demands. The *spatial coverage* is determined by the size of the pool, i.e. 50m by 25m. The biggest limitation in terms of *spatial coverage* was the presence of the water, which creates a very harsh operating environment. Specifying *low power consumption* of swimmer worn nodes minimises the footprint of the nodes, which are to be attached to the swimmer. Note: the scale of the current *network* is limited by the data capacity of the prototype system, typically six nodes for real-time transmission of raw data.

A *star* network was selected as the preferred topology for the prototype system as it was found to satisfy all of the requirements specified for the system. Future developments may require a shift towards a different topology, e.g. if a significant increase in the number of nodes or spatial coverage is necessary.

Table 3-8: Components of packet information

Field	Definition	Comments
PREAMBLE	Radio synchronization	Inserted by Radio Hardware (HW)
SYNC	Radio synchronization	Inserted by Radio HW
LENGTH	Length of remaining frame in bytes	Inserted by Firmware (FW) on Transmit (Tx), Partially filterable on Receive (Rx).
MISC	Radio dependent (needed for future IEEE radio support)	Currently set to 0.
DSTADDR	Destination address	Inserted by FW. Least Significant Byte (LSB) filterable. 0x00 and 0xFF LSB values reserved for broadcast. LSB: Most Significant Byte (MSB) formatted.
SRCADDR	Source address	Inserted by FW
PORT	Application port number (Bits 5-0)	Inserted by FW. Port 0x20-0x3D for customer applications, Port 0x00-0x1F for Network (NWK) applications
DEVICE INFO	Receiver type (bit 7-6), Sender Type (5-4) & Hop count (2-0)	Inserted by FW.
TRACTID	Transaction ID	Inserted by FW. Discipline depends on context.
APP PAYLOAD	Application data	$0 \leq n \leq 52$ (50 if Frame Check Sequence (FCS))
FCS	Radio append bytes	Cyclic Redundancy Check (CRC) checksum (Tx), Received Signal Strength Indicator (RSSI), Link Quality Indicator (LQI) and CRC status (Rx)

In addition to the physical broadcasting nature of a wireless channel, the logical topology of the network should be referred to. For the prototype system developed, a Carrier Sense Multiple Access (CSMA) system was employed, specifically a CSMA/ Collision Detection (CD) protocol. Within a CSMA protocol each node listens for a free channel before transmitting the message. A free channel is indicated by a low received signal strength indication (RSSI) value at the input of the transmitting node. Within the /CD variation, if two nodes transmit simultaneously and their messages collide, each of the nodes reset and waits an random period of time before attempting to retransmit. Alternatively a /Bitwise Arbitration (BA) method can be used, whereby nodes have a ranking assigned, such that if simultaneous transmission occurs, one has predefined priority. Due to the small scale of the current network and limited spatial coverage, CSMA/CD was found to be capable of generating robust communications for this prototype.

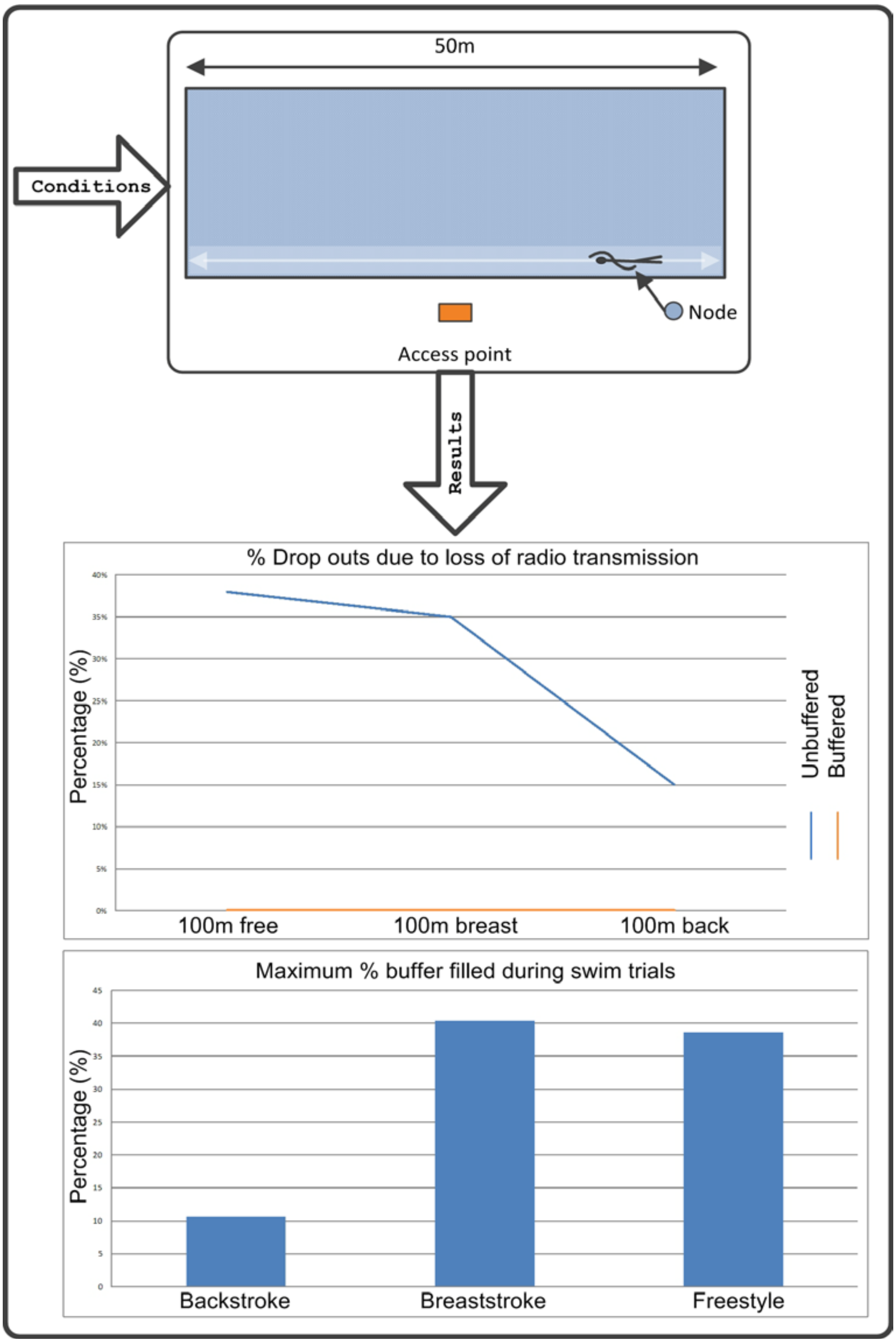


Figure 3-29: Buffer usage in swimming trials

Testing was undertaken on the prototype solution to quantify typical data losses with and without the *external memory* buffer functionality. Freestyle, breaststroke and backstroke were tested where the node was positioned in the small of the back for the prone strokes and on the stomach for backstroke. A number of 100m trials were used to collect the data, in each stroke two lengths were recorded with and two without the buffer, the results of which are presented in Figure 3-29.

It was found that without an *external memory* buffer data losses ranged from 15% in backstroke to almost 40% in freestyle. Using the developed buffer 0% drop out rate was observed. During the buffered testing the percentage of the buffer capacity filled was monitored. The maximum buffer use was recorded during breaststroke where 40% of the buffer was used. These testing outcomes suggest that the developed buffer was successful in eliminating data losses and that the buffer size appeared to be ample for the application.

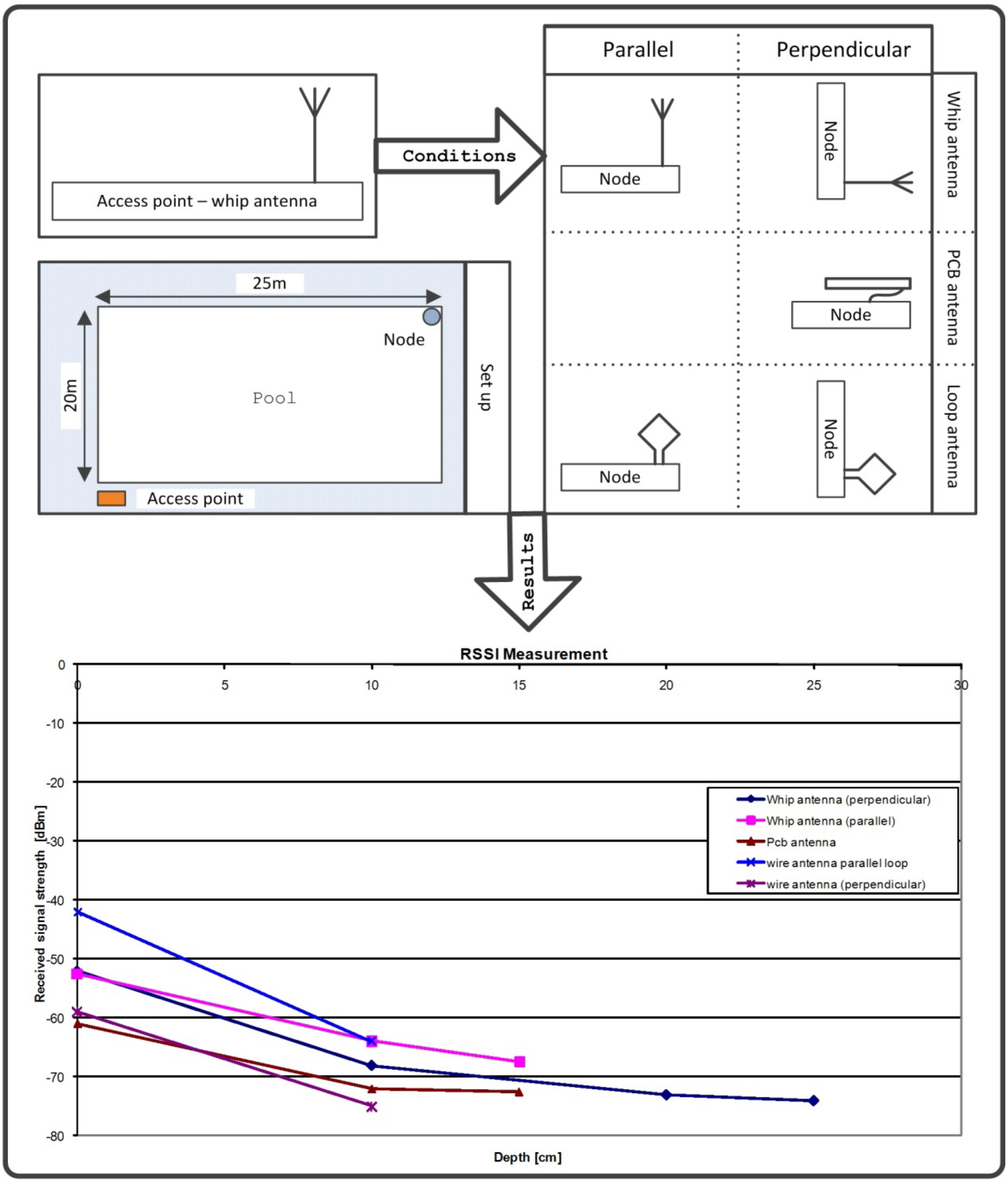


Figure 3-30: Results from antenna testing in the swimming pool

The developed prototype was also tested in the pool using different antenna solutions. Three antennas were tested, a standard *¼ length whip antenna*, a *printed circuit board (PCB)* antenna and a *¼ length wire loop antenna.* The *whip* and *PCB* antennas were tested in both parallel and perpendicular orientations, the PCB just in the perpendicular orientation. Each test was carried out in the opposite corner to the access point in a 25m pool set up, i.e. the furthest point from the access point. Each set up was tested at increments of 5cm in depth until signal was lost, see Figure 3-30.

It was found that the *whip* antenna positioned perpendicularly to the receiving node performed to a depth of 25cm before losing transmission. The *wire loop* antenna performed the worst of all the solutions, i.e. communications were lost at half of the depth achieved with the whip antenna.

3.4.1 Signal processing of node data

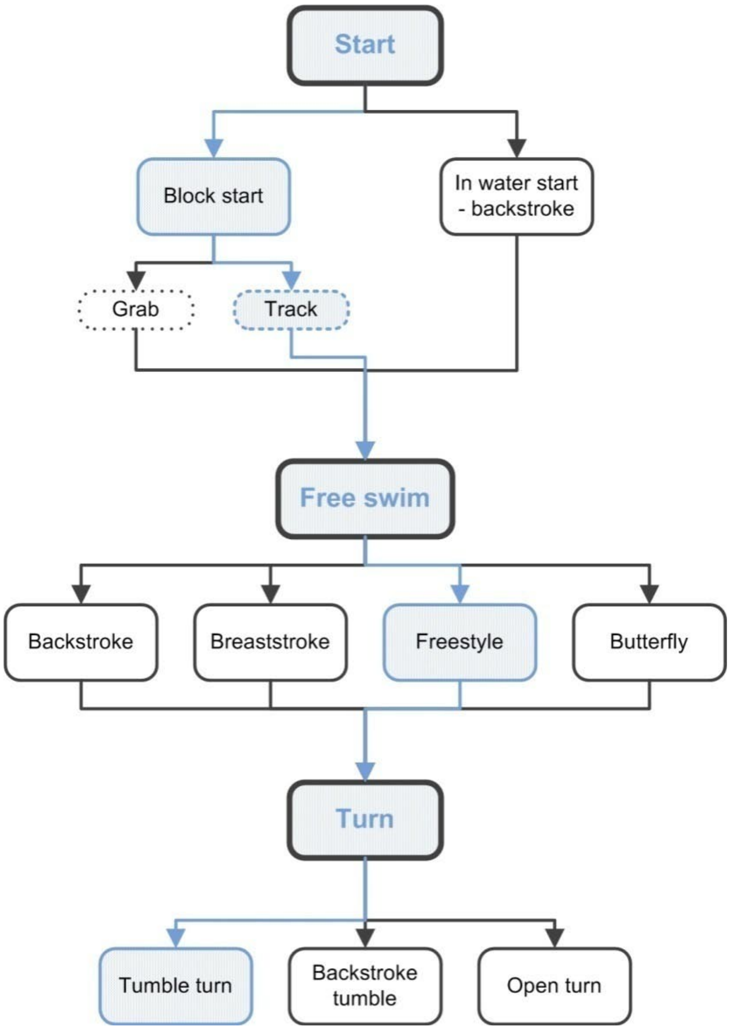


Figure 3-31: Components of swimming selected for initial analysis

Pool swimming can be broken into three core components; *starts*, *free swimming* and *turns*, see Figure 3-31. The *start* can either be from the block, as is the case for freestyle, backstroke and breaststroke, or in the water, as in backstroke. Block starts can be further decomposed into grab or track techniques. Track starts can be either rear weighted, front weighted or a swing start used in relay events. A rear weight start describes a technique whereby as the swimmer is stood on the block in their 'take your marks' position, their weight is on their back leg, a front weighted describes the opposite, i.e. with weighting occurring on the front leg.

The *free swim* component includes four competition strokes: backstroke, breaststroke, freestyle and butterfly. These are either performed as individual events or may be all included within a single event, i.e. the individual medley, where butterfly is followed by backstroke, breaststroke and freestyle.

The type of *turn* used is dependent on the event. Butterfly and breaststroke use open turns where the swimmer touches both hands on the wall and then pushes away with their feet. The tumble *turn* is used for freestyle events, where the swimmer performs a kind of forward roll into the wall, pushing off with only their feet. In backstroke a similar tumble *turn* technique is used but instead of the swimmer rotating back into a prone position out of the *turn* they remain on their back.

An individual component of each *start*, *free swim* and *turn* was selected to provide the focus for initial investigation. The block start was selected as they are used in the majority of events. The track start was specifically targeted as it represented the preferred start technique of the university and elite swimmers based at Loughborough. Freestyle was selected as the focus for free swim analysis as freestyle represents a significant volume of all swimmers training, regardless of their preferred competition stroke. This meant that there was a large potential testing population, all of which who were competent at performing freestyle swimming. As freestyle was selected as the predominant free swim stroke it was decided that the associated turn technique, i.e. the tumble turn, should also provide the focus for initial investigation.

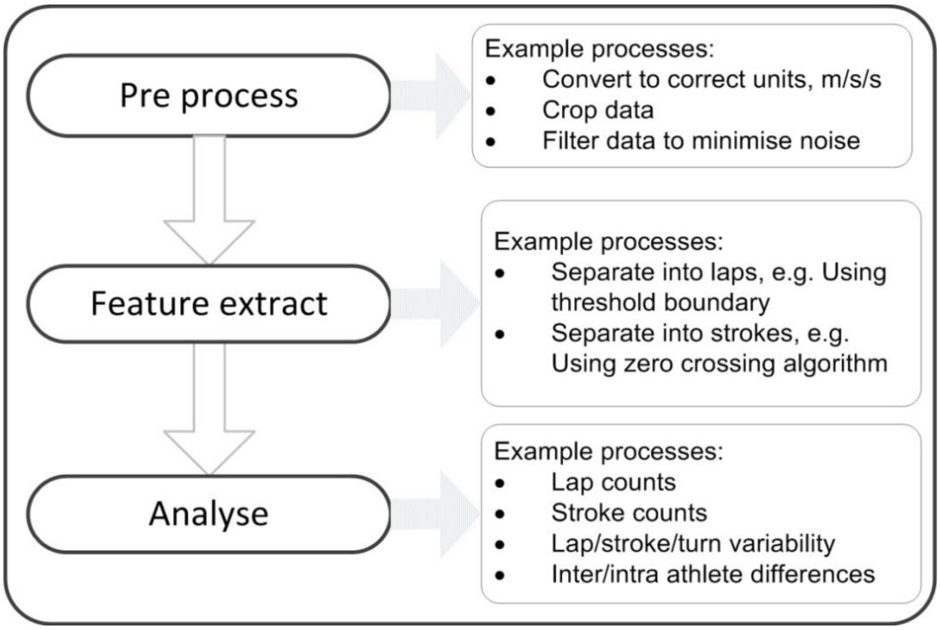


Figure 3-32: Processes of data analysis

To derive information automatically from data three basic procedures were followed, *pre processing, feature extraction* and *analysis*, see Figure 3-32. Firstly data were *pre processed* to a point where it was in a workable format for subsequent processing. This included functions such as converting raw data values to useable units, e.g. m/s/s or gravity (g), cropping data to remove unnecessary volume and filtering data to remove noise.

Feature extraction algorithms were applied to the *pre processed* data. Features taken from the data varied from simple *threshold crossings* to more complicated *pulse analysis*. *Analysis* of the extracted features is the point where relevant parameters pertaining to swimming performance are derived. For example, zero crossings algorithms allowed stroke counts to be derived, pulse analysis of these strokes gave more information regarding timing and consistency of the athlete. The three stage method outlined above has been applied to each of the aspects of swimming (see Figure 3-32).

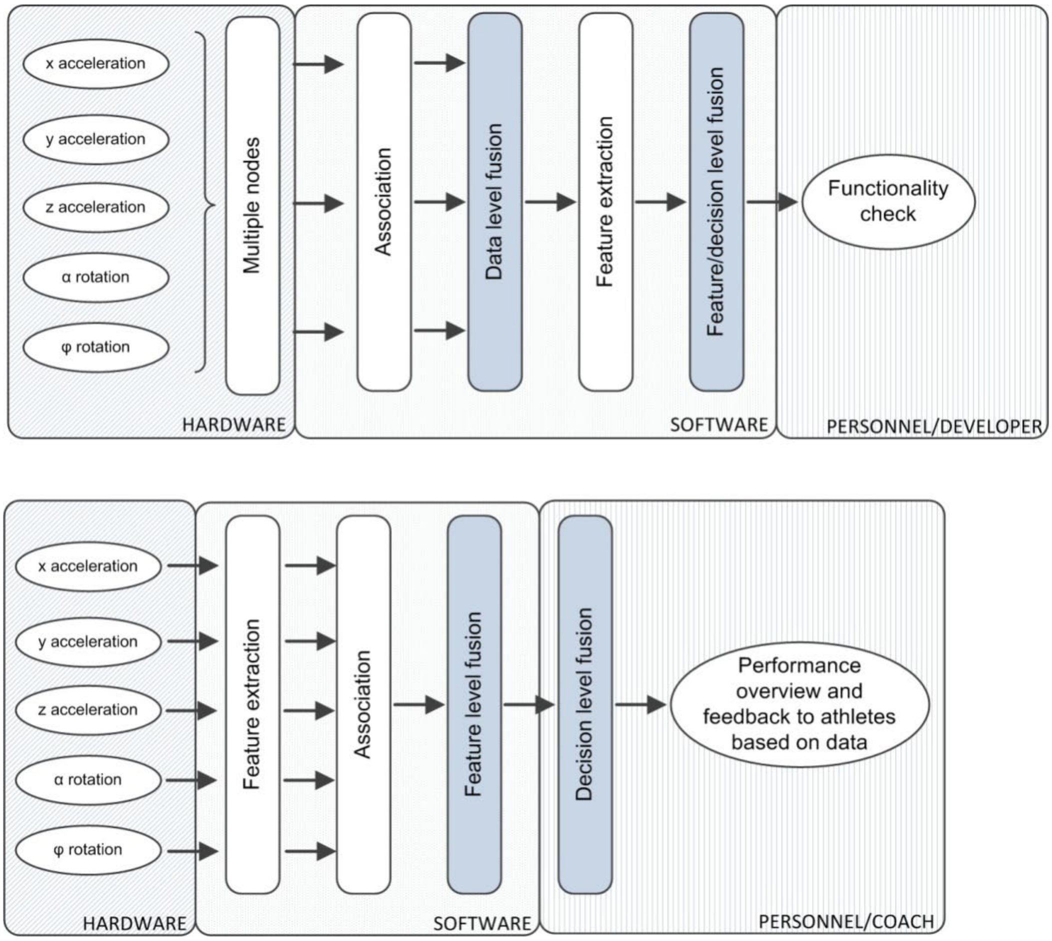


Figure 3-33: Diagram of data level fusion (top) and feature level fusion (bottom) of data processes. Adapted from Yang, 2006

The process outlined above in which data from sensors is transformed into relevant features can be described by three levels: *data level fusion, feature level fusion* and *decision level fusion*. When describing feature extraction, three additional classifications may be used to explain how sensor data is used: competitive, complementary and cooperative. Competitive fusion is where sensors provide equivalent data, typically this is useful for calibration situations to ensure sensors are operating reliably. Complementary fusion describes a system where sensors produce different information outputs, for example, a swimmer worn node may provide acceleration data in three individual axes. Cooperative fusion explains a process where sensor data must be integrated in order to derive information, that could not be possible with a single sensor, for example systems where acceleration, gyroscope and magnetometer data is integrated to establish position coordinates of movement.

The use of data fusion within the analysis presented in this thesis include both *data level fusion* and *feature level fusion*. Data level fusion has been used as a calibration tool for sensors where multiple nodes return the same sensor data about a certain event, i.e.

swim phases as outlined in the top image in Figure 3-33. Features have been extracted from these data, e.g. maxima/minima, to indicate whether sensors or nodes were performing as intended. An example of this type of fusion is used for the calibration of three axes of acceleration where the node was oriented in positions perpendicular to gravity and readings were adjusted to ensure that each axis reads +/- 1g as they were rotated through 90 degree increments.

Feature level fusion has been used to derive swimming specific performance parameters from sensor data, see bottom image in Figure 3-33. Algorithms have been developed to enable features to be extracted from acceleration sensor data. These features are combined to provide information during the start, free swim and turning phase of swimming (see Chapters 4, 5 and 6, Sections 4.3, 5.3 and 6.3). Decisions are then made as to whether parameters values are significant and if so what useful feedback can be provided. An example of this would be analysing swimming data during a succession of lap repetitions. Lap times, stroke counts and stroke durations, derived from the features in the data, could be integrated to provide information regarding a swimmers consistency and fatigue. This may allow coaches to understand better when their athlete is tired and how they demonstrate this fatigue in variations in performance features.

Currently the complete data fusion process is structured such that the hardware is used to collect the data, features are extracted by software algorithms and decisions are made by personnel, i.e. humans, to give insight into what the features actually mean.

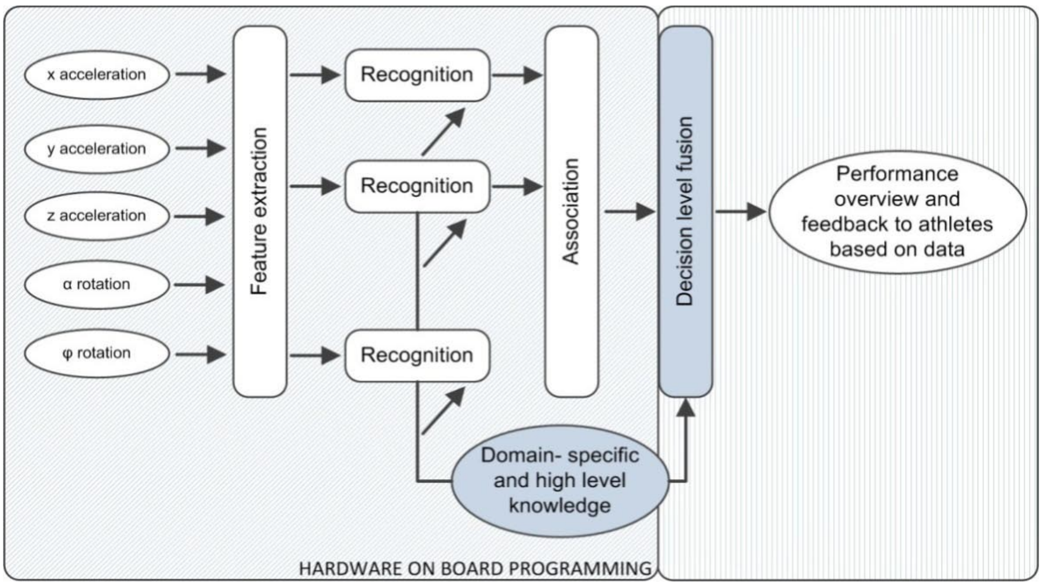


Figure 3-34: Diagram of decision level fusion. Adapted from Yang, 2006

It is envisaged that ultimately a *decision level* structure would be implemented to provide real-time feedback to athletes. A key difference of the envisaged system is a shift of the feature extraction in software embedded onto the hardware node, see Figure 3-34, leaving the software functionality to present the data in appropriate manner to the coach. The advantage of this structure, even more so than *feature level fusion*, is that by extracting features and being able to recognise their relevance and impact on performance means that the amount of data transmitted by the system is minimised to summary statistics. These statistics can then be presented to the coach in a way in which they can understand and therefore make decisions on performance. Future iterations of this development will further reduce the need for human judgement as with volume of data, knowledge can be established where relevant features can be associated with performance indicators. It is important to note that a realistic prototype will require some processing on the embedded hardware, i.e. where processing is commonly repeated for all operations, however, an ideal solution will integrate a development environment with an easy to use human machine interface (HMI) for continuing progression of analysis.

Table 3-9: Filter types and associated advantages and disadvantages

Filter	Advantages	Disadvantages
Moving average	• Simple	• Can flatten signals which are ideally preserved as equal emphasis is placed on each point
Low pass filter – perfect	• Simple • Digital cut off transition	• Cannot be performed in real-time
Butterworth low pass	• Can be implemented in real-time • Can alter order to minimise memory • No pass band ripple	• Less steep cut off transition than perfect and Chebyshev filters
Chebyshev low pass	• Can be implemented in real-time • Can alter order to minimise memory • Steeper transition than Butterworth	• Pass band ripple introduces noise into the data

A key *pre process* method used in the data analysis was the application of an appropriate filter to smooth the data by removing noise without removing important information. A number of filters were considered to perform this operation as listed in Table 3-9. A *moving average* filter presents a simple solution, however, it can significantly flatten peaks in signals which may remove important information from data, especially if features such a signal amplitudes are considered important.

A *perfect low pass filter* has a "digital" cut off transition and removes high frequency noise above a defined frequency. The disadvantage of this filter is that it cannot be implemented in real-time as it requires all data points in a set before it can be applied. Two alternative low pass filters were considered that are relevant to real-time applications. The *Butterworth filter* provides a low pass filter that results in no pass band ripple, however, has a less steep cut off than the perfect filter. The order of the filter can be selected to optimise memory usage.

As with the *Butterworth filter*, a *Chebyshev filter* can be implemented in real-time and the order of the filter can be selected to optimise the performance (e.g. memory usage). The advantage of the *Chebyshev* filter is that the cut off transition can be steeper than the *Butterworth*. However, this filter does suffer from pass band ripple which can introduce noise into the data.

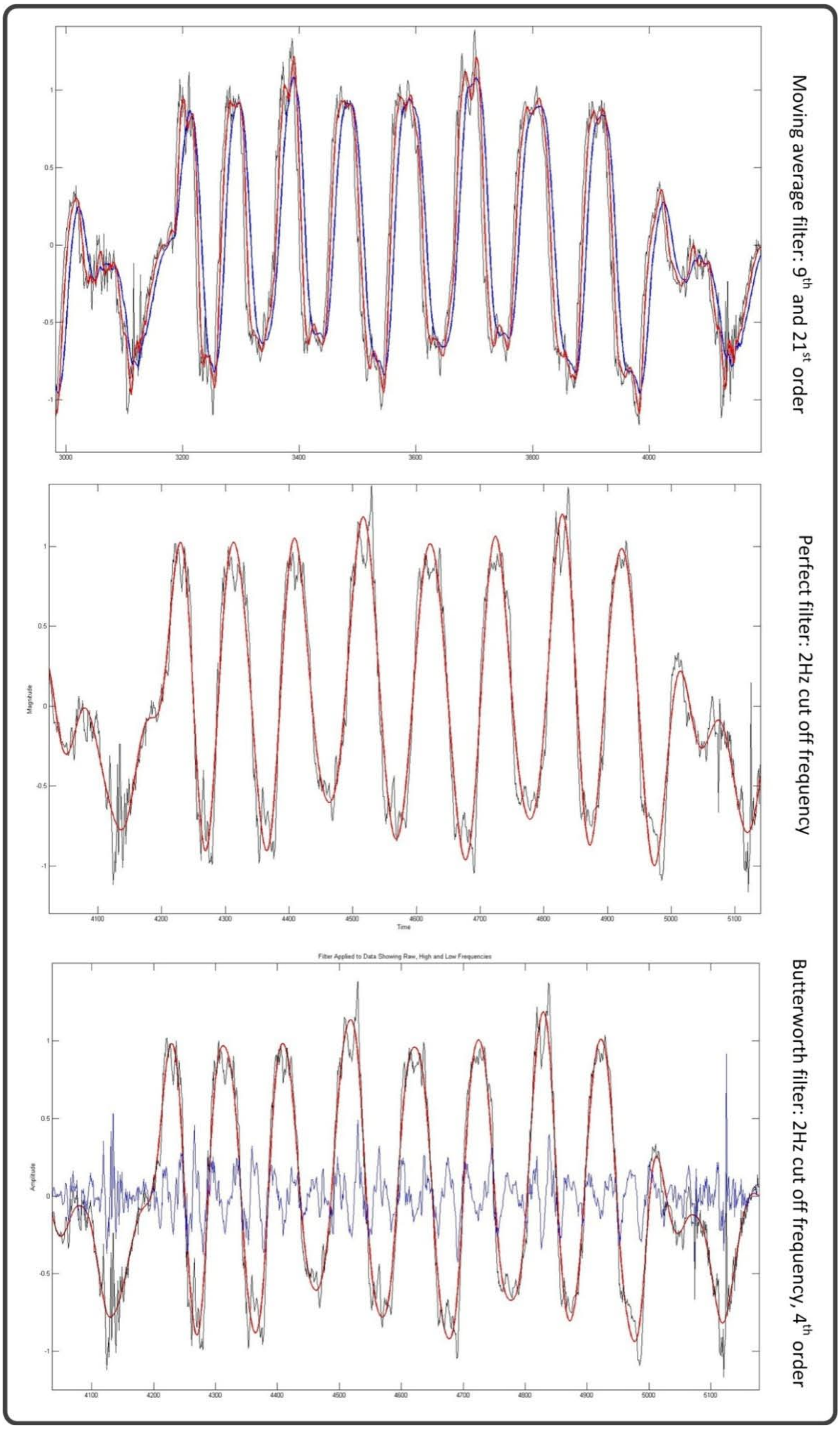


Figure 3-35: Applying different filters to swimming data

Three filter types were tested for the pre processing of data: a *moving average filter* of different orders, a *perfect filter* with a 2Hz cut off frequency and a fourth order *Butterworth filter* with a 2Hz cut off frequency, presented in Figure 3-35. Both the *perfect* and *Butterworth filters* treat the data in the frequency domain and return outputs in the time domain. It was found that the *moving average filter* tended to reduce the amplitude of peaks in the data significantly. The *perfect filter* was able to maintain the amplitude and shapes of the signal while removing noise components. The cut of frequency of 2Hz smoothed the data to a very simple wave form. A higher cut off frequency would allow the preservation of the shapes in the signal.

The *Butterworth filter* with an order of four had the same 2Hz cut off frequency as the perfect filter. The results were similar to those of the *perfect filter* with the advantage of supporting real-time implementation. The order of the filter determines the gradient of the cut off transition. A higher order equates to a steeper cut off. However, a higher order requires a larger number of data points to be collected before the algorithm can be implemented.

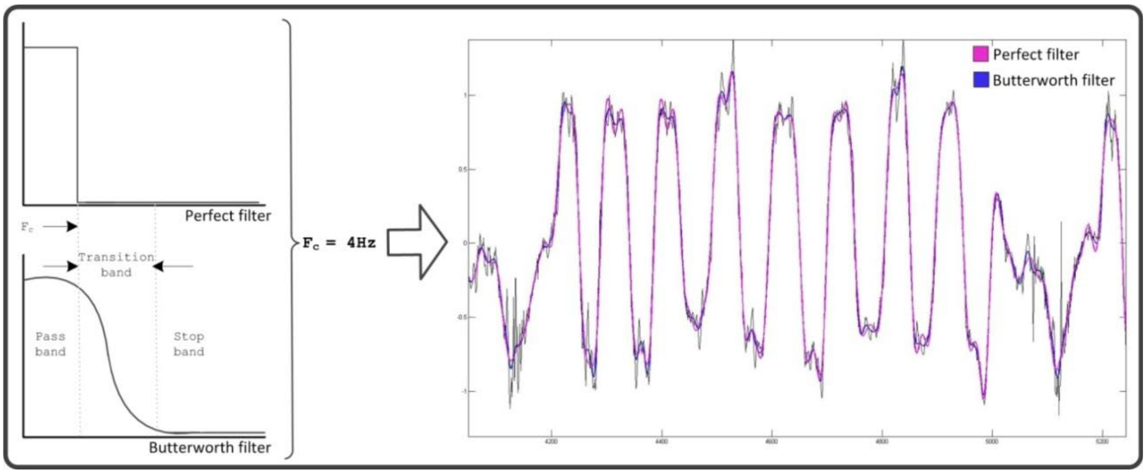


Figure 3-36: Comparison of perfect and Butterworth filter applied to raw swimming data

The transfer functions of the *perfect* and *Butterworth filter* are plotted in, Figure 3-36. The digital nature of the *perfect filter* means that all values associated with events occurring at less than 4Hz were preserved completely and all higher frequency contributions were completely removed. The *Butterworth filter* however has a transition band and some higher frequency components were still included, in part, in the output signal. The filter applied used a 4Hz frequency cut off, allowing the shape of the signals to be preserved better than the previously observed 2Hz cut off. The *Butterworth filter* was of order 4. This relatively low order presented a solution with a quick initiation time and low memory requirements, however, the transition band was not particularly steep.

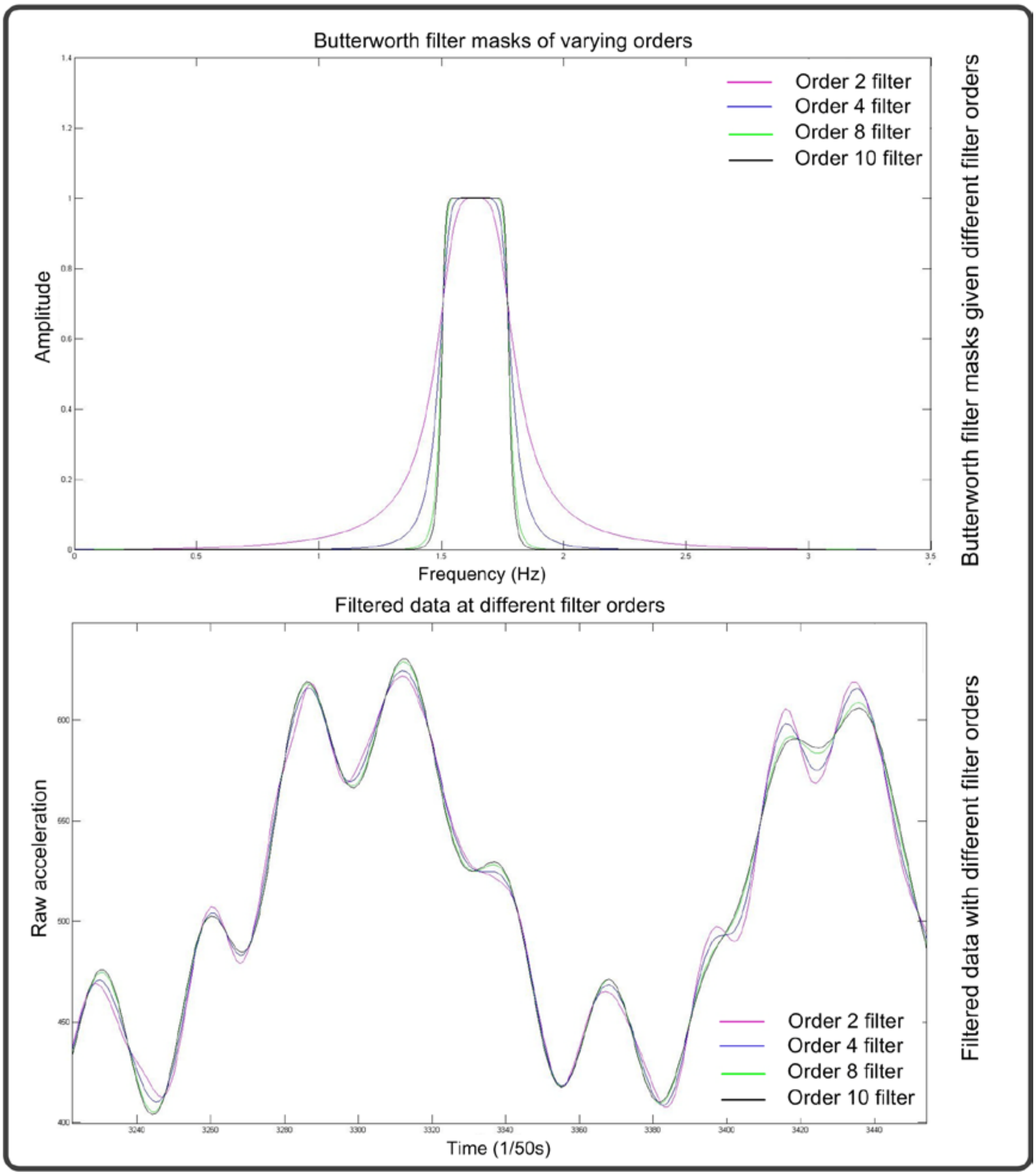


Figure 3-37: Different Butterworth filter masks applied to raw data

Increasing the order of the *Butterworth filter* increases the gradient of the transition band, which means that less high frequency components, above the cut off are included in the output signal. This trend was observed when varying filter orders were applied to the same data set, see Figure 3-37. A higher order filter was found to minimise peaks associated with higher frequency components in the signal, whereas the lower orders were not able to remove these components.

Figure 3-38: Butterworth filter equation

Initial analysis implemented a *Butterworth filter* in Matlab, future developments transferred these operations to C to enable the filter to be embedded within the hardware. The Butterworth filter requires three key input variables to run: the *filter order*, the *sampling frequency* of the data and the required *cut off frequency,* see Figure 3-38. The filter generates coefficients which were used to develop the filter mask. The filter mask is then applied to the data in the frequency domain and then returned to the time domain as a smoothed signal.

Having pre processed the data, features are extracted from the signals to try and qualify characteristics and eventually associate them with performance indicators. Feature extraction has been approached from the *time domain* and the *frequency domain*, examples of which are shown in Chapter 5: Case Study – Free Swimming, Sections 5.3.2 and 5.3.3. *Time domain* features include waveform characteristics and statistics. Characteristics quantify simple features within the signal such as maxima/minima, pulse durations and pulse repetitions. In addition waveform statistics quantify how these characteristics vary within the data stream, for example zero crossings were used to establish strokes and then the time between the occurrences of these crossings was used to indicate stroke durations. The stroke durations were then statistically analysed over a number of lengths to establish the swimmers consistency by looking at their standard deviation to indicate how their stroke cycle varied. Subsequent lengths and data from different athletes were observed to identify difference that may occur due to swimmer fatigue or traits demonstrated by individual swimmers.

Table 3-10: Time and frequency domain characteristics of data

Time domain analysis	**Frequency domain analysis**
Waveform characteristics, e.g. amplitudes, maxima/minima, pulse duration, pulse repetition intervals, zero crossings	Periodic frequency structures in time domain
Waveform statistics, e.g. Mean, standard deviation, peak to valley ratio	Fourier analysis

Frequency domain characteristics were concerned with the number of times a feature occurred during a known time period. Fourier analysis was used to observe the spectrum of frequencies present in the pre processed signal. It was thought that repetitive, cyclic features such as stroke rate would be readily extracted from the data through this analysis.

3.5 Summary

3.5.1 RQ1 Vision methods for automated vision analysis

Variability of currently used manual vision analysis techniques has been quantified to give an indication of inter and intra person consistency. The outcome of this analysis is used as a performance benchmark against which automated methods are compared.

The development of automated vision systems and processes associated with their implementation have been discussed. Temporal and spatial methods are explored and their appropriateness for the analysis of swimming performance evaluated. LED markers were designed to maximise signal to noise ratio of the AOI and therefore maximise the potential to segment specific landmarks robustly from the image.

3.5.2 RQ2 Design and development of an instrumented starting platform

An instrumented starting platform was design to be consistent with current blocks in terms of dimensions and texture. Four Kistler force transducers were mounted into the top plate allowing measurement of force in three axes during the block phase of the swimming start. The resulting block was calibrated by loading each axis individually with known weights. Horizontal (y) and vertical (z) axes were calibrated and found to be accurate to 1.28% and 10.63% respectively. It was found that the x axis, pertaining to lateral motion, did not read out expected forces, but instead forces equating to approximately 50% of the actual load. This was diagnosed as a problem with the read out from two of the force components. This axes, therefore could not be considered as reliable when testing. It was possible, however, to determine centre of pressure (CoP) values to provide an indication of sideways movement, as this did not require x forces to be calculated.

3.5.3 RQ3 Design and development of a wireless sensor node

A wireless sensor node was developed to allow real-time analysis of swimming performance. Hardware was specified that incorporated an integrated transceiver operating at 433MHz, tri axis accelerometer, dual axis gyroscope and memory to allow a buffer capacity. A network protocol was developed around the basic SimpliTi protocol provided with the CC1110 processor. An external memory buffer has been implemented to eliminate data loss through loss of communications in the water. In this case data are stored in the buffer and re-transmitted once communications has been re-established.

Processes for signal processing and feature extraction were discussed. A simple filter was applied to data to smooth noise and ease further analysis. More specific examples of how signals were processed and relevant features extracted are detailed in future chapters.

Chapter 4

4. CASE STUDY – STARTS

4.1 Chapter Overview

The parameters that are required to categorise fully the swimming start have been determined in Chapter 1: Quantification of the Stakeholder Requirements. A summary of the simple i.e. single measurement and compound parameters (i.e. derived from a combination of simple measurements) are re-visited in Table 4-1. Analysis of currently measured swimming start performance parameters, highlighted in bold, are routinely obtained via manual vision analysis techniques that require a high time penalty, operator expertise, cost and suffer from inherent variability due to human judgement. The focus of the research outlined in this Chapter is targeted on the evaluation of a complete solution enabling the measurement of the specified needs listed in Table 4-1 in a reliable, timely and efficient manner.

Table 4-1: Start measurement parameter requirements

	Simple	Compound
Starts	• Time from gun to first movement • **Block time** • Angle of entry • **Time to entry** • Distance of entry • Maximum depth • Break out distance • Break out time • First stroke timing	• Velocity off blocks • Velocity of glide • Velocity at break out

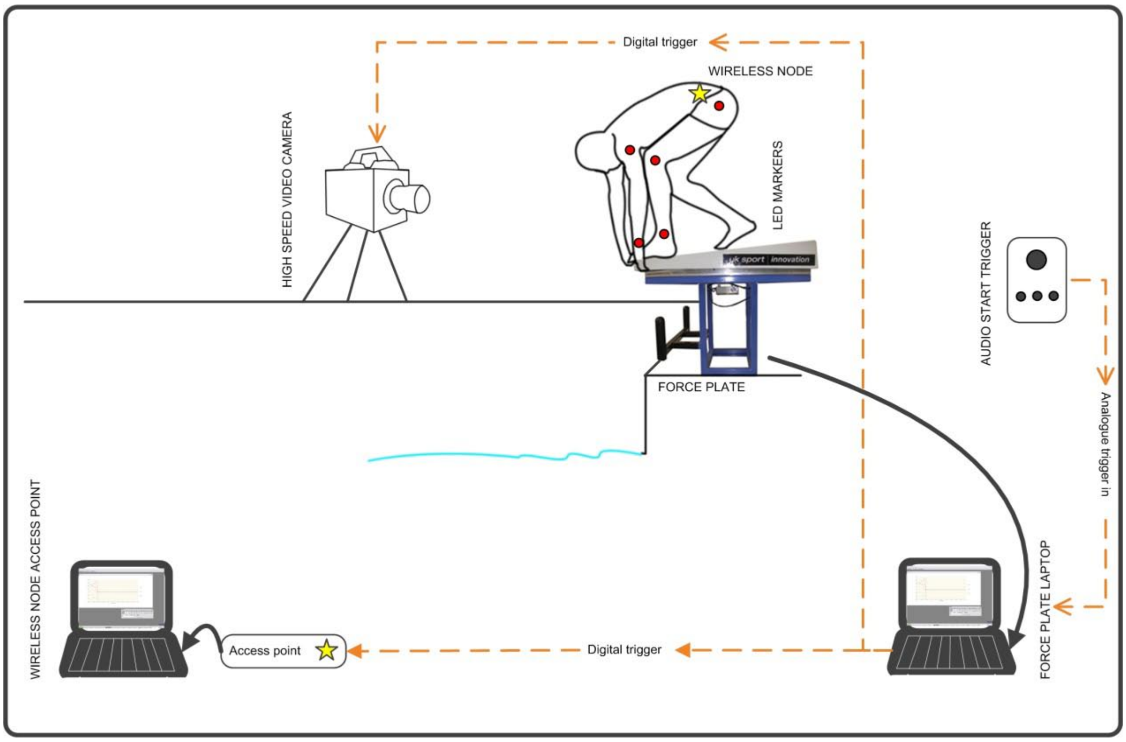


Figure 4-1: Component set up for starts testing

The research presented in this Chapter is concerned with the development of system components suitable for the analysis of swimming starts. Analysis methods include the use of automated vision, force plate and wireless sensor node technologies (see Figure 4-1). Data collection is synchronised for each of the components to allow integrated investigation. Individual components were initially developed and validated in isolation and then integrated as part of a complete system.

4.1.1 Research Questions (RQs)

RQ1 Automated Vision

a. Are there any vision-based methods that can provide a robust and acceptable solution targeted analysis of swimming start performance, pertaining to the requirements of the stakeholders?
b. What techniques are available to maximise the signal to noise ratio within the pool environment to allow robust automated vision analysis?

RQ2 Force Plate

a. What are the performance indicators that can be derived from the force generated during the block phase of the start?

RQ3 Wireless Node

a. What start specific parameters are evident in accelerometer data?

4.1.2 Chapter Structure

The structure of this Chapter is divided into three core themes addressing each of the stated research questions. Vision methods are applied to enable automated analysis of the starts. Both temporal and spatial thresholding techniques are tested to determine the most appropriate solution for this application.

Performance measurements during the block phase are explored using a starting platform instrumented with force transducers. Performance indicators are sought from raw data. Further to this, raw data is used to predict initial and subsequent flight characteristics and results are discussed. Finally observations of measurement parameters and their relationships with swimmer competency is considered.

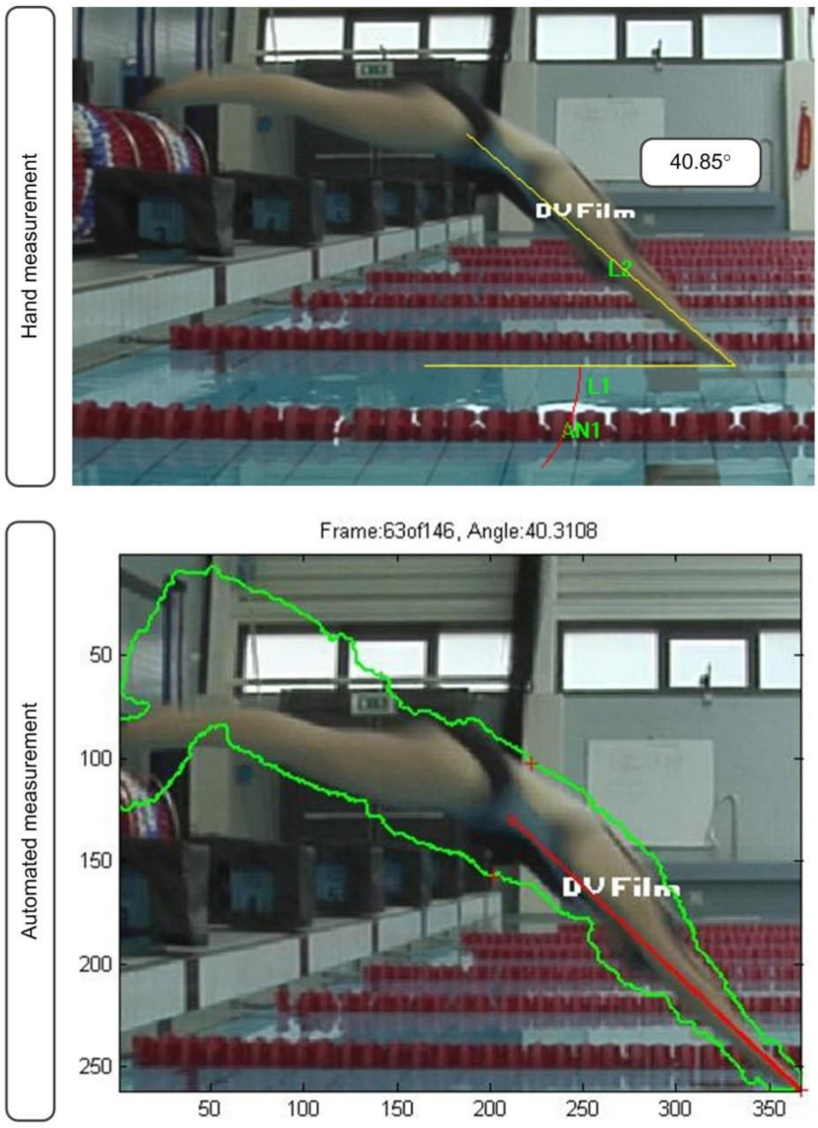
A wireless accelerometer node is synchronised with force plate and vision data to give a greater insight into performance parameters pertaining to the start. An example is presented and discussed.

4.2 Vision methods for automated vision analysis of starts

The use of manual vision-based techniques combined with hand timing is the most prevalent method reported in literature on swimming starts analysis. However manual analysis is costly in terms of setup, analysis and maintenance time and suffers from inherent variability between measurements and users.

Two methods of image segmentation, i.e. temporal and spatial thresholding, can be applied to distinguish a feature from an image [Amat et al 1999, Cho et al, 1997]. Temporal thresholding enables an object of interest to be extracted from background noise in the image by observing the difference between one frame and the next in time. Spatial thresholding on the other hand is concerned with determining object specific features from the individual pixel values in an image. Initially it was hypothesised that, assuming no other swimmers were within the field of view (as is usually the case for starts training), the image of a swimmer performing a dive could be discriminated from the background via temporal thresholding. This relies on the fact that the swimmer would be the only object within the image frame that was moving through time.

4.2.1 Temporal thresholding



Returned an angle	Within +/- 1SD	Within +/- 2SD	Outside 2SD
21	1	4	16
Total tested			55

Figure 4-2: Comparison of hand measured dive angle and automated technique using temporal thresholding

Filming of 55 dives was undertaken at a Loughborough University swimming club training session. Swimmers were filmed performing their normal dive training during the session. Dive analysis was then performed in two ways, firstly using manual digitisation methods and secondly using the developed automated process (see Figure

4-2). The process of temporal thresholding, developed in Matlab, involved determining the absolute difference between a frame and the subsequent frame in each case. It was thought that this would isolate the swimmer as their movement would be represented by the difference in each frame, assuming the background was stationary. Using the absolute difference image, the frame could be thresholded into a binary (i.e. black and white pixels only) and the boundary of the “swimmer” could be traced.

For the manual analysis, each of the dives was hand measured three times and an average of these measurements was taken as the “dive angle”. Typically, repeated hand measurement of the dive angle by the same “experienced” person results in a standard deviation (SD) of ±1.1° (n=3). Comparisons of the *manual dive angle* and the angle measured using the movement thresholding algorithm, were used to give an indication of the accuracy and repeatability of the algorithm. Given a normal distribution it is expected that 68% of angles should fall within 1 SD of the hand measured mean, 95% within two SD’s and 99% within three SD’s. A measurement outside of 3 SD’s is considered an unacceptable result as it is not within reasonable constraints of variability.

Of the 55 dives filmed, only 21 dives returned a dive angle using the automated algorithm, i.e. 38% success rate. Of these dives one fell within one standard deviation of the hand measured mean, four within two standard deviations and the remaining angles were outside three standard deviations of the mean. This equates to 24% of the dives that returned an angle that were considered reasonable measurements of dive angle. However in the context of the total sample, i.e. 55 dives, only 9% measured gave a reasonable measurement of dive angle using the original algorithm.

A typical boundary tracing outcome for one of the successful automated analyses is given in Figure 4-2. This demonstrates the limited level of resolution that was achieved using the movement thresholding algorithm. It can be seen that the boundary deviates from the true outline of the swimmer which impacts of the ability to extract performance measurements with confidence. Additionally other objects moving in the field of view create noise, e.g. other people, the movement of the water and the affects of changing lighting. These were the main reasons for the limited success of using the algorithm on raw image data.

4.2.2 Spatial thresholding

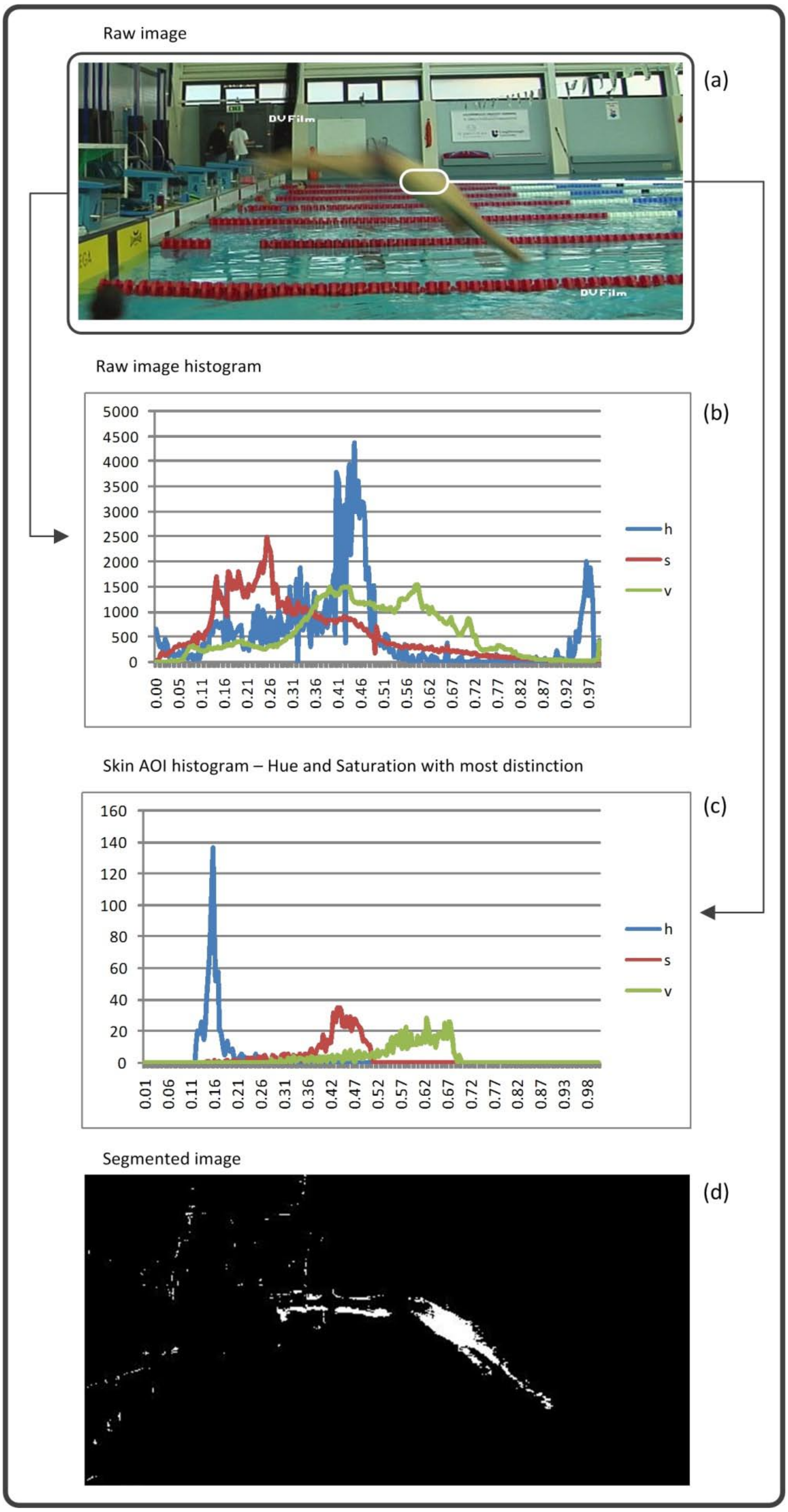


Figure 4-3: Using histograms to identify pixel characteristics for "skin" spatial thresholding

Spatial thresholding can be used to segment the swimmer from the background by specifying specific pixel characteristics unique to the swimmer to determine an area of interest (AOI). By separating colour channels within an image, each channel can be individually thresholded to isolate the AOI and then recombined to produce a single binary image (see Figure 4-3). The potential of thresholding the swimmer from the background with no additional controls in place (i.e. coloured garments, hats, lighting) was first considered using the an area of exposed body as the thresholding feature (see Figure 4-3) as this would impact least on set up and processing methods, i.e. current procedures would be maintained. An overview of the flow of processes that were used to perform spatial thresholding is given in Figure 4-5. In this case a raw video image is captured and the field of view is cropped appropriately. Red, green and blue (RGB) colour channels are separated and individually thresholded to segment the AOI, in this case the swimmers garment. The resulting image is binarised and the boundary traced. From this boundary, performance metrics could be determined.

4.2.2.1 Spatial thresholding: skin

In normal training a male swimmer will tend to wear briefs and a female swimmer a regular swimsuit, i.e. minimal swimwear. This means that typically there is a large amount of skin exposure on a swimmer. For this reason it was assumed that thresholding using the colour content of the skin would provide potential for differentiating the swimmer from the background.

It has been reported that using the hue, saturation, value (HSV) colour channels yield the best results when performing skin thresholding for face recognition (Cho et al, 2001). Based on this, an algorithm that segmented the swimmer by thresholding the HSV colour channels was developed. A flow diagram and sample Matlab code are illustrated in Figure 4-3.

Histograms were used to determine the threshold boundaries that should be applied to the image. The raw image histogram in HSV is given in Figure 4-3(b). An area of interest (AOI) centre on the exposed diver's torso was identified and a histogram was generated for this isolated region. The difficulty in thresholding the skin from the raw image can be appreciated by comparing histograms for the raw image and the AOI in Figure 4-3(b) and (c) respectively. There is significant contribution in the raw image in the AOI channels of the skin area that is due to features other than the swimmers skin present in the image. It is unlikely that the remaining skin area (i.e. outside the selected AOI) is the reason for this overlap. Hence there is likely to be a significant background noise level in the thresholded image. The algorithm, developed in Matlab that separated the HSV colour channels, thresholded given the information on the histogram and then recombined the channels to give a resulting binary image is listed in Figure 4-5. This process allowed the central area of the swimmer to be differentiated from the background, however, when applying boundary tracing algorithms and subsequently deriving measurements from this boundary.

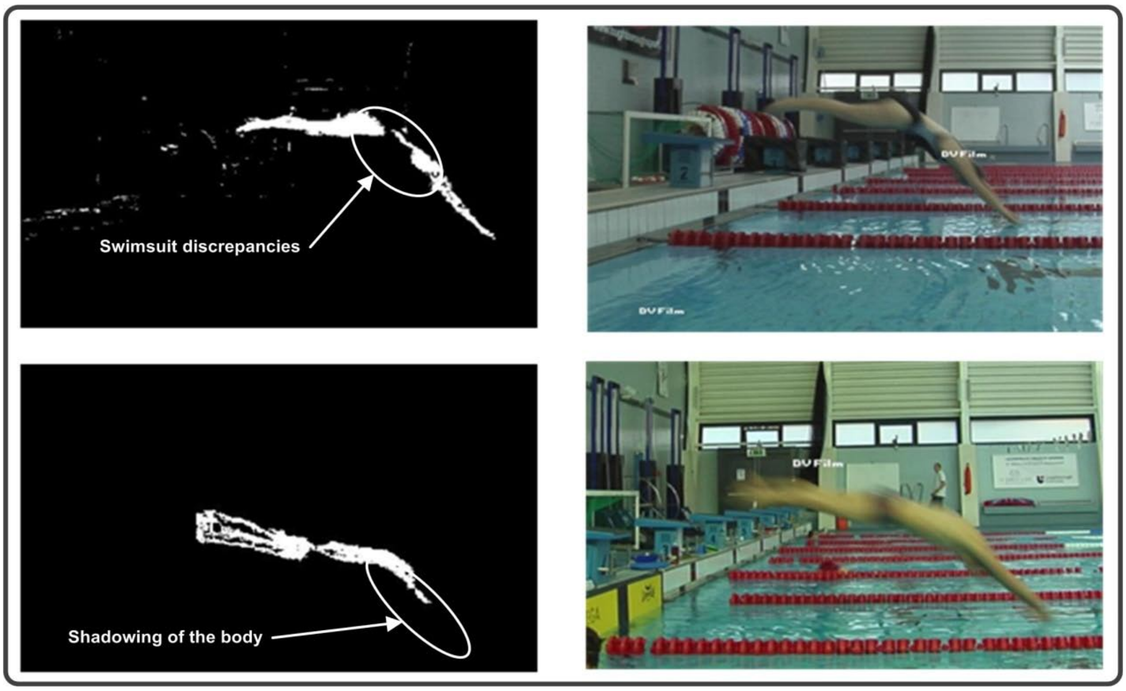


Figure 4-4: Effects of shadowing and swimwear on the ability to threshold swimmer boundary

Discrepancies occurred where the body was either shadowed or at the edges of the swimwear, see Figure 4-4. This was particularly significant for female swimmers where swimwear distorted a large proportion of the torso (see Figure 4-4). These limitations meant that when the boundary was traced it did not give a true representation of the outline of the swimmer and therefore measurements derived from this boundary were not accurate or realistic, this was the case in all videos tested, i.e. for a trial of 10 videos. Uniform characteristics in colour space of the complete body of the swimmer was required.

4.2.2.2 Spatial thresholding: garment

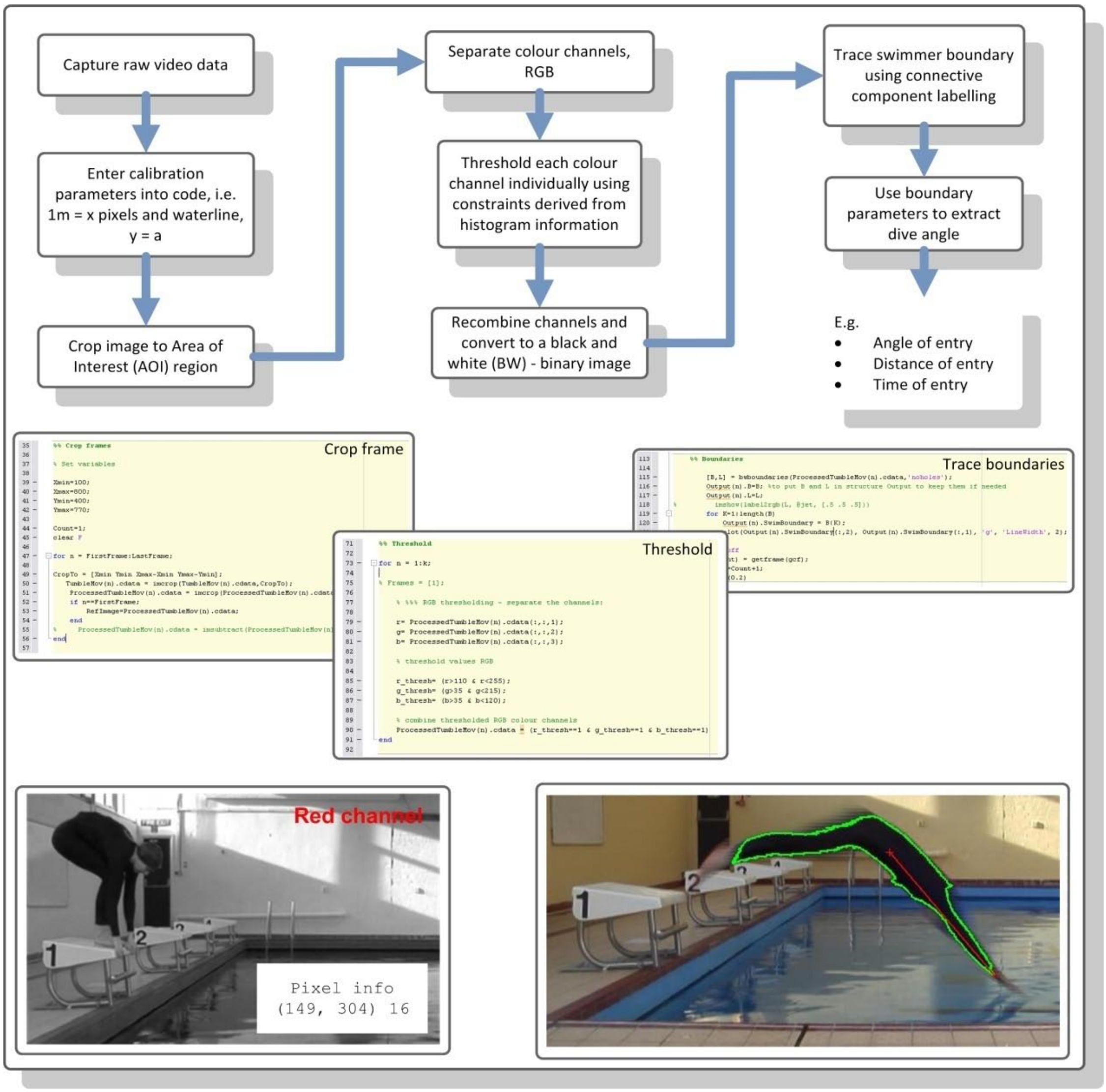


Figure 4-5: Process flow of performing spatial thresholding

An automated image processing algorithm was developed to segment the swimmer from the background image based on the (RGB) characteristics of their cover up suit using the process steps described in Figure 4-5. Using this segmented binary image the boundary of the swimmer was traced and performance parameters extracted.

The developed algorithm takes a raw video of a swimmer diving from the blocks as input. Calibration parameters are then entered to establish the physical scale within the image (Note: this step could be eliminated by establishing a set protocol which enforced camera position set up and zoom settings). The video is then cropped to eliminate unnecessary areas of the field of view and minimise the amount of image that requires processing, which in turn minimises the processing time the algorithm takes to run. In the next step the RGB colour channels are separated and individually thresholded using the characteristics of the cover up suit. The RGB channels were then recombined to produce a single binary image. A boundary tracing algorithm was applied to the binary image to trace the area of interest (AOI), i.e. the body of the swimmer. In this case *bwboundaries*, a Matlab function, was used to perform the boundary tracing. This performs a connective component labelling function to derive the boundary line [Kong and Rosenfeld, 1996]. The boundary was then used to derive performance parameters such as angle and distance of entry.

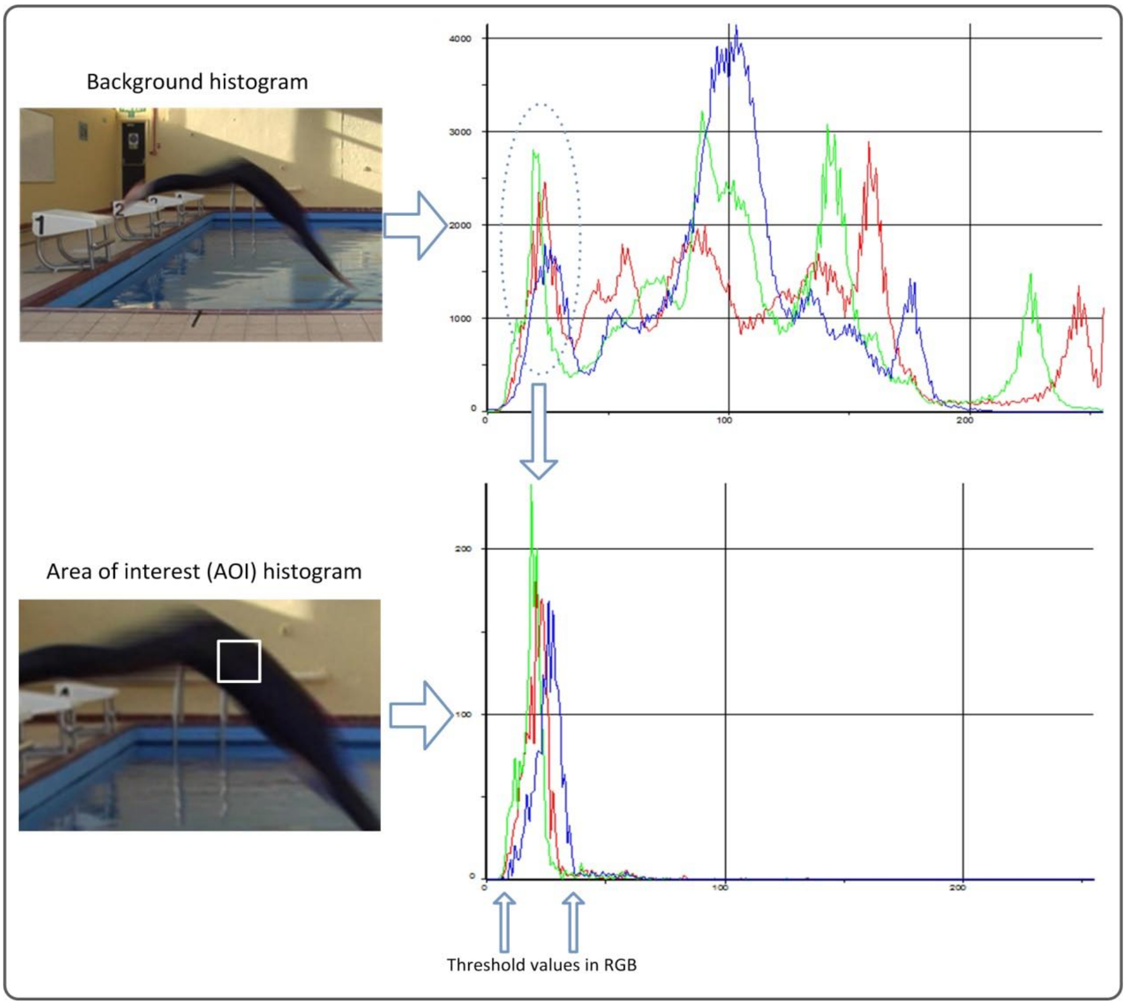


Figure 4-6: Observation of RGB image histograms for a complete and AOI within an image

The current trend for competition swimmers has been to wear full body garments that cover from the wrists to the ankles. Using a uniform coloured swimsuit as a unique feature in the image could increase the success of the thresholding algorithm to differentiate robustly the swimmer from the background using automatic methods. To avoid the previous problems with shadowing, the swimmer was requested to wear a dark control garment.

As with previous methods, image histograms were used to determine threshold parameters for the complete swimsuit. Both HSV and RGB colour channels were evaluate in this trial. By scrutinising the image histograms it became apparent that there was a greater potential for success using the RGB thresholding over the HSV. When comparing the background histogram to the swimsuit in RGB colour space the suit properties could be clearly isolated as a feature in the background histogram (compare images in Figure 4-6). However, in the HSV equivalent histograms this trend was not so apparent (compare Figure 4-7 (b) and (c)). The clear discrimination of suit (i.e. RGB values) within the raw image gives increased confidence in the potential ability to isolate the suit as a component within the background.

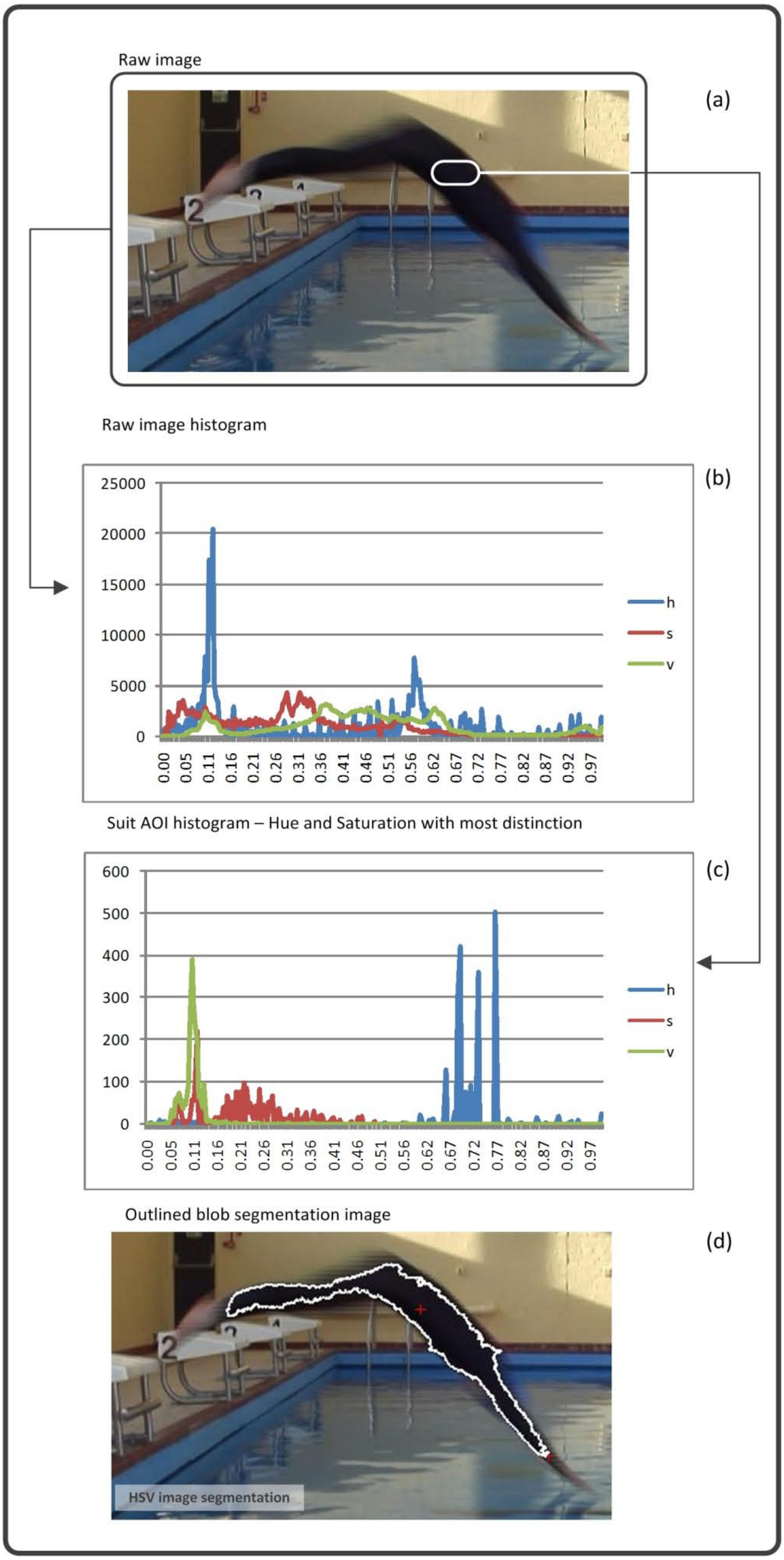


Figure 4-7: Observation of HSV image histograms for a complete and AOI within an image

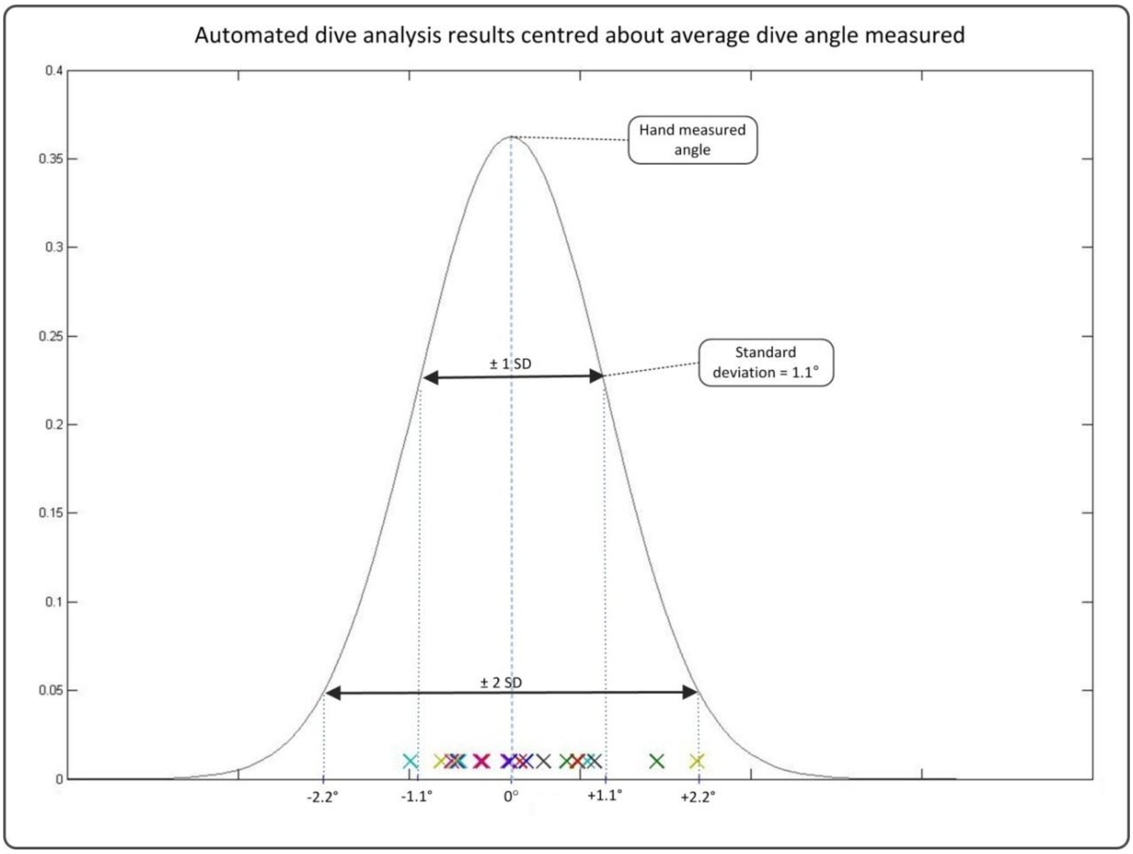


Figure 4-8: Comparison of automated and hand measured dive angles

To test the robustness of the developed algorithm, 20 dives, filmed in two pool environments, were analysed using both manual and the automated methods of angle measurement. As discussed previously, each dive was hand measured three times and the average was taken as the "dive angle". Comparisons of the manual "dive angle" and the angle measured using the RGB thresholding algorithm, were used to give an indication of the accuracy and robustness of the algorithm.

The results indicate that 17 of the 20 dives fell within one standard deviation of the hand measured mean, i.e. within ±1.1°, i.e. 85% of the dives analysed (see Figure 4-8). The three remaining dives all fell within +/- two standard deviations. These results gave confidence in the ability of the algorithm to measure accurately dive angle in repeated trials.

There were two major limitations to using the complete swimsuit: (i) body landmarks (e.g. wrist, elbow, shoulder) had to be approximated given the traced boundary and (ii) feedback from end users voiced concerns about the practicalities of having to put on a suit to enable analysis. Even considering the accuracy and robustness of the algorithm, using a complete (i.e. full body) swimsuit was considered impractical and unpopular amongst coaches and swimmers and had too great an impact on the current starts analysis process to be adopted.

4.2.2.3 Spatial thresholding: markers

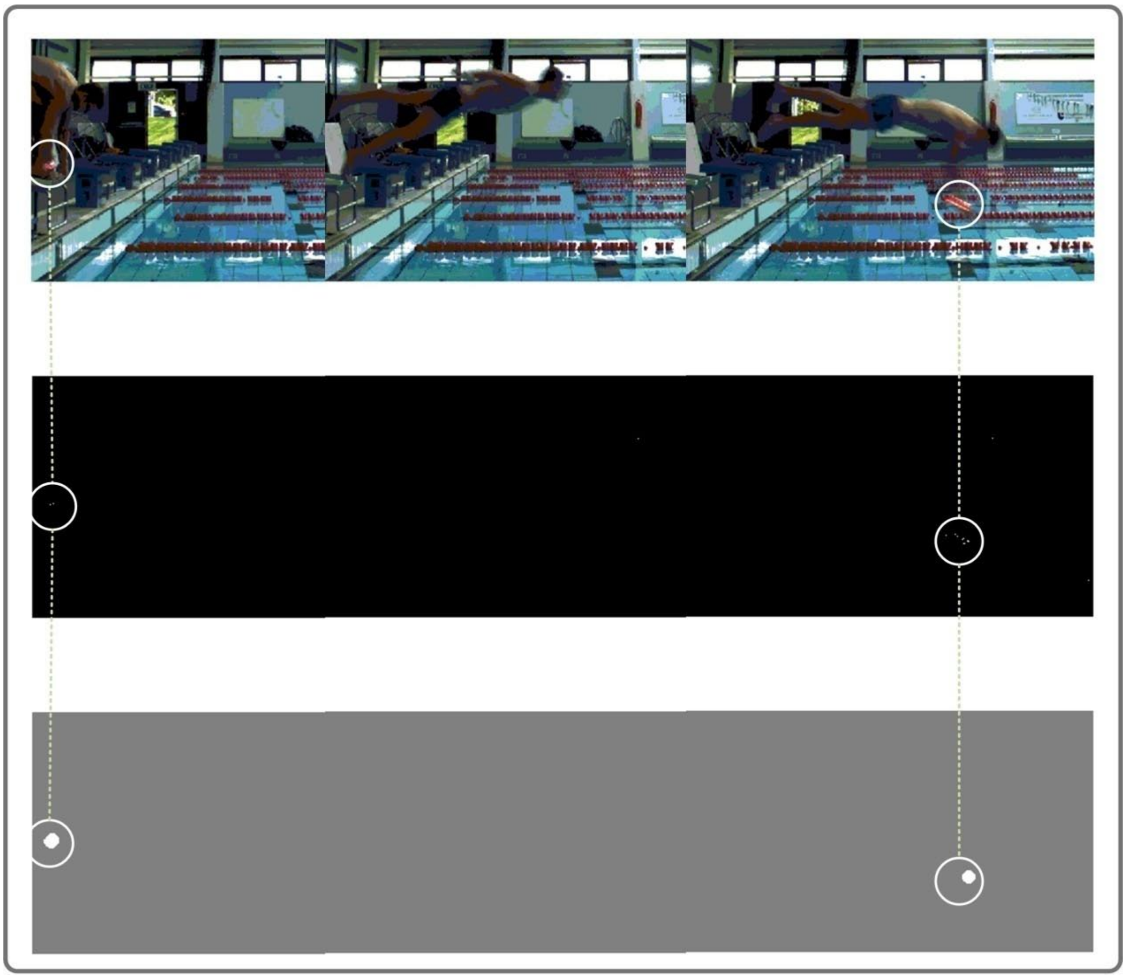
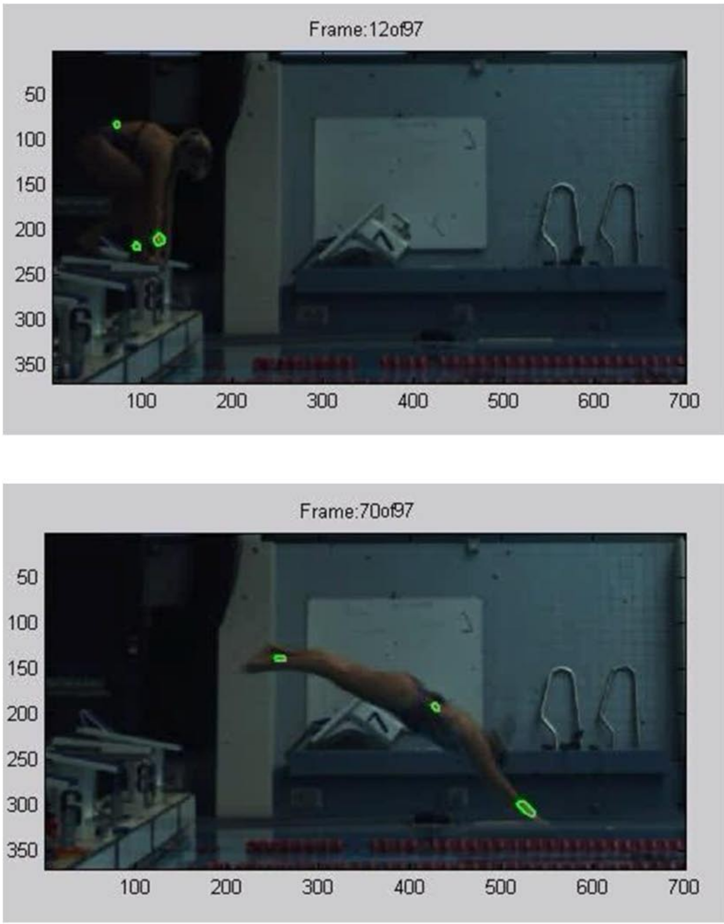


Figure 4-9: Tracking a wearable LED marker through a swimming block start

A lightweight optical marker (using self illuminating red light emitting diodes (LED's)) was developed that could be worn by the swimmer on specific body landmarks, such as the wrist, hip and ankle. These markers were designed to maximise signal to noise ratio in the pool environment, which was essential given their limited size within the camera's field of view. For example when the field of view is set-up to include the complete dive (e.g. see Figure 4-9) the size of the marker (e.g. ~100mm^2) is such that it occupies approximately 100 pixels within a complete field of view (i.e. 1024x1024 pixels) of 1 mega pixels.

Thresholding techniques, (using RGB value (see Figure 4-5)), were used to isolate the LED marker from the background in order to track it through the field of view in the analysis of a dive (see Figure 4-9). The frequency of the LED's enable the markers to be readily traced within the images. However the directionality of the LED was such that depending on the orientation of the swimmers arm it was sometimes occluded (see Figure 4-9. The second revision of the design located LED's around the entire circumference of the limb (using a flexible circuit substrate) to increase its visibility in all orientations.



Dive	Hand measured angle	Automated angle	Hand measured distance	Automated distance
1	51.74	51.34	2.17m	2.19m
2	45.58	45.73	2.27m	2.32m

Figure 4-10: Tracking second generation LED markers during a swimming block start

Three second generation LED markers were placed on the wrist, hip and ankle of a swimmer to investigate the robustness and accuracy of the marker system. As in previous cases, manual measurements were taken to analyse the angle of entry of the swimmer and the distance from the wall at which they entered the pool. An automated algorithm was used to determine the same parameters by tracking the LED markers, using the thresholding methods outlined in Figure 4-5.

In this preliminary analysis only two dives were analysed in detail. It was found that using automated analysis the dive angles were 51.34° and 45.73° respectively, compared with 51.74° and 45.58° for manual techniques (see Figure 4-10). The difference between the measurements were 0.4° and 0.15° respectively. These differences are not significant given the typical intra-person variability of manual measurements, i.e. 1.1°. Similarly the algorithm estimated distance of entry to +2cm and +5cm the manual measured equivalent.

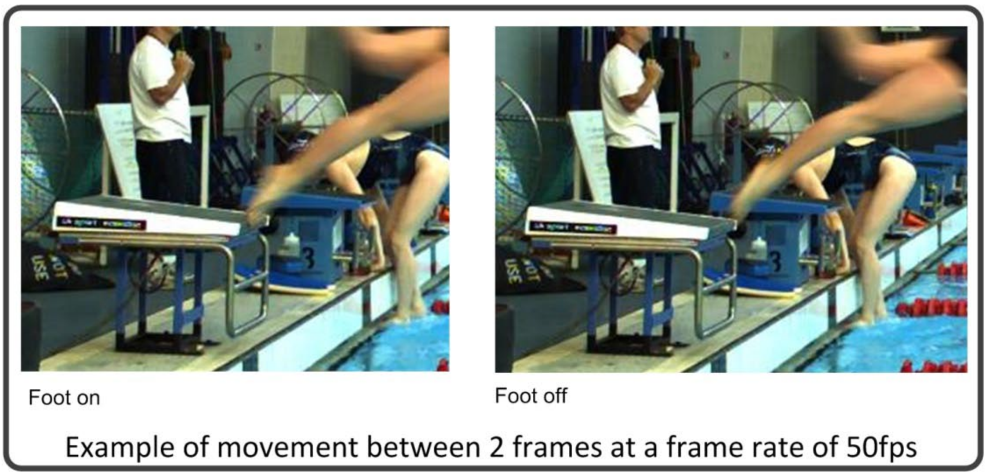


Figure 4-11: Example of foot movement between two frames at a frame rate of 50fps

Vision based techniques have enabled automated analysis of core performance measurements identified in the stakeholder requirements (i.e. time of entry, angle of entry, distance of entry). However parameters such as time to first movement and block time could not be confidently extracted given the resolution of image processing techniques. For example, to determine block time, the time where the foot leaves the block must be confidently identified. Even at 50 frames per second, which is double the frame rate of the current cameras used by British Swimming, there is uncertainty associated with the exact time the foot leaves the block, see Figure 4-11, due to the amount of movement occurring between two consecutive frames, i.e. 0.02s. For a 'normal' camera, operating at 25fps this uncertainty is aggravated. For this reason it was considered that additional components, integrated with vision techniques, would have to be used to supplement analysis, provide additional performance metrics and ultimately satisfy more of the stakeholder requirements.

4.3 Performance measurements during the block phase using force plate technology

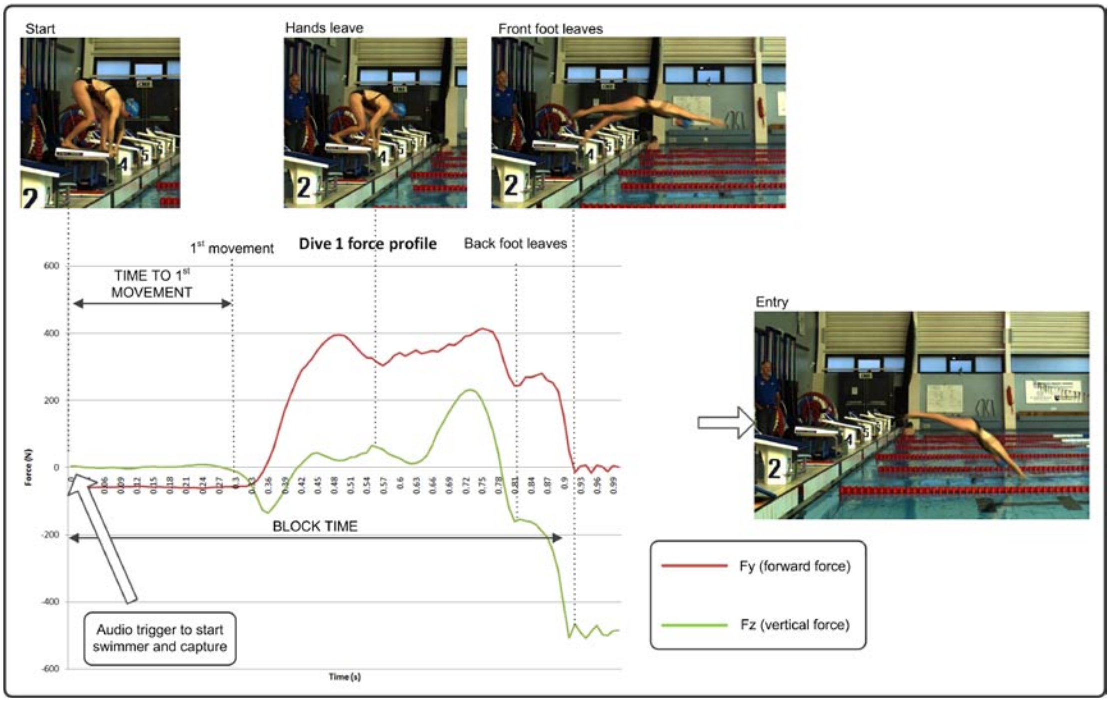


Figure 4-12: Force profile of a block start aligned with vision data

Improvement in the initial part of a start depends on understanding how the athlete responds to the start trigger and generates forward velocity on the starting blocks. Detailed understanding can be best achieved by instrumenting the starting blocks (i.e. for force-time measurement) and integrating with other measurement technologies (e.g. vision systems, accelerometers). Using the instrumented starting block developed in Loughborough (see Chapter 3: Development of Component Technologies, Section 3.3), force data were collected of a number of swimmers performing a block start (see Figure 4-12). The aim was to determine information on the required parameters *Time from gun to first movement, Block time, Time to entry, Distance of Entry and Velocity off Blocks*. It was also anticipated that other indicators of performance could be determined from the recorded force profiles.

Data capture was initiated by a physical analogue trigger into the start block which also generated an audio signal to alert the athlete to start. A simultaneous capture trigger was input into the video camera (see Figure 4-12). This allowed video and force data to be synchronised and hence force profile features could be attributed to actions seen on the video. *Time from gun to first movement* could be readily distinguished by the time from the trigger to when the force profiles start to deviate from the baseline levels. In addition, when the back foot leaves the block during a track start (see Figure 4-12), a step in the unload profile in both the y and z axes is produced. Hence *Block time* can be readily determined as the time between the start trigger and the time when the force profiles settle at an unloaded value. Note: the difference between the z axis baseline levels prior to the trigger and after the athlete has left the block equals the weight of the athlete.

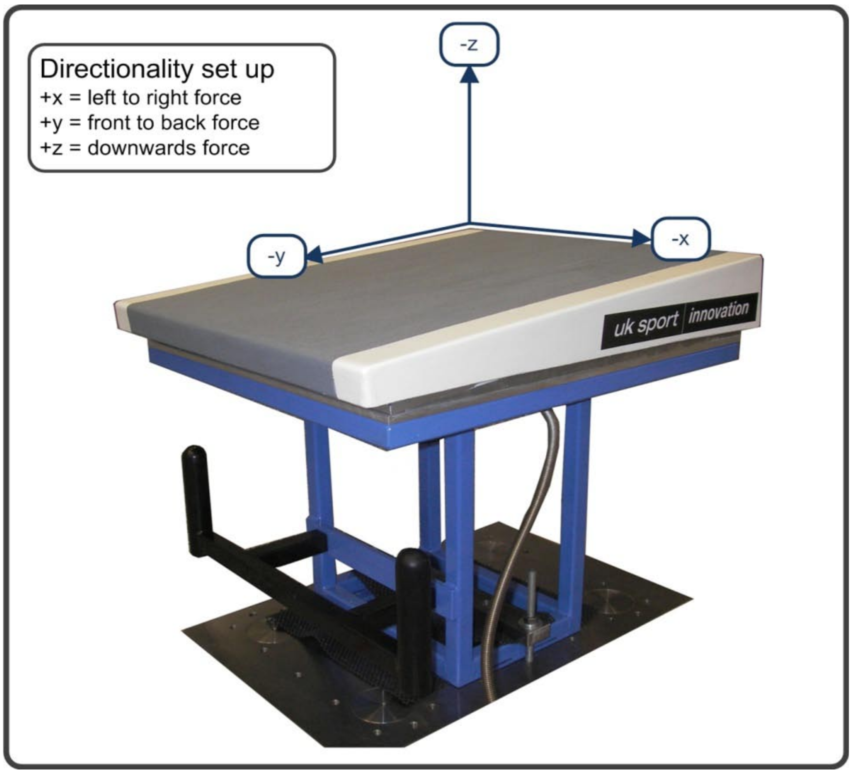


Figure 4-13: Orientation of axes on instrumented start block

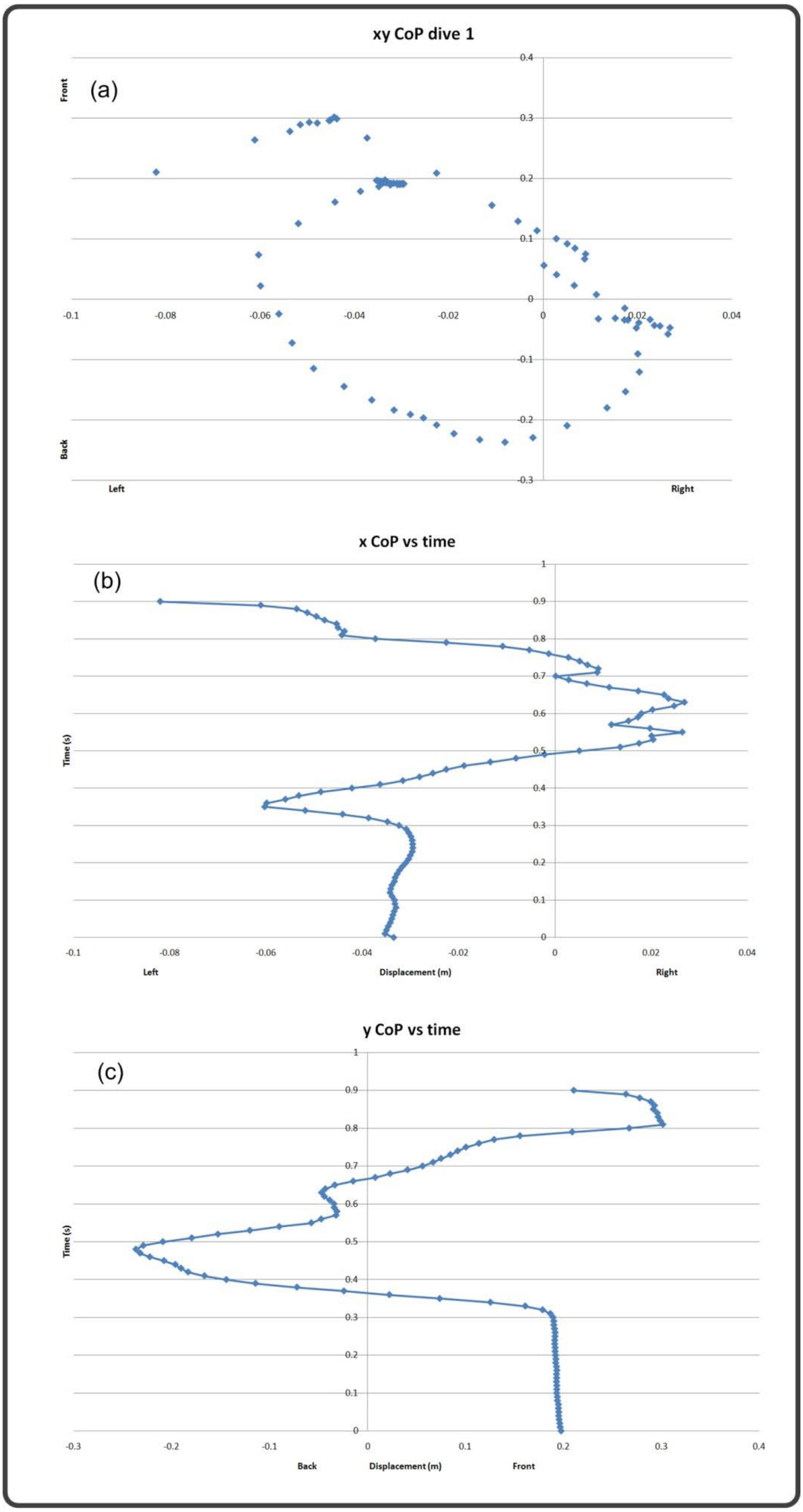


Figure 4-14: Centre of Pressure (CoP) data for a track start

In addition to multi-axis force data, the time variation in the *centre of pressure* (CoP) on the block can obtained from the force plate (see Chapter 3: Development of Component Technologies, Section 3.3). The CoP enables the movement of the centre of force during the time on the blocks to be visualised. Sideways movement is described by the x CoP, while forward movement is indicated by the y CoP. Typical traces are given in Figures 4.13 Figure 4-14(a), (b) and (c). For this dive the centre of pressure moved from slightly (~3cm) towards the left of centre, through to slightly to the right (~ 3cm) after 0.5 s and returning towards the left of centre (~8cm) as the swimmer leaves the block after 0.9 s. This profile is expected where a swimmer is performing a track start with their left leg as their front foot, i.e. they will be expected to show a left dominant force on leaving the block as their right leg is no longer in contact with the block. It is important to note that although the swimmer appears to be shifting their force on the block, the values of displacement are in centimetres suggesting a relatively central force production overall. The y CoP was seen to move from slightly in front of centre (~20cm) in the ready position, indicating a front weighted track start. Note: this identification of technique was confirmed in the video. The force then shifted (~25cm max) towards the back of the block (between 0.36 and 0.66s) as the swimmer pushed back and down onto their back leg. The CoP then returned to forward of centre (~30cm) as the swimmer's centre of mass travels forward and leaves the block after 0.9s. Note: The displacement of y CoP in this axis was much greater than the x CoP, i.e. +/- 20-25cm. This was expected as the swimmer shifted weight from a front weighted start position to then driving off the back and then front leg. Only by integrating the video data with the force profile data was it possible to understand in detail the movement in the y axis in terms of the shifting of weight throughout the start.

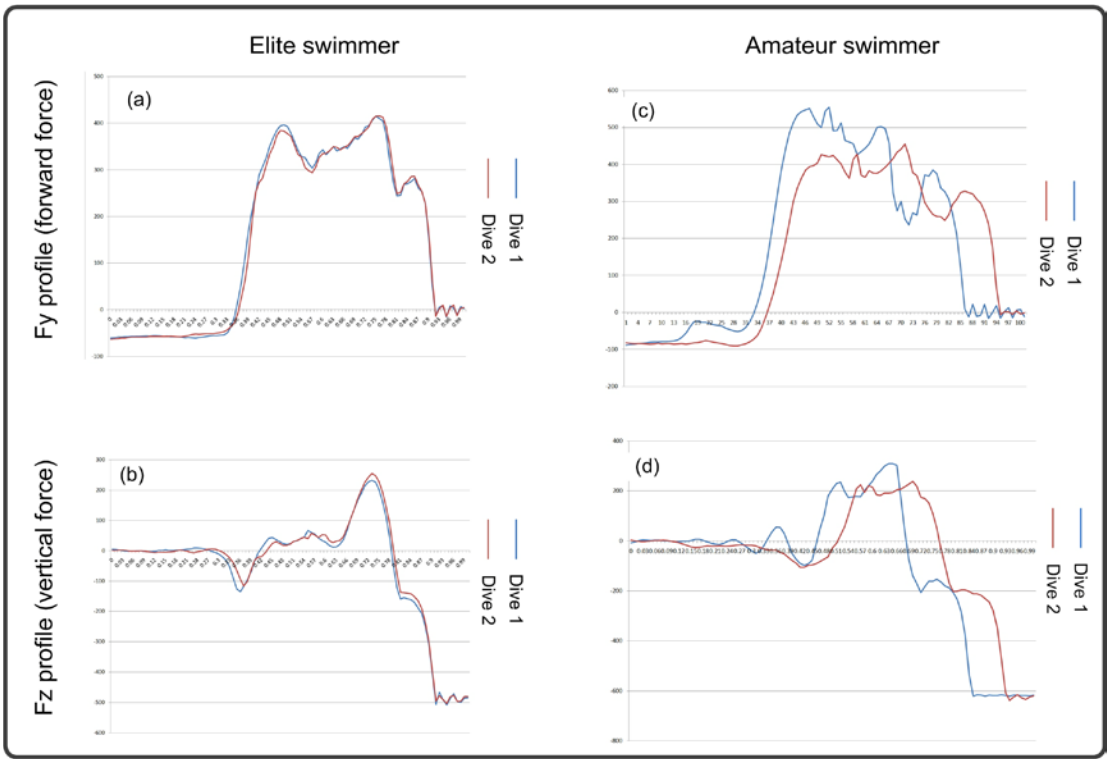


Figure 4-15: Force profiles from two different athletes

Force data have been collected for a number of different starting strategies for a number of different athletes of different capabilities such that variability's in technique and ability could be observed. An example of these data for an elite and an amateur swimmer are given in Figure 4-15(a)-(d). Both swimmers performed their preferred track starts from the block. Data are shown for two consecutive dives for the elite swimmer performed and three consecutive dives for the amateur. They were both instructed to dive maximally for each of their starts. The elite swimmer generated two highly consistent dives which were demonstrated in the "identical" nature of the timing and amplitude of the force profiles in both y and z directions. For these two dives the magnitude for the y and z axes were 1N and 23N, respectively, with a timing difference of 0.01s and 0.00s. The amateur swimmer however produced two force profiles displaying highly variable timing and amplitude outputs in both y and z directions, relative to the elite swimmer. For these two dives the magnitude for the y and z axes were 99N and 71N, respectively, with a timing difference of 0.19s and 0.06s. Even though the timing and magnitude for the values of the three dives were noticeably different, some shape consistency can be seen in Figure 4-15(c) and (d). The observed profiles can easily identify one swimmer as performing with a consistent technique whereas the other was presenting very inconsistent outcomes, attributed to their ability and experience.

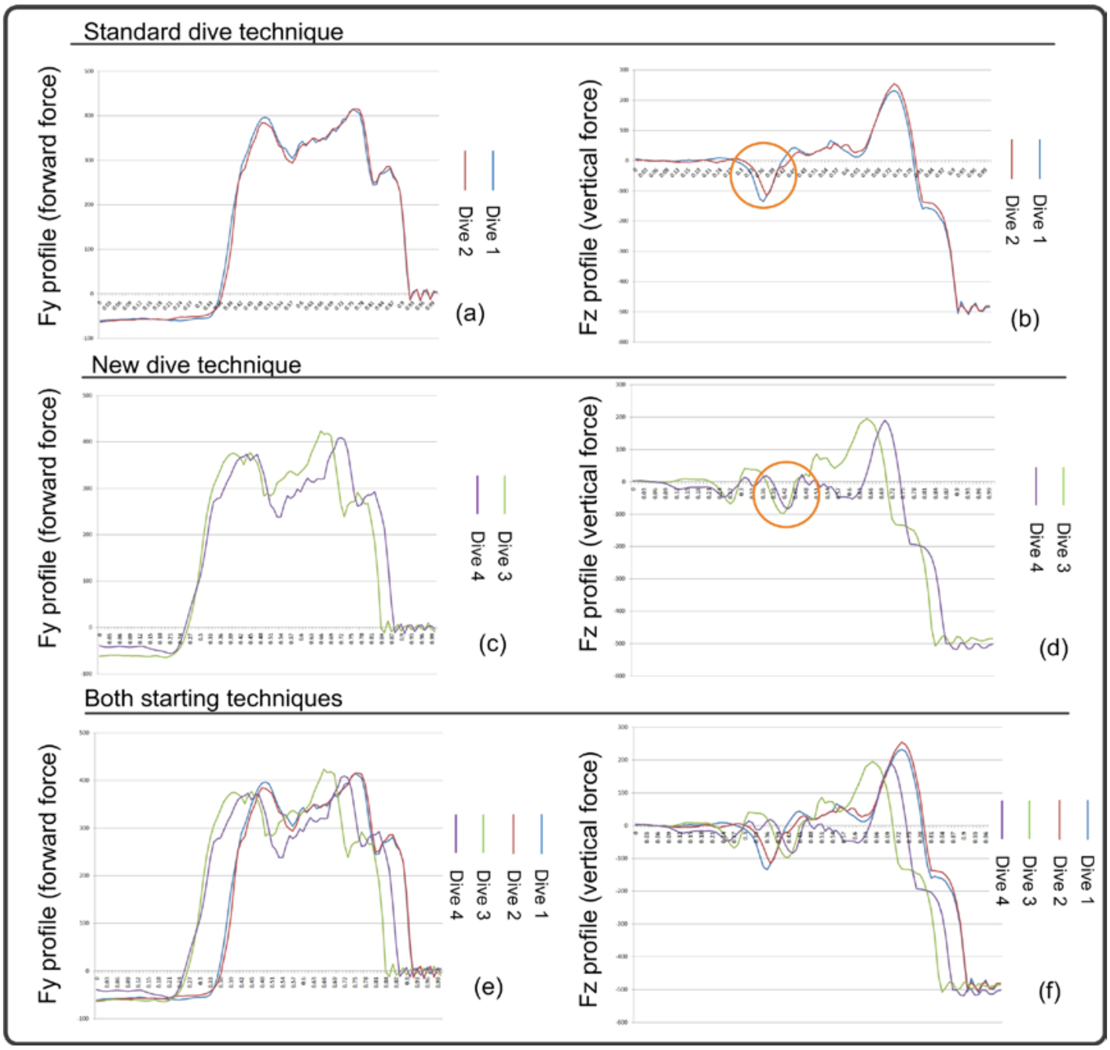


Figure 4-16: Force profiles from a single athlete performing two different techniques

The ability of an elite swimmer to improve their technique and learn new skills is evident from the force profiles in Figure 4-16. The swimmer performed four track starts, the first two using their *standard* technique and the second with an *alternative* technique. Instead of gripping the front of the block with their thumbs resting on the top surface (i.e. *normal*) they were directed to bring the thumbs forward, such that the thumbs were not opposing the fingers and applying force onto the top of the block (i.e. *adjusted*).

Results from the *adjusted* trials (Figure 4-16 (c) and (d)) produced force profiles which were slightly less consistent than the *normal* trials (Figure 4-16 (a) and (b)). This variability in timing and amplitude was attributed to the inexperience of the swimmer using the new technique i.e. developing a new skill. Nevertheless, both dives, normal and adjusted share similarities in shape which is not unexpected considering the minor change in technique that was adopted. However it is interesting that the timing and magnitude profiles are different as evidenced by overlaying the four dives in Figure 4-16 (e) and (f). It was apparent that the new technique started to generate forward force earlier than the previous technique (Δ t= 0.1s). However, the negative peak in the z axis, circled in Figure 4-16, probably due to the pull up of the arms, occurred later (Δt ~ 0.06s) using the new technique. The impulse from the swimmers first two dives, i.e. using their normal technique, equated in both cases to 444N. Using the alternate technique impulse was reduced to 403N and 411N respectively. Given the limited trial data it cannot be concluded whether this 10% reduction in impulse is significant for overall performance. Nevertheless the time between the arms pulling up on the block and the swimmer leaving the block was reduced (Δt ~ 0.05s) using the new technique.

Detailed understanding of the benefits of the *adjusted* starting technique could not be completely understood given this limited testing exercise. Nevertheless, the ability of force data to highlight differences in techniques and performance differences between different swimmers has been demonstrated. This in itself is useful in understanding the progression of athlete performance over time and in quickly quantifying how changing technique can affect overall dive characteristics.

4.3.1 Calculating parameters from force data

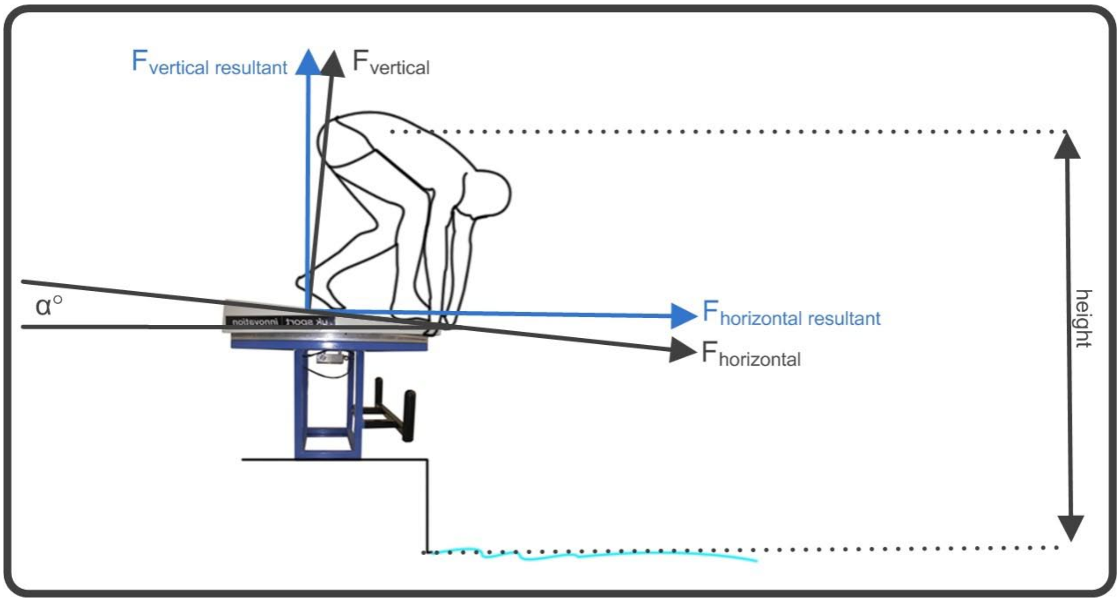


Figure 4-17: Resultant forces off the blocks

The initial phases of the start up until entry into the water are totally dependent on the forces generated on the block. Once the athlete has left the block with an initial velocity it should be possible to determine time to entry and distances from Newton's Laws of motion. In order to determine the vertical and horizontal forces with respect to the Earth's surface (i.e. with gravity in the vertical plane) the forces (and / or velocities) measured from the start block data have to be corrected for the 5 degree angle of the block (i.e. angle α in Figure 4-17). Additionally the height of the swimmers centre of mass has to be estimated and the height relative to the waterline for use when predicting the *Time to entry* parameter.

4.3.1.1 Predicting velocity using the impulse-time relationship

$F = force$

$m = mass$

$a = acceleration$

$F_z = force_{vertical}$

$F_x = force_{horizontal}$

$$F = ma$$

$$F(t) = ma(t)$$

$$a(t) = \frac{F(t)}{m}$$

$$v = \int a(t)dt = \int \frac{F(t)}{m}dt = \frac{1}{m}\int F(t)dt$$

$$v_{z0} = \frac{1}{m}\int F_z(t)dt$$

$$v_{x0} = \frac{1}{m}\int F_x(t)dt$$

Calculate impulse via trapezium rule:

$$\int_0^t Fdt = \left(\frac{a+b}{2}\right) * t$$

$a = value(x)$

$b = value(x+1)$

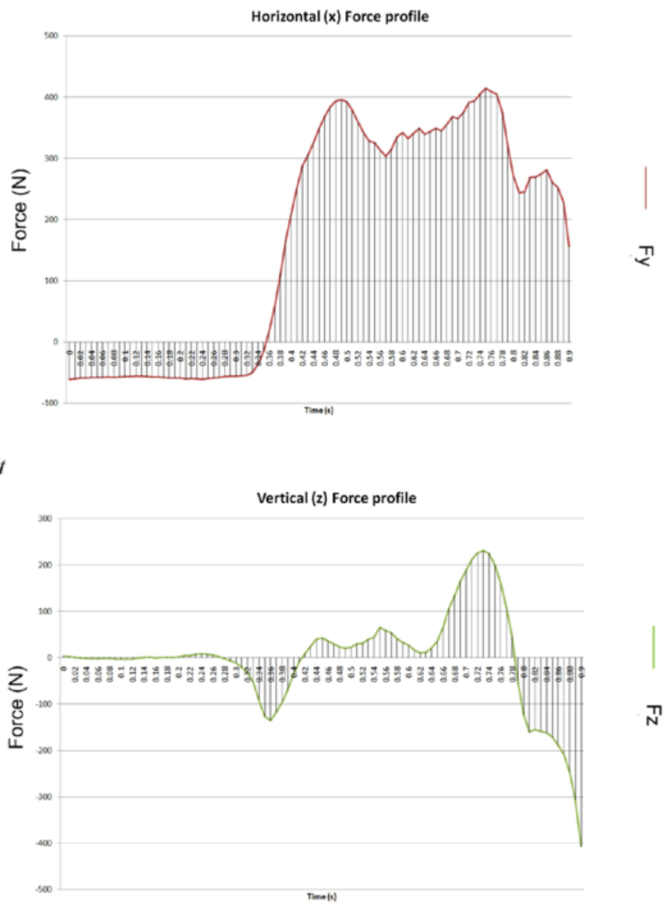


Figure 4-18: Predicting velocity off the blocks using force data

The horizontal (v_{y0}) and vertical components (v_{z0})of the velocity of the swimmer off the blocks can be predicted from the respective force-time (i.e. impulse) profiles as indicated in Figure 4-18. Essentially the velocities can be determined by calculating the area under the respective profile and dividing by the mass of the swimmer. The limits of the integration need to be chosen carefully since it is not immediately apparent from the profile which elements are contributing to the forward projection of the swimmer and which correspond to biomechanical movements that are part of the technique. In this case the force generated from the initial start signal (i.e. t=0s) up until the time the swimmer left the blocks (i.e. t=0.9s when it was unloaded), was used to determine the impulse (i.e. $\Sigma\ F_{z0|y0}\ t\ dt$) of the start. Impulse was calculated using the trapezium rule and determined for both horizontal and vertical force components. The weight of the swimmer was subtracted from the raw vertical force data prior to the velocity calculations. The resulting output was a prediction for the instantaneous vertical and horizontal velocities relative to the vertical and horizontal axes of the block.

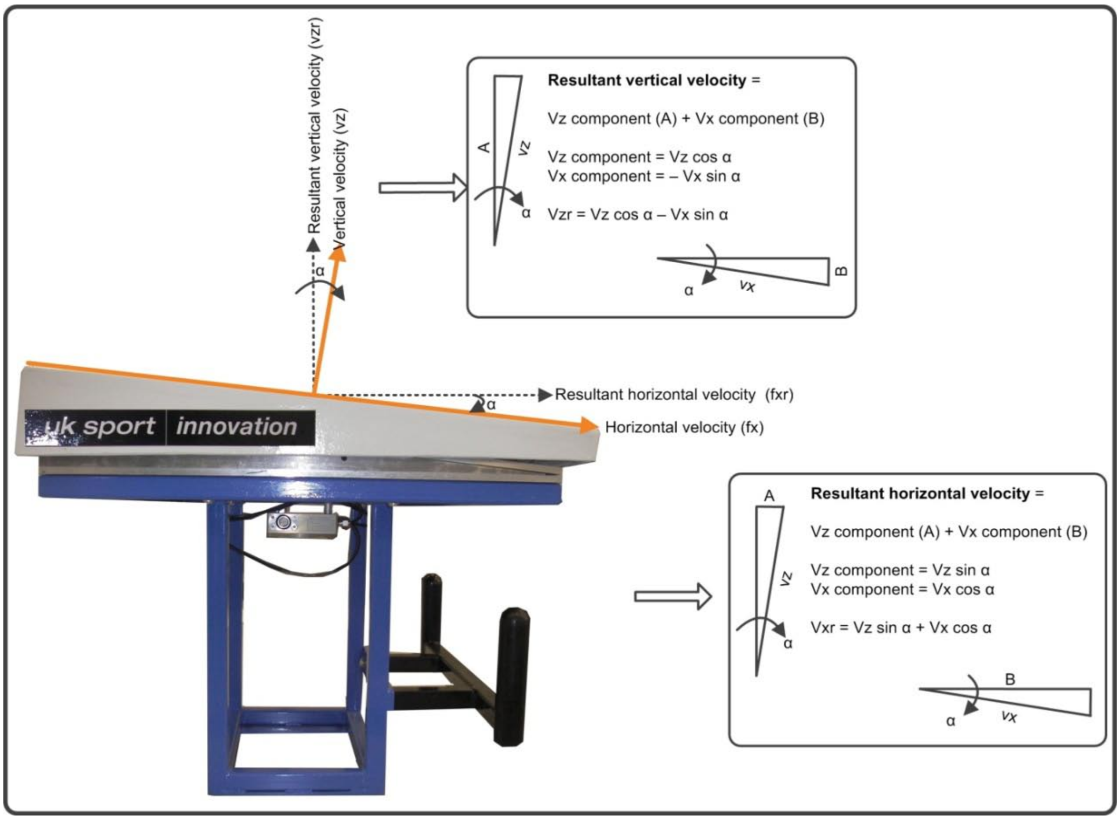


Figure 4-19: Calculating resultant velocities given block angle

Velocities relative to the force plate were resolved into components relative to the waterline as detailed in Figure 4-19 using the 5 degree angle of the plate. The resulting transformed velocities are made up from components of both the x and z velocities relative to the block (see Figure 4-19). This transformation allows comparisons to be made between velocities predicted from force data and velocities measured using other techniques, such as digitising video images since as the coordinate frames (and origins) are the same.

Equation 4.1: Predicting velocity, constant acceleration equations

$$v = velocity_{final}$$
$$u = velocity_{initial}$$
$$a = acceleration$$
$$t = time$$

$$v = u + at$$

$$horizontal$$
$$v_x = velocity_x$$
$$v_{x0} = velocity_{at\_xo\_position}$$
$$x = displacement_x$$
$$x_o = displacement_{at\_x0\_position}$$

$$v_x = v_{x0} \Rightarrow x = x_0 + v_{x0}t \Rightarrow x = v_{x0}t$$

$$vertical$$
$$v_y = velocity_y$$
$$v_{y0} = velocity_{at\_yo\_position}$$
$$y = displacement_y$$
$$y_o = displacement_{at\_y0\_position}$$
$$v_y = v_{y0} - gt \Rightarrow y = y_0 + u_{y0}t - \frac{1}{2}gt^2 \Rightarrow y = v_{y0}t - \frac{1}{2}gt^2$$

Knowledge of the components of velocity enables the calculation of flight time, flight distance and entry velocities using standard equations of motion (see Equation 4.1). Calculation of the flight time (and subsequently the distance to entry) of the swimmer requires the height of the centre of gravity of the swimmer relative to the waterline to be known as they stood on the blocks. Rearranging Equation 4.1for the vertical component resulted in a quadratic solution for the time to entry (see Equation 4.2).

4.3.1.2 Predicting flight time and distance

Equation 4.2: Solving quadratic equation for time

$$y = -h = v_{z0}t - \frac{9.81}{2}t^2$$

$$0 = 4.9t^2 - v_{z0}t - 0.7$$

$$t = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} = \frac{v_{z0} \pm \sqrt{v_{z0}{}^2 - (4 \cdot 4.9 \cdot -h)}}{9.81}$$

$$t = \frac{v_{z0} \pm \sqrt{v_{z0}{}^2 + 19.6h}}{9.81}$$

$$x = v_{xr}t$$

Solutions to Equation 4.1 provide a prediction of flight time (Equation 4.2). The flight time multiplied by the predicted horizontal velocity at take off is used to generate an estimate of the flight distance. It is important to note that the predicted flight time and flight distance are relevant for the *centre of mass* of the swimmer (i.e. not the tips of the fingers) and therefore if results are to be compared with those derived from other techniques, for example manual digitising of video images, times and distances relevant for the centre of mass and not the swimmer's from hands and /or toes need to be derived.

4.4 Results from force data predictions

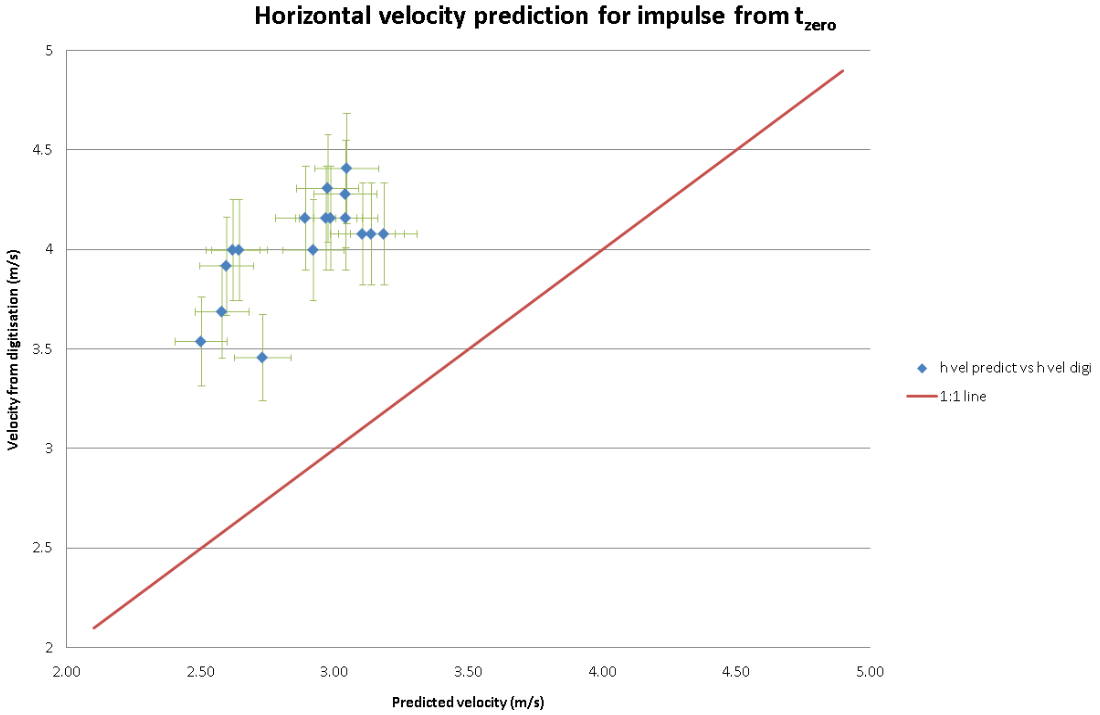


Figure 4-20: Comparison of the digitised horizontal velocity from video images with the force predicted horizontal velocity from the force plate data

Force data was used to predict the instantaneous *force predicted horizontal velocity* (FPHV)of the swimmer on leaving the starting block for 18 track starts (see Equation 4.1). The range of the integral used for these predictions was from *time zero*, i.e. the start of the capture (the point when the starting signal was activated), to the point where the block was completely unloaded (as indicated in Figure 4-18). Each of the starts was concurrently filmed and the video was digitised to give an equivalent measure of velocity off the blocks . Digitising the time sequences of images was chosen as the standard method for determining components of velocity as it is the currently accepted method used in the swimming domain. When digitising the video, a point on the axis of the line between the small of the back and stomach was tracked to provide a consistent feature in a relatively central position on the swimmer. This position was chosen to give a prediction of overall, gross body movement. Video was calibrated using measured dimensions within the field of view (for distances) and knowledge of the frame capture rate (e.g. 50 fps for time).

For the dives analysed the *FPHV* from the force plate data is lower than the *digitised horizontal velocity* (DHV) equivalent by on average 28%, (with a standard deviation of 4%) (see Figure 4-20). Nevertheless, a correlation between the digitised and force plate predicted velocities is evident (i.e. best fit line equation was, y=0.8153x+1.68, with an R^2 value of 0.49).

Error bars have been used on the graph to indicate the level of uncertainty inherent in both the digitising and force analysis techniques. To ascertain these values for the digitised data, the same dive was analysed five times and the average variability of the calculated velocity in both horizontal and vertical directions was recorded. This equated to 6.3% and 7.9% for horizontal and vertical velocities respectively. The error in the *FPHV's* were quantified by asking three experienced analysts to determine the point at which they would judge the block was unloaded. On average this equated to a 3.9% variability. This variability could be eliminated in future analysis by using fixed thresholds and recognised features within the force profiles rather than human judgement to decide where the impulse integration limits.

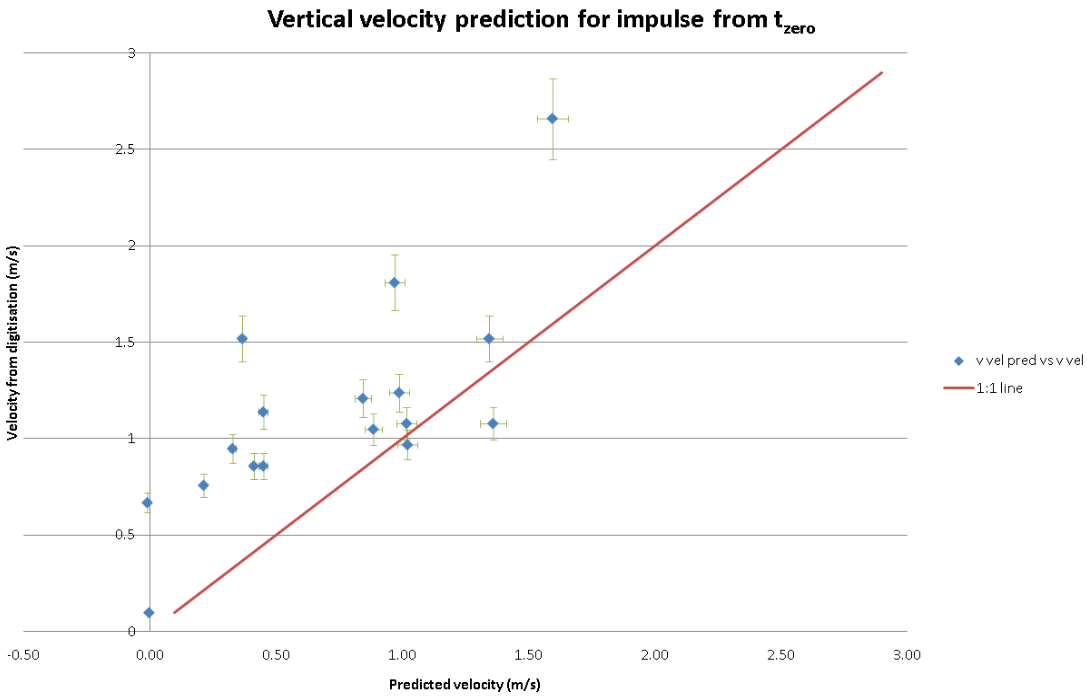


Figure 4-21: Prediction of vertical velocity off the blocks vs. digitised equivalent

A comparison of the digitised vertical velocity (DVV) and *force-predicted vertical velocity* (FPVV) components is given in Figure 4-21. Error bars (determined by the methods outlined above) have been included to indicate inherent uncertainty. As with the horizontal velocity predictions, the vertical velocities are lower than the digitised equivalents (i.e. by 42% on average). However it is important to note that the *variation* in these differences is high (i.e. standard deviation associated with these differences was 36%) which implies indicates a high variability in the vertical force profile measurements of the swimmers.

4.4.1.1 Predicting flight time and distance

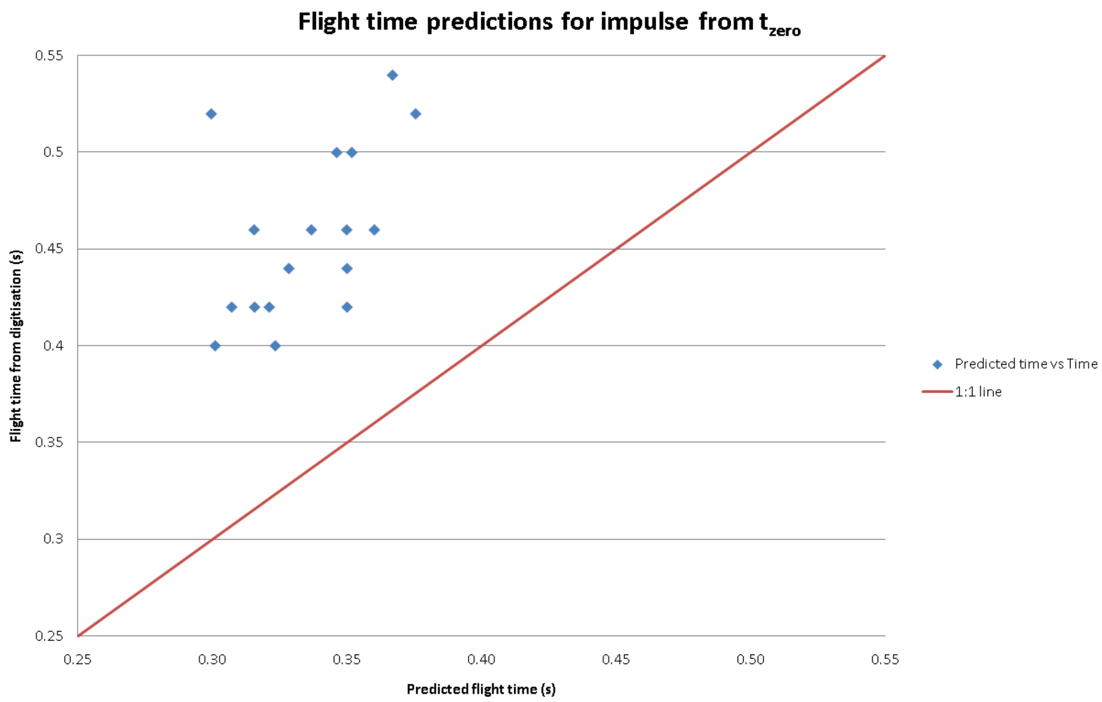


Figure 4-22: Prediction of flight time vs. digitised equivalent

The *flight time* of the swimmer depends on the point that is chosen to determine the entry into the water (i.e. fingertips, head, centre of mass). The *force predicted flight time* (FPFT) determined using the FPVV (see Equation 4.2) and an approximation of the height of the swimmers centre of mass on the start block is compared with the digitised flight time (DFT) in Figure 4-22. The DFT represents the time from the point at which the swimmers feet leave the blocks to the point at which their central marker point enters the water. The average difference between the FPFT and the DFT was 26% with a standard deviation of 6%.

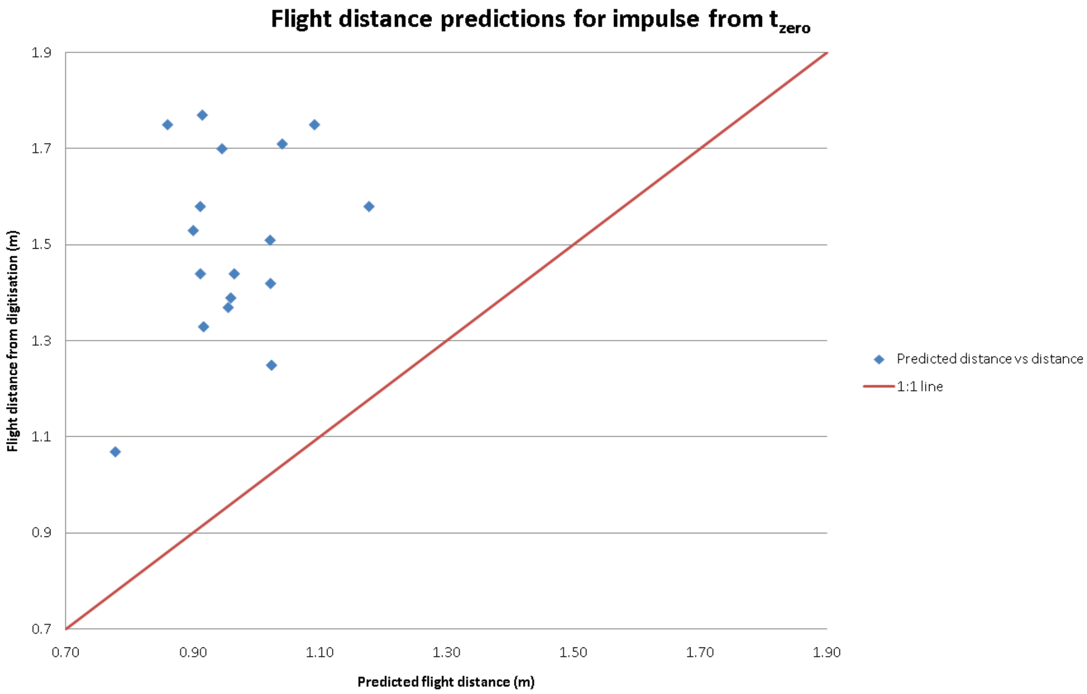


Figure 4-23: Prediction of flight distance vs. digitised equivalent

Force predicted flight distance (FPFD) is determined by multiplying the FPHV by the FPFT. The digitised flight distance (DFD) was determined from the distance the central marker on the swimmer's torso moved from the time the swimmer's foot left the blocks to the time that the same marker entered the water. Note: the differences in the FPHV component (Figure 4-20) and FPFT (Figure 4-22) will be mirrored in FPDE values, see Figure 4-23.

In the analysis above, the force predicted measures consistently underestimate the parameters when compared with the digitised values. The key factor determining the predicted values is the horizontal impulse of the start on the blocks. The time from the *start of the capture* to the *unloading of the block* may not be the most appropriate impulse time period to take (see Figure 4-18). For example a better estimate of the impulse contributing to the generation of horizontal velocity may be derived by integrating between the *time to first movement* up to *unloading of the block* hence removing the negative contributions (i.e. forces in the opposite directions to motion) to the impulse (see Figure 4-18). Time to first movement can be readily selected on a typical force profile at the start of the trace (see Figure 4-12). The negative value at the start of the trace indicates that the swimmer was in a front weighted starting position. This negative value when multiplied by the reaction time (i.e. time to first movement) reduces the total impulse of the start which in turn would lower the predicted horizontal velocity from the blocks hence reducing the differences between the predicted values with those of the digitised video data.

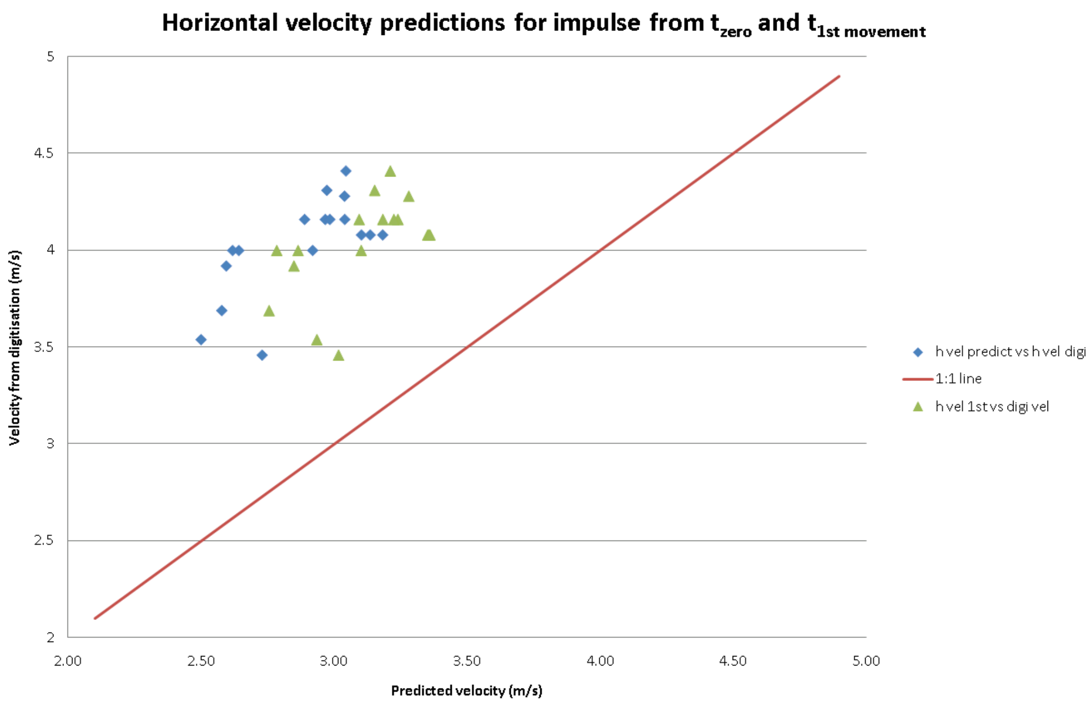


Figure 4-24: Horizontal velocity predictions for impulses taken from time zero and time 1st movement

Digitised horizontal velocities (DHV's) and force-predicted horizontal velocities (FPHV's) from the block derived by using the start time (t_{zero}) and the time to first movement ($t_{1st\ movement}$) as the lower limits of the integration. The upper limit of integration in both cases is taken as the point of the block unloading (see Figure 4-24). As expected, using $t_{1st\ movement}$ shifts the predicted velocities towards the 1:1 ratio line. Consequently the average difference is reduced from 28% to 23% with a standard deviation of 4% to be compared with 4.8% calculated for using the impulse from time zero.

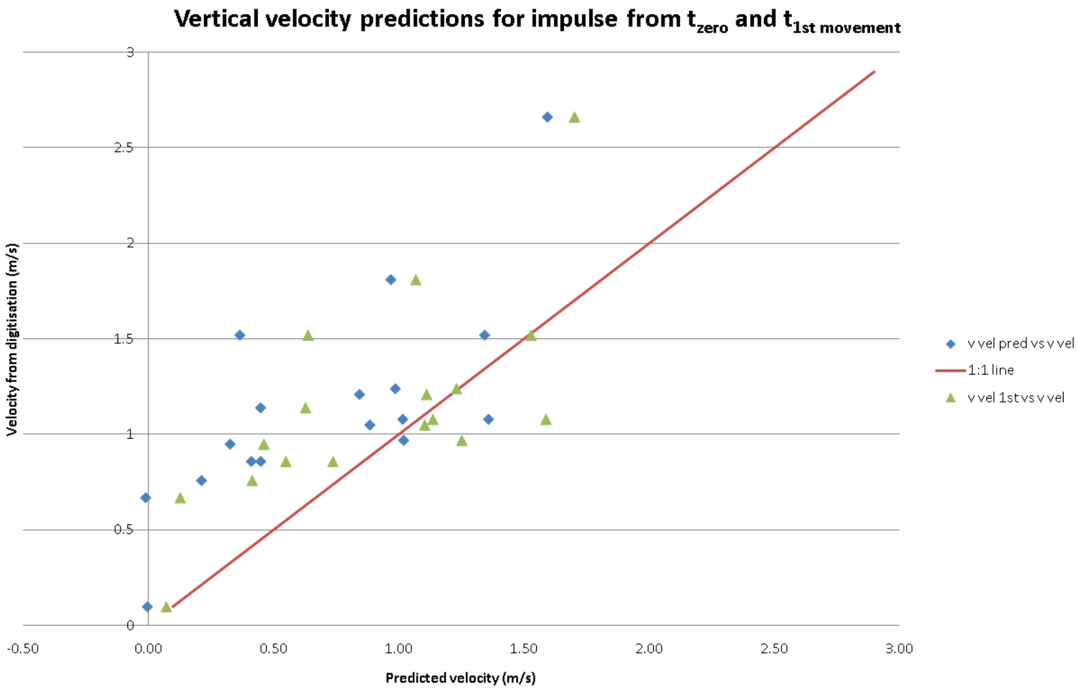


Figure 4-25: Vertical velocity predictions for impulses taken from time zero and time 1st movement

Vertical velocities were also predicted using the impulse determined from $t_{1st\ movement}$, see Figure 4-25. As with the horizontal velocity predictions this shifted the results towards the 1:1 line. The average difference between digitised and force-predicted vertical velocity was reduced from 42% to 21%, however, there was still a very high standard deviation associated to these differences, (i.e. 36% c.f. 33%).

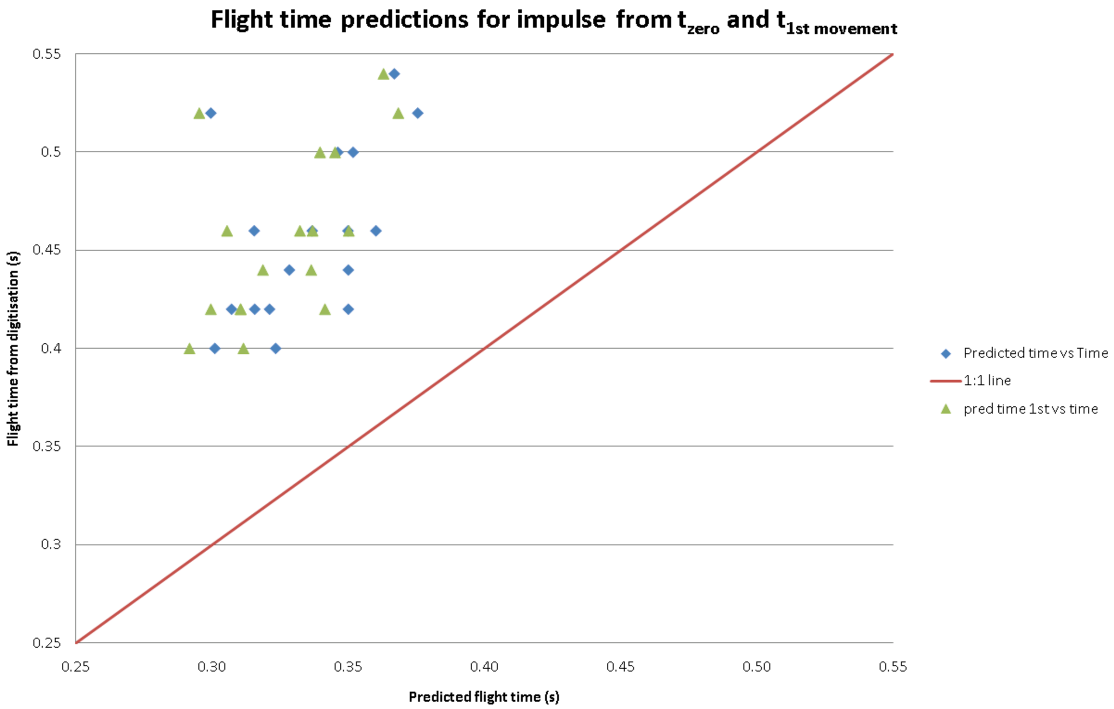


Figure 4-26: Flight time predictions for impulses taken from time zero and time 1st movement

Predicted flight time using the $t_{1st\ movement}$ impulse produces similar results to using impulse from t_{zero} (Figure 4-26). The error seen however, was increased slightly from 26% to 28%, with very similar standard deviations, i.e. 6% and 5.5% respectively.

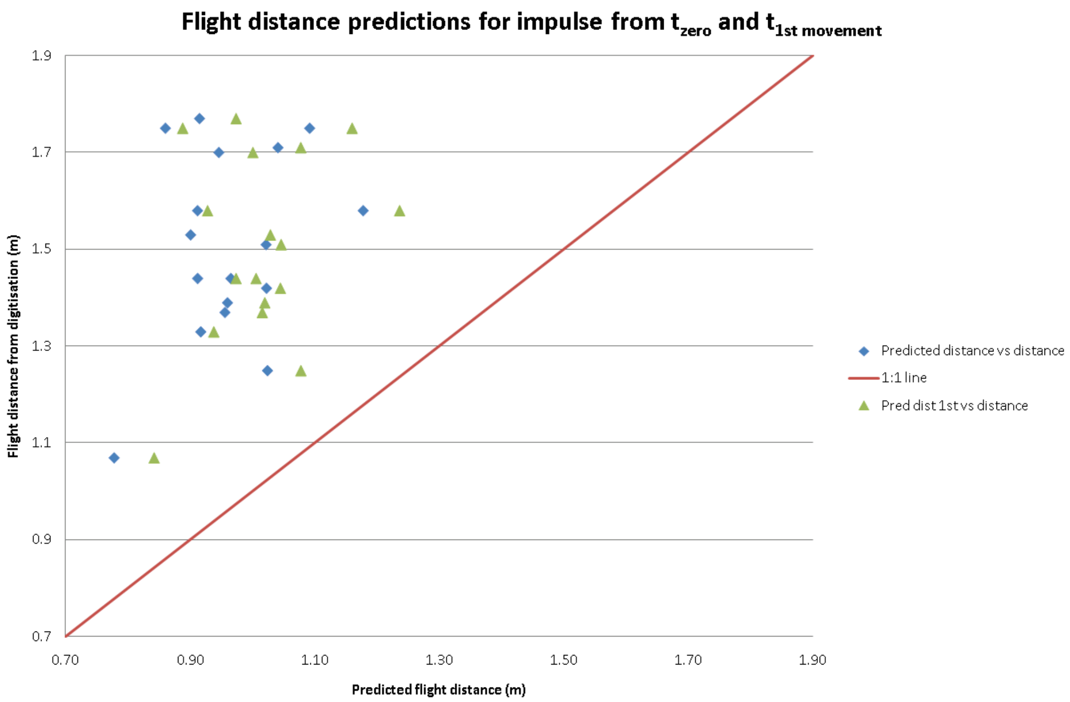


Figure 4-27: Flight distance predictions for impulses taken from time zero and time 1st movement

Force-predicted flight distance using $t_{1st\ movement}$ resulted in similar variability to predictions from t_{zero}, mainly due to the dependence of this parameter on the FPHV, Figure 4-27. On average the difference was 31%, (previously 35%), with similar standard deviations in both cases, i.e. 8.6% and 9.1%. It is noted that neither of the force predicted measures are able to provide a method of predicting the horizontal velocity off the blocks and flight time that enable an accurate determination of the flight distance of the centre of mass. However key points to note are that: (i) predictions focussed on the centre of mass may not be as easily understood, interpreted and accepted by swimming coaches and sports scientists since current "standards" deal with absolute measures of distance i.e. distance from the wall to fingertip or head entry and (ii) accurate / absolute determination of parameters is not required if the aim is to provide information on changes in performance both within and between athletes' performance profiles. Scaling can always be applied if comparisons with digitised video determined parameters are required.

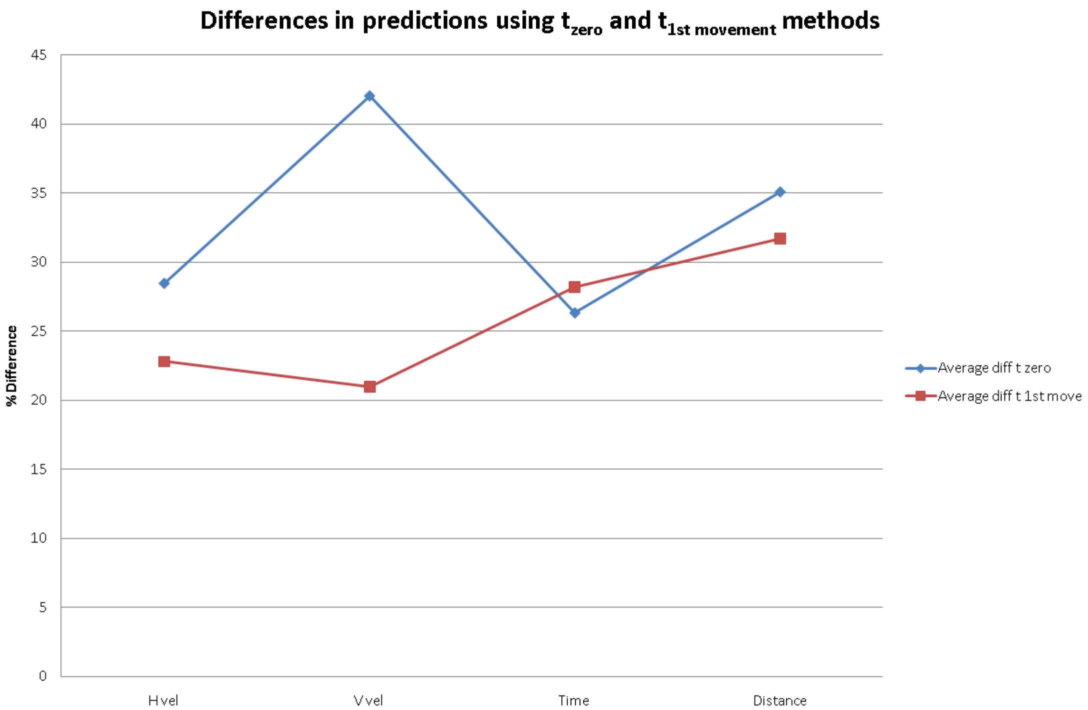


Figure 4-28: Comparison of proximity to hand measurement for methods using impulse from time zero and time 1st movement

A summary of the average differences between the two *force-predicted* and the *digitised* parameters are compared in Figure 4-28 (i.e. for horizontal velocity, vertical velocity, flight time and flight distance). It is concluded that predictions using $t_{1st\ movement}$ results in force-predicted parameters closer to the digitised values than those using t_{zero} for all parameters with the exception of flight time. Although these data suggest $t_{1st\ movement}$ is the more accurate method, the relatively small number of samples mean that future work should be focussed on gathering a larger quantity of data to confirm these trends. Similarly it may be advantageous to use more complex digitising techniques to predict the centre of gravity of the swimmer [Dempster, 1955], rather than tracking a single point approximated to the centre of mass of the swimmer. Note: the centre of gravity, which, may be outside the body at points due to the relative position of the legs, torso and arms at certain points within the dive.

4.5 Results from force plate starts analysis

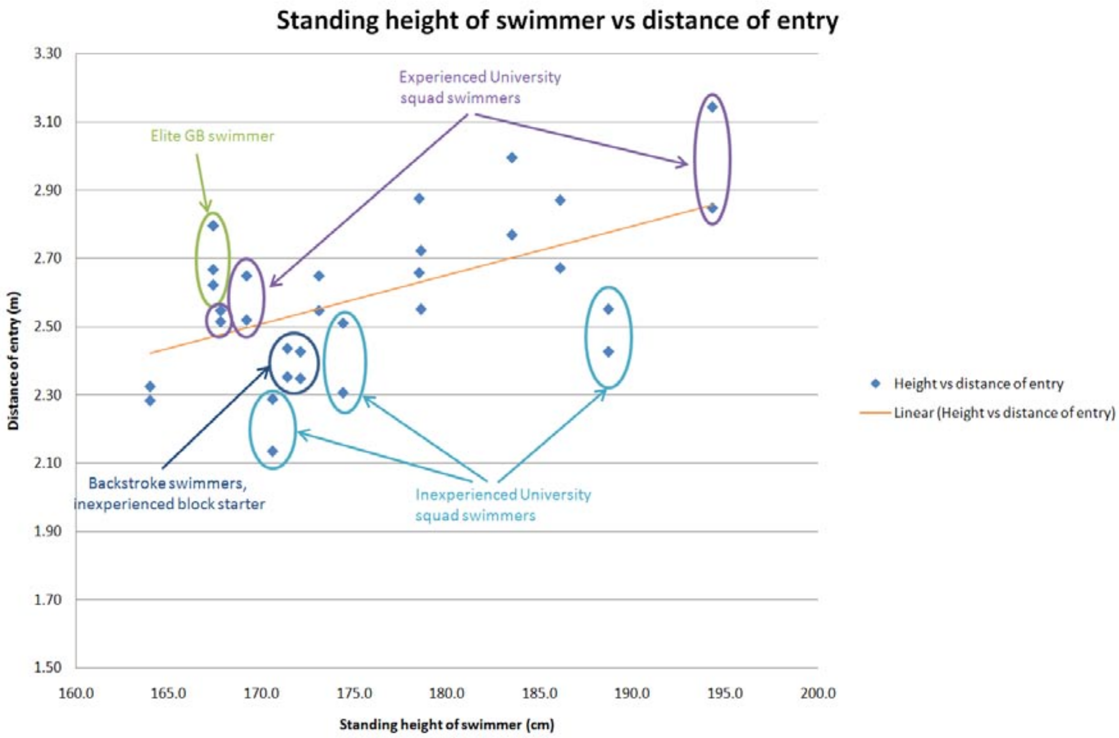


Figure 4-29: Standing height of swimmer vs. distance of entry

Synchronised force and video data have been analysed for 18 swimmers each performing at least two starts. Video data was used to obtain the distance of fingertip entry from the wall. The standing height of the swimmer was also recorded. The distance of entry is compared with the standing height of the swimmer in Figure 4-29 to illustrate the relationship between height and distance of entry (i.e. taller swimmers would naturally enter the water further from the starting blocks). Swimmers tested included one elite swimmer and University squad swimmers with a range of experience at block starting.

The general trend within the data illustrates the obvious fact that taller swimmers dive further. However it is also apparent that more experienced swimmers produced dive distances above than the best-fit line (see Figure 4-29) (i.e. dived greater distances for their heights). Inexperienced swimmers, including backstrokers, underperform when diving from block starts. A more appropriate performance indicator than the current distance of entry could be the ratio between distance of entry and height (i.e. a normalised distance of entry), rather than the absolute distance.

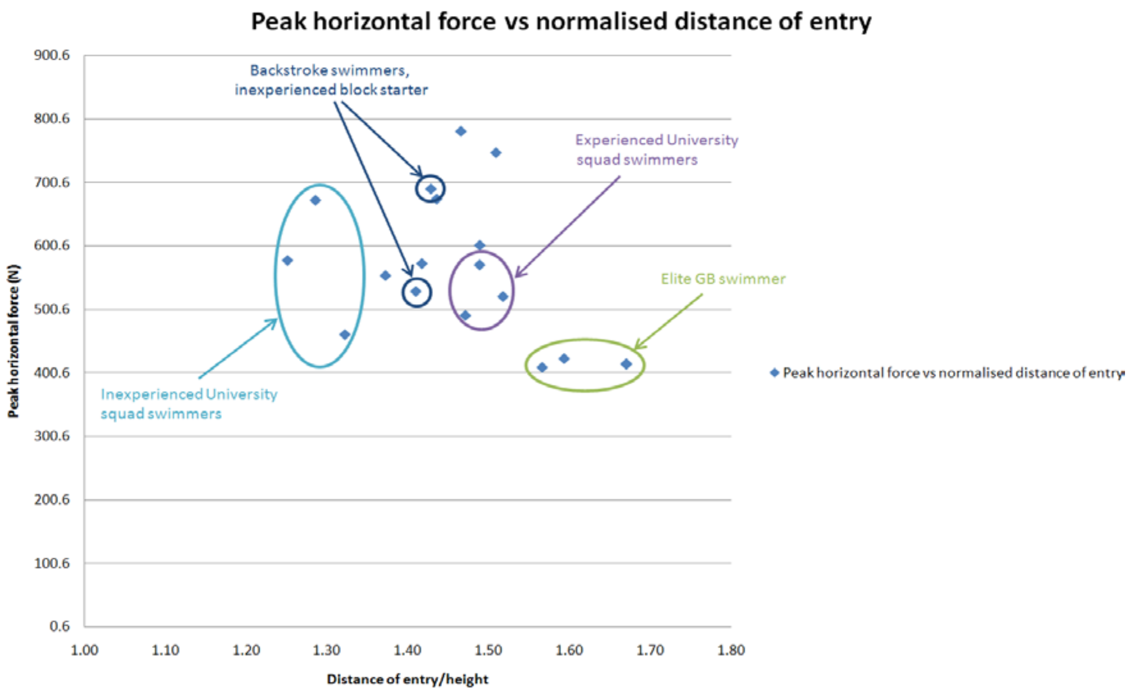


Figure 4-30: Peak horizontal force vs. normalised distance of entry

Peak horizontal forces are plotted against distance of entry to height ratio for 18 track starts performed by 8 different swimmers in Figure 4-30. The results highlight two key factors. Firstly experienced swimmers produce a higher distance of entry to height ratio than less experienced swimmers. Secondly it is noted that the more experienced swimmers generate further normalised distances at lower peak horizontal forces than less experienced swimmers indicating increased efficiency in generating distance of the blocks.

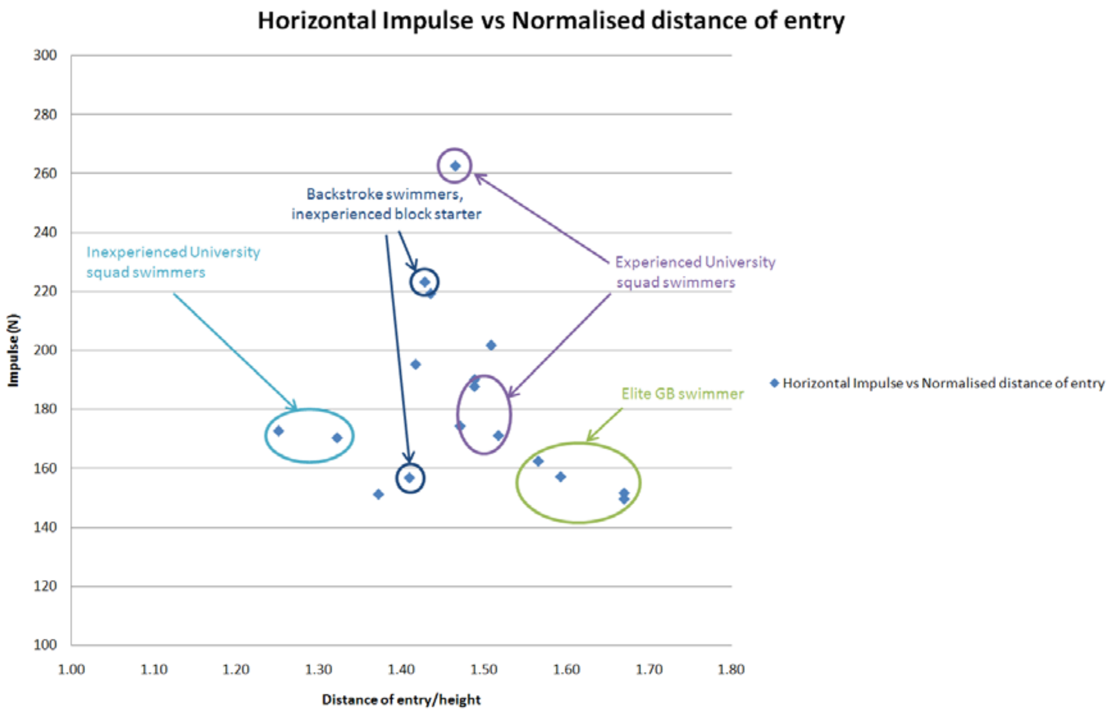


Figure 4-31: Horizontal impulse from time zero vs. normalised distance of entry

Horizontal impulse provides a measure of the time integrated variation in horizontal force. The horizontal impulse (integrated from time zero until the block was unloaded) is plotted against the distance of entry to height ratio for the previous dives in Figure 4-31. From the data presented it is possible to conclude whether a higher impulse is preferable for dive performance. Seven out of the eight dives identified as elite or experienced produced relatively low to mid range impulses. The elite GB swimmer exhibited the furthest normalised distance performance (~1.60m) for low horizontal impulse indicating an efficiency in generating forward motion off the starting blocks. The data indicate that it is not necessary a requirement to have a high impulse for a good dive but instead that better swimmers are able to travel further than inexperienced swimmers using less or equal impulses on the blocks.

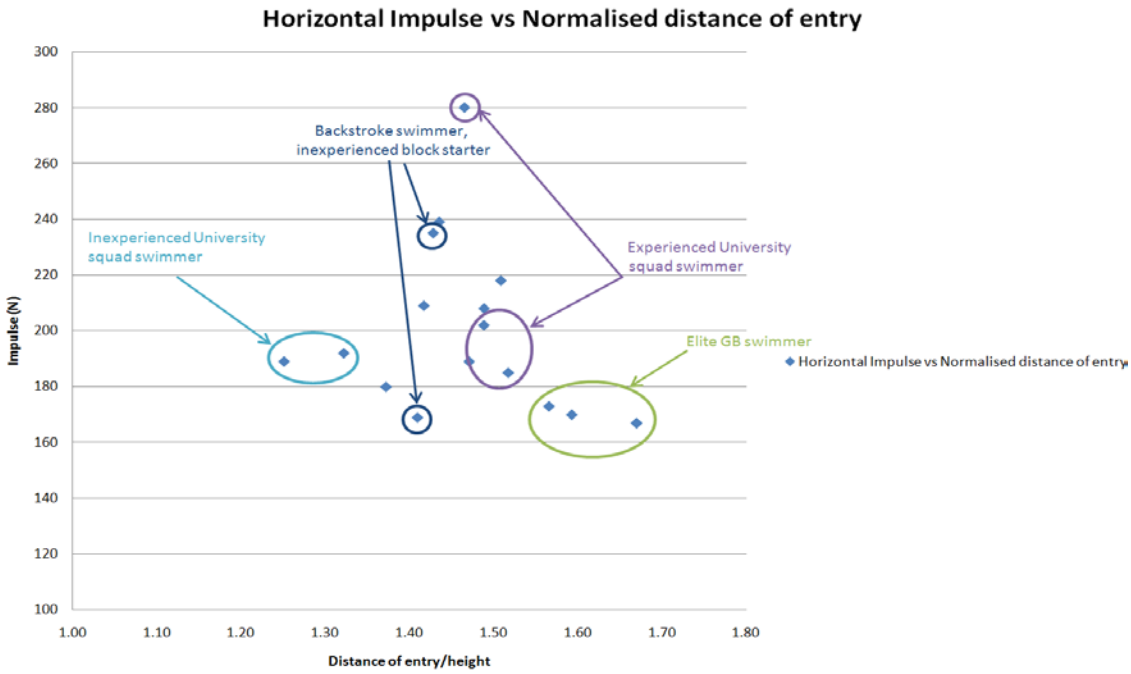


Figure 4-32: Horizontal impulse from time 1st movement vs. normalised distance of entry

The same comparison between horizontal impulse and distance of entry to height ratio was made using the impulse calculated from first movement, rather than from time zero, see Figure 4-32. As expected the results produced higher impulses for each of the athletes by on average 16N.

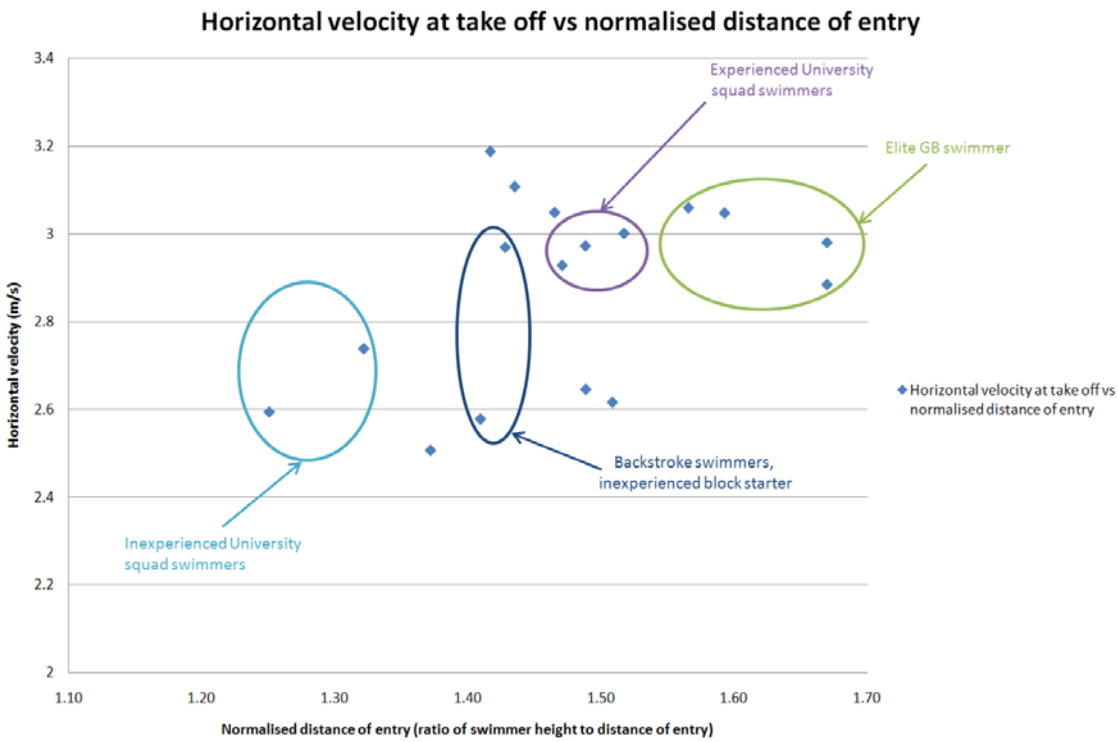


Figure 4-33: Horizontal velocity at take off, predicted from time zero vs. normalised distance of entry

Horizontal velocity predicted from force data is compared to the normalised distance of entry in Figure 4-33. The elite or experienced swimmers generated higher velocities off the block than those identified as inexperienced swimmers. This supports the hypothesis that high instantaneous horizontal velocities at take off result in a greater distance of entry [Breed and Young 2003, Welcher et al 2008, Mason et al 2007]. However since one of the inexperienced block starters had a predicted horizontal velocity comparable with those of the experienced swimmers, even though horizontal velocity may be a good indicator of performance, when used in isolation it may not always accurately identify good from bad technique.

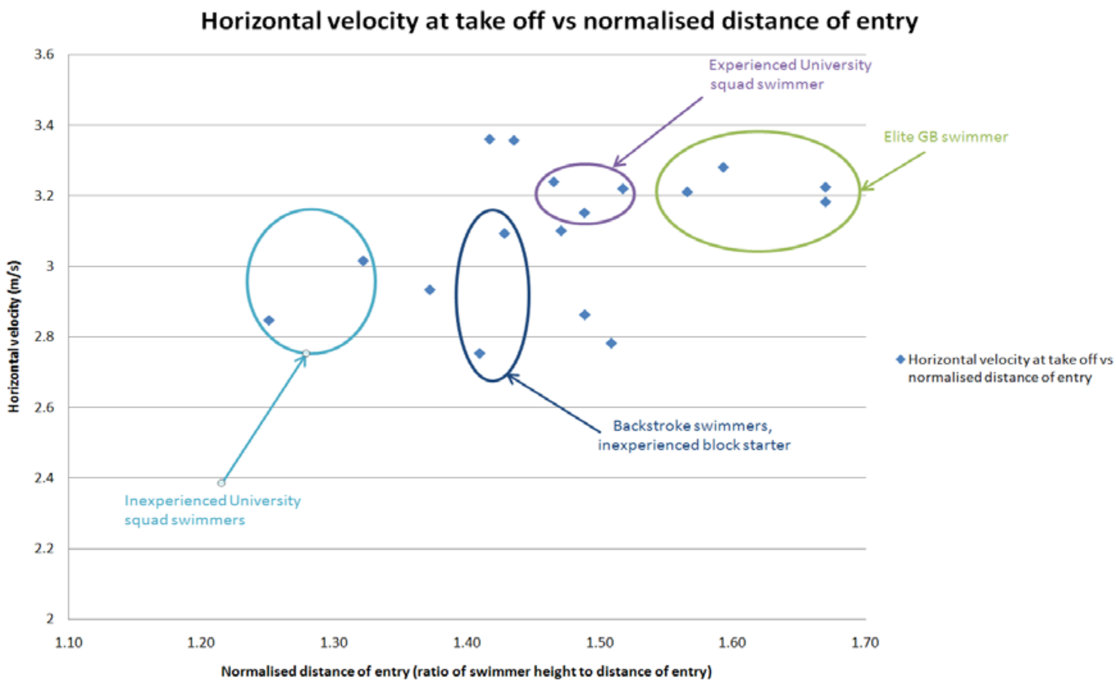


Figure 4-34: Horizontal velocity at take off, predicted from time 1st movement vs. normalised distance of entry

Predicting horizontal velocity from $t_{1st\ movement}$ increased the predicted velocity, on average by 0.22m/s. This did not affect greatly the gross trends in the data seen in Figure 4-34, i.e. the differences between the experienced and non-experienced swimmers remained relatively unchanged (i.e. 7.4% for two dives performed by the elite GB swimmer and 9.95% for two dives performed by an inexperienced squad swimmer)

Two derived parameters appear to support the discrimination of performance of a swimmers dive. Firstly the distance of entry has to be normalised by the swimmers standing height. In all cases the experienced swimmers were able to travel further per metre of height than less experienced swimmers. In addition horizontal velocity was found to be a better indicator of dive performance than either horizontal impulse or peak horizontal force. It is important to note that additional data, beyond the raw force data were required to carry out the analysis, i.e. standing height of the swimmer, height of the swimmers centre of gravity on the block and the distance of entry. The height of the swimmers centre of gravity on the block and distance of entry could be obtained via automated vision techniques where a marker could be placed on the central part of the body.

4.6 Starting parameters derivable from acceleration data

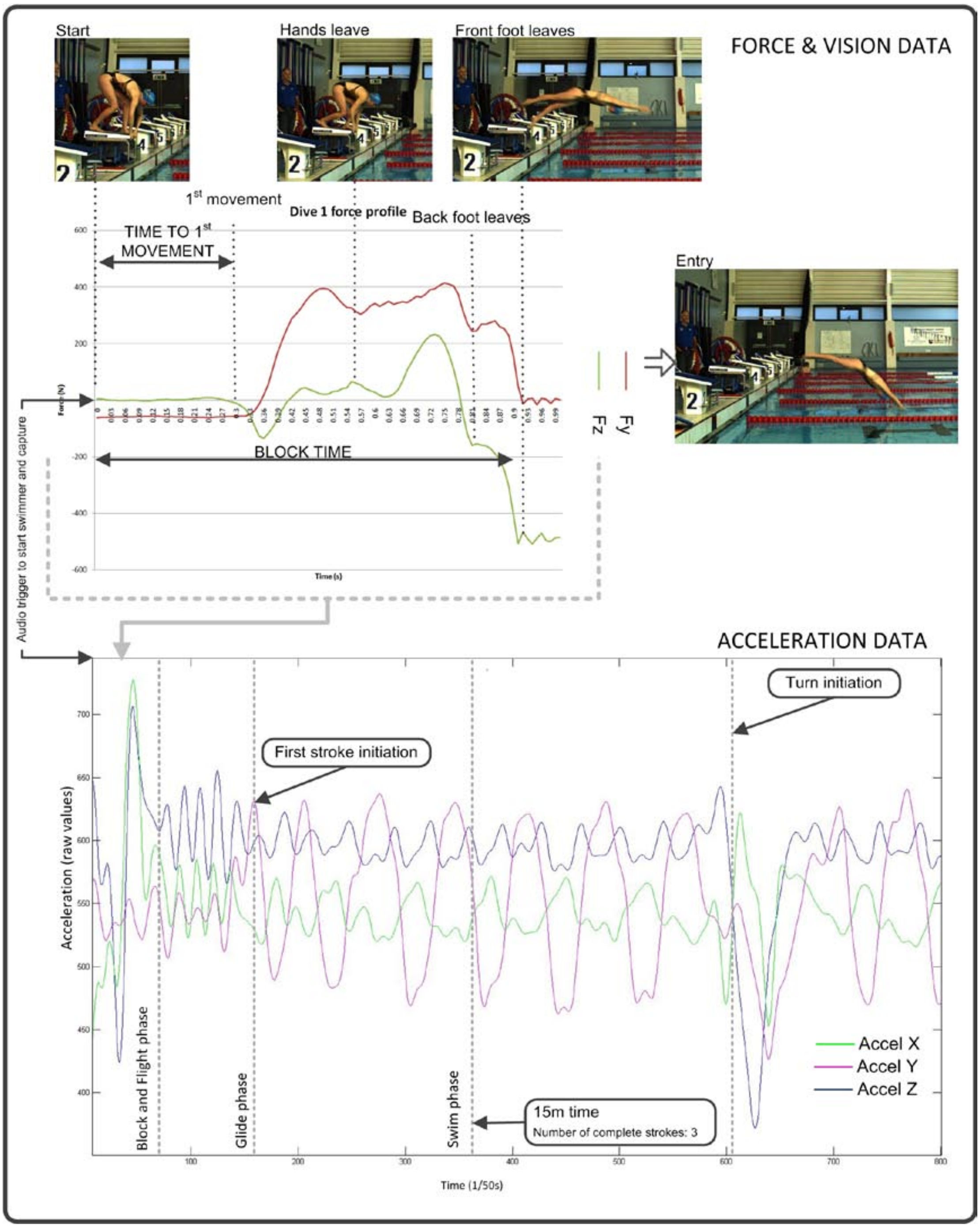


Figure 4-35: Synchronised start data from vision, force plate and accelerometer component technologies

Pilot testing was undertaken in which complete integrated data sets were collected, comprising synchronised vision, force and acceleration data. Example data sets are presented in Figure 4-35. The addition of the acceleration component facilitates the automatic measurement of additional parameters including *time to first stroke* from the start, *stroke count* and *time to turn*. The synchronised video was used to support the identification of features evident in the acceleration data. Acceleration signatures within the block, flight and glide phases were not established within these initial pilot tests, however, future work should look to ascertain these profiles. For example during the glide phase, the acceleration signature evident in Figure 4-35 may represent movements associated with dolphin kicks occurring prior to first arm pull.

The combination of all measurement components enables more complete analysis of swimming performance to be undertaken. Force data is particularly effective at providing insight into the block phase and initial flight parameters of the swimmer. However, in isolation, parameters derived from force data would only supply limited information regarding the overall starting performance. Acceleration data is useful in establishing parameters such as stroke initiation, stroke count and lap timing. However, further high speed integrated video analysis is required to enable the acceleration profiles during the block and flight phases to be completely understood. The potential to use automated vision analysis techniques have been evaluated. Initial, small scale trials, using the developed LED marker system was capable of providing information for the over water phase of the dive. Additional trials must be undertaken to prove the robustness of this system. Raw video footage is integral to in supporting the validation for other technologies, enabling data to be understood and interpreted properly.

4.7 Summary

Three component technologies have been developed and their ability to add value to starts analysis evaluated in this Chapter. The capability of each component has been tested and proven for a number of applications.

Table 4-2: Start measurement parameter requirements

	Simple	Compound
Starts	• **Time from gun to first movement** • **Block time** • **Angle of entry** • **Time to entry** • **Distance of entry** • Maximum depth • Break out distance • Break out time • **First stroke timing**	• **Velocity off blocks** • Velocity of glide • Velocity at break out

Parameters that have been quantified and proven as indicators of diving performance within this chapter are highlighted in bold in Table 4-2. Automated vision techniques and / or integrated pressure transducers could enable the maximum depth and velocity of glide to be measured. It is also possible future work could focus on the integration of the accelerometer data within appropriate limits to derive the outstanding velocity information during the glide phase.

4.7.1 RQ1 Automated Vision

Vision based methods have been explored in this Chapter and their ability to provide performance analysis information about the swimming start assessed. Automated vision analysis techniques have been applied for the analysis of start performance. The use of a controlled garment has been proven capable of robust analysis however, stakeholders were not comfortable with wearing additional garments for testing. The development of wearable LED markers provide an alternate solution that in initial trials show promising results, suggesting they may also be capable of providing a robust image processing solution, this however, must be proven using a greater number of trials. Spatial thresholding techniques were found to be more capable of robust segmentation, over temporal techniques. In addition the use of markers allows more specific landmarks (e.g. wrist, elbow, shoulder, torso, hip, knee, ankle) to be tracked for biomechanical analysis. To maximise the signal to noise ratio, red LED markers are employed which create a unique, consistent distinguishable feature that does not suffer from vision analysis issues associated with varying lighting conditions. The use of wearable LED markers was preferred to track specific landmarks and facilitate the analysis of specified performance parameters, as stated within the stakeholder requirements. These included: angle of entry, distance of entry and time of entry. The ability to track landmarks, although not presented within these examples, would also enable automated measurement of velocity off the blocks.

There were a number of advantages identified as a result of introducing automation into vision analysis techniques. These included a significant reduction in the time associated with analysis enabling timely feedback, i.e. within the session, rather than post session. Vision analysis code, even in the development environment, i.e. Matlab, took less than a second to process. Typically, manual analysis will take a time equivalent to at least twice that of the event to perform analysis, e.g. if a swimmer takes 8 seconds from the gun to 15m, it will take at least 16 seconds to measure parameters such as angle of entry, usually longer. In addition the use of algorithms meant that performance could be quantified in a repeatable manner, i.e. removal of the variability associated with human judgement. In turn this removed the reliance on operator expertise, which would previously have impacted on the "quality" of measurements.

4.7.2 RQ2 Force Plate

Force plate analysis of the start has been undertaken using an instrumented starting block with synchronised vision. It has been found that consistency in force profiles could indicate athlete performance without the need to supplement data with vision. The instrumented diving platform is able to provide automatically information regarding time to first movement from the gun and block time parameters as specified within stakeholder requirements.

Force data collected was also used to predict the flight parameters of the start. These include horizontal and vertical components of velocity, flight time and flight distance. Initial results suggest that force is capable of predicting the velocity of the centre of the mass. Flight time can be predicted using the height of the swimmers centre of mass on the start block combined with vertical velocity components. Refinement was achieved by adjusting the time window during which the impulse integrated. This adjustment translates the force predicted results towards expected velocities determined from digitised video data.

Finally derived measured parameters were plotted against distance of entry to highlight differences between experienced and inexperienced starters. Discrimination of swimmer ability and performance there is evident by plotting parameters against a normalised distance of entry parameter i.e. (distance of entry / standing height). More competent swimmers are able to travel further per metre of height than less accomplished swimmers using smaller horizontal forces an impulses. In addition, horizontal velocity was found to be a better indicator of dive performance than either horizontal impulse or peak horizontal force, given this trial. Further work should be undertaken with larger numbers of athletes to investigate these relationships and conclude whether they hold in most cases.

4.7.3 RQ3 Wireless Node

A wireless node was used to provide acceleration data regarding starting performance. Features found in data provide information regarding timing of the first stroke from the start trigger. It is believed that acceleration features in the block, flight and glide phases can enable automatic measurements of parameters such as underwater kicking, block and flight times. Although it has been proven that block and flight times can be derived from force data, the ability to distinguish these characteristics from acceleration data would mean that information could be gathered in the absence of an appropriate instrumented block.

Chapter 5

5. CASE STUDY – FREE SWIMMING

5.1 Chapter Overview

The measurement requirements for free swimming are listed in Table 5-1. Distance per stroke and stroke rate (highlighted in bold) are the parameters that are currently monitored and these only determined for race analysis. because the parameters have to be obtained manually they are not monitored routinely during training. The research detailed in this chapter is focussed on providing measurement of the parameters listed in Table 5-1 in a reliable, timely an efficient manner using wireless acceleration data integrated with vision and hand timing components.

Table 5-1: Free swimming measurement parameter requirements

	Simple	Compound
Free swimming	• Stroke count • **Distance per stroke** • Stroke duration • Rotation during the stroke: longitudinal and vertical • Variations in stroke cycles • Split times	• **Stroke rate** • Swimming velocity • Variations in velocity throughout a stroke cycle • Indicators of skill

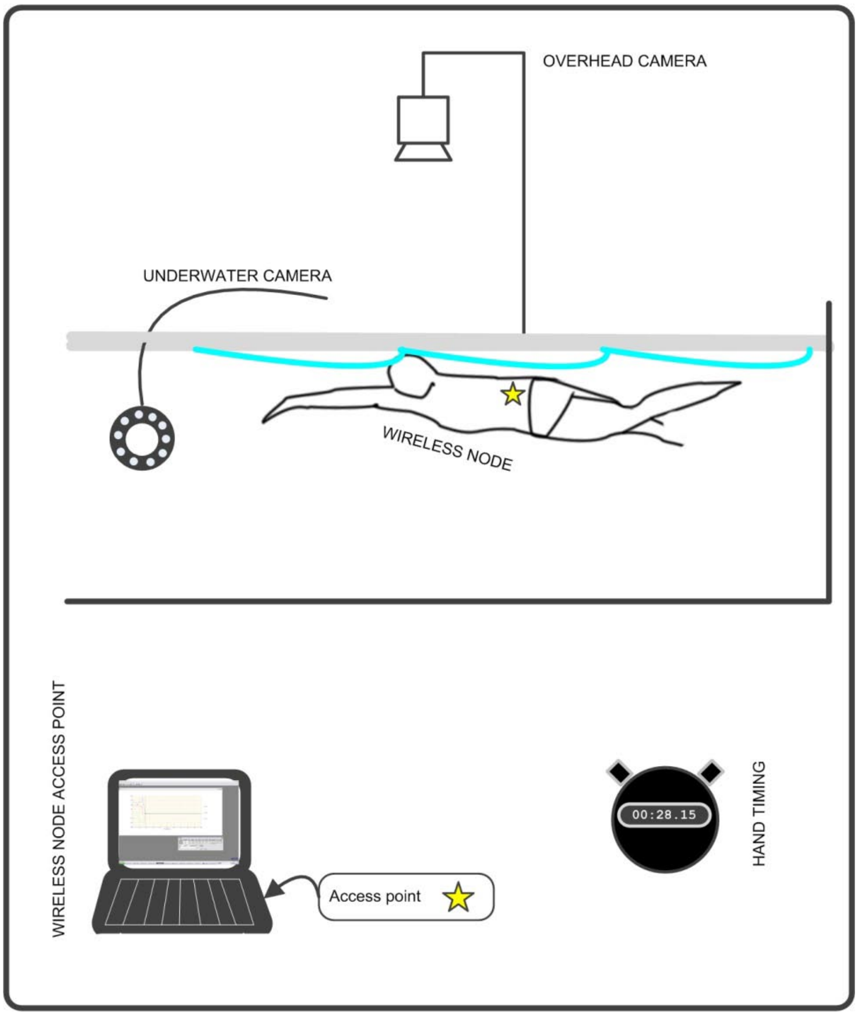


Figure 5-1: Component set up for free swim testing

5.1.1 Research Questions (RQs)

RQ1 Automated Vision

a. Are there any vision based methods that can provide a robust and acceptable solution for free swimming performance analysis?

b. What techniques are available to maximise the signal to noise ratio for both over and underwater environments to allow robust automated vision analysis?

RQ2 Wireless Node

a. What free swim specific parameters are evident in accelerometer data?

b. What are the most appropriate methods for the development of automated signal analysis?

5.1.2 Chapter Structure

Vision methods for automated vision analysis of free swimming, specifically spatial thresholding of skin, coloured hats and markers were tested for both over and under water applications. Noise associated with underwater scene characteristics are discussed and methods for maximising the signal to noise are detailed. An example of tracking using active led markers is presented and information on parameters that can be derived from the markers reported.

Free swim parameters that can be derived from acceleration data are detailed in this chapter. In addition, time and frequency domain methods are evaluated and recommendations for most successful techniques for signal processing of acceleration data are made.

5.2 Vision methods for automated vision analysis of free swimming

The value of automated vision techniques has been demonstrated for swimming starts analysis in Chapter 4: Case Study - Starts. The research detailed in this section is focussed on determining how vision techniques can be utilised to characterise free swimming performance. of the parameters listed in Table 5-1, it was anticipated that stroke count, distance per stroke, stroke duration, variations in stroke cycles, stroke rate, swimming velocity, variations in velocity throughout a stroke cycle and time to 15m could be determined using automated vision analysis. However for complete coverage of the pool either a camera located on a track or a system integrating multiple cameras would be required. The practicalities of implementing complete coverage have hence limited the analysis to the determination of a vision based timing gate to determine the time a swimmer passes pre-defined distances i.e. time to 15m (see Table 1-1).

5.2.1 Overwater tracking using spatial thresholding: timing gate application

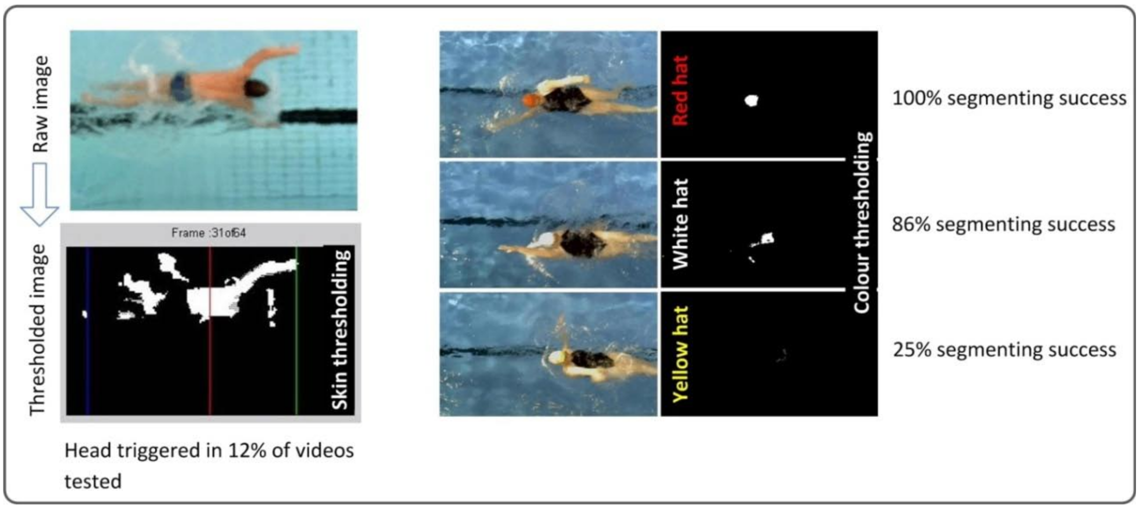


Figure 5-2: Example of skin and colour thresholding for a plan view camera of free swimming

The implementation of a timing gate using automated vision analysis is illustrated in Figure 5-1 (system schematic) and Figure 5-2 (example images and segmentation results). The swimmer's head was chosen as the fixed reference point for the timing recording. A standard web camera (Microsoft Lifecam VX-6000) was mounted above a lane and used to record the swimmer as they passed through the field of view (typically

+/- 2 m around the *timing gate*. determined by the height of the camera (2m) and its focal length). The main concerns were to differentiate the swimmer's head from the extremely noisy pool environment and ensure that the timing recoding was not pre-triggered by either noise or the swimmers arms. To improve the signal to noise ratio: (i) swimmers were asked to wear different coloured caps (i.e. red, white, yellow) and (ii) a number automated image processing thresholding algorithms were tested. The algorithms used either *skin thresholding* (see Chapter 4: Case Study – Starts, Section 4.2) as well as blue, red, white and yellow *colour thresholding*, see Figure 5-2. Each technique segmented the image within pre-defined threshold limits and tracked the resulting AOI within the field of view . when the AOI reached the centre of the frame, i.e. 15m in the pool, the time is recorded. Manual digitisation of the video was used to determine a benchmark or *expected time*, which the automated measure could be compared with.

Skin thresholding was tested on a total of 74 trials and was able to segment the swimmer from the background when the swimmer was on or near the surface of the water (i.e. 100% of images). When the swimmer was deeper the success of the segmentation was reduced . The limitation of the skin thresholding algorithm was the uncertainty with regards to what part of the swimmers anatomy or feature within the images triggered the timing recording. The swimmer's head was found to trigger the timing in only 12% of the videos. The swimmer's arms or shoulders were most likely to cause a trigger, 64% and 24% respectively. The other problem was that the small wake preceding the swimmer tended to trigger the system and not the swimmers anatomy. This introduces variability into the timing and although small (typical pre-triggering of the order of 0.12s), limits the accuracy of the algorithm. When the system was pre-triggered by the arm of the swimmer the difference between when the head would have triggered could be as much as six frames which for the 25fps camera used in the testing equated to an uncertainty of 0.24s.

Due to the uncertainties introduced using skin thresholding, testing was carried out in which the swimmer was asked to wear a swim hat of a given colour to enhance the swimmer's head in the images. In total 94 videos were analysed for red, white, blue and yellow hats. The different colour choices demonstrated a variability in their robustness, i.e. whether the hat could be effectively segmented in the video. The success of the thresholding algorithm depended significantly on the colour of hat:

- 38 red hat videos segment (100%)
- 24 white hat videos segment (86%)
- 20 blue hat videos segment (100%)
- 2 yellow hat videos segment (25%)

It is not surprising that the red hat was the most successful since there are no other red features evident within the image (see Figure 5-2). The success with the blue hat was more surprising although it is important to note that despite 100% of the blue hat images being segmenting successfully the AOI tracking algorithm was limited by presence of additional *blue noise* in the image (i.e. primarily caused by the line markings on the bottom of the pool and swimwear (see Figure 5-2). Timing based upon triggers from the red hat was by far the most accurate and repeatable since the head could be segmented 100% of the time and the uncertainty in the times when compared with manual digitisation were within one frame (0.04s). Note: Failure to segment the yellow and white hats as mainly the result of overlapping colour values (i.e. RGB values) with the light reflecting from the water's surface and the wake generated by the swimmer.

5.2.2 Underwater tracking using spatial thresholding

To observe the positions and velocities of the arms, legs and torso within free swimming it is necessary to view the swimmer from under the water. Currently this is achieved by using a waterproof closed circuit television (CCTV) camera which is lowered into the pool. The International pool at Loughborough University also has a facility to record the swimmer through a purpose built viewing window in the wall of the pool. This is less frequently used by the Performance Scientists as the location of the window is inconvenient for most training sessions which are carried out in the opposite end of the pool. The CCTV camera provides a more portable and configurable solution for underwater viewing. Analysis performed on the recorded videos is currently limited to subjective methods (supplemented with hand timing in the case of turns).

The ability to isolate the swimmer from the background given the underwater environment is vital for this automated vision analysis, see Figure 5-3. As with the out of water vision analysis a number of methods were tested to determine their viability for differentiating the swimmer from the background. These include: *skin thresholding*

(2), *colour thresholding (3.i)* of the swimmer and *colour thresholding (3.ii)* of the swimsuit, see Figure 5-3. It was found that thresholding techniques using RGB colour channels produced a large amount of noise around the swimmer's *form* within the segmented image. Maximising the signal to noise ratio was essential for a robust system.

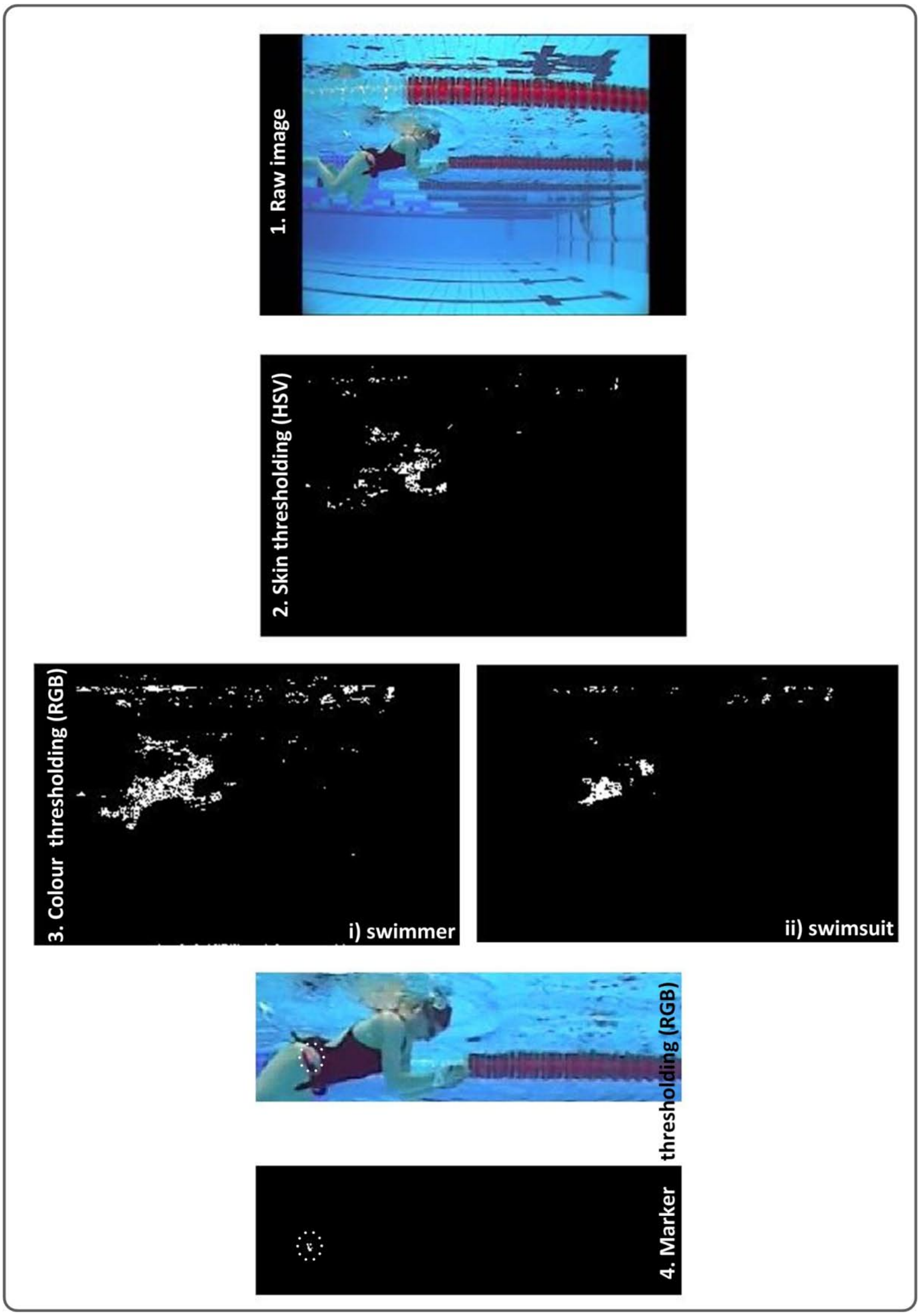


Figure 5-3: Examples of spatial thresholding under water

Overlapping body parts makes it difficult to determine the exact motion of the swimmer, which is essential when: (i) monitoring the velocity of a swimmer as a fixed position must be tracked through time or (ii) looking at technical skills like the turn (see Chapter 6: Case Study - Turns). Any lack of confidence in the exact location of the point being tracked will result in erroneous measurements of swimmer position and subsequently velocity, rotation or other parameters being derived from this position. For this reason the use of LED markers placed on key landmarks was tested in underwater applications, *(3.c)* see Figure 5-3.

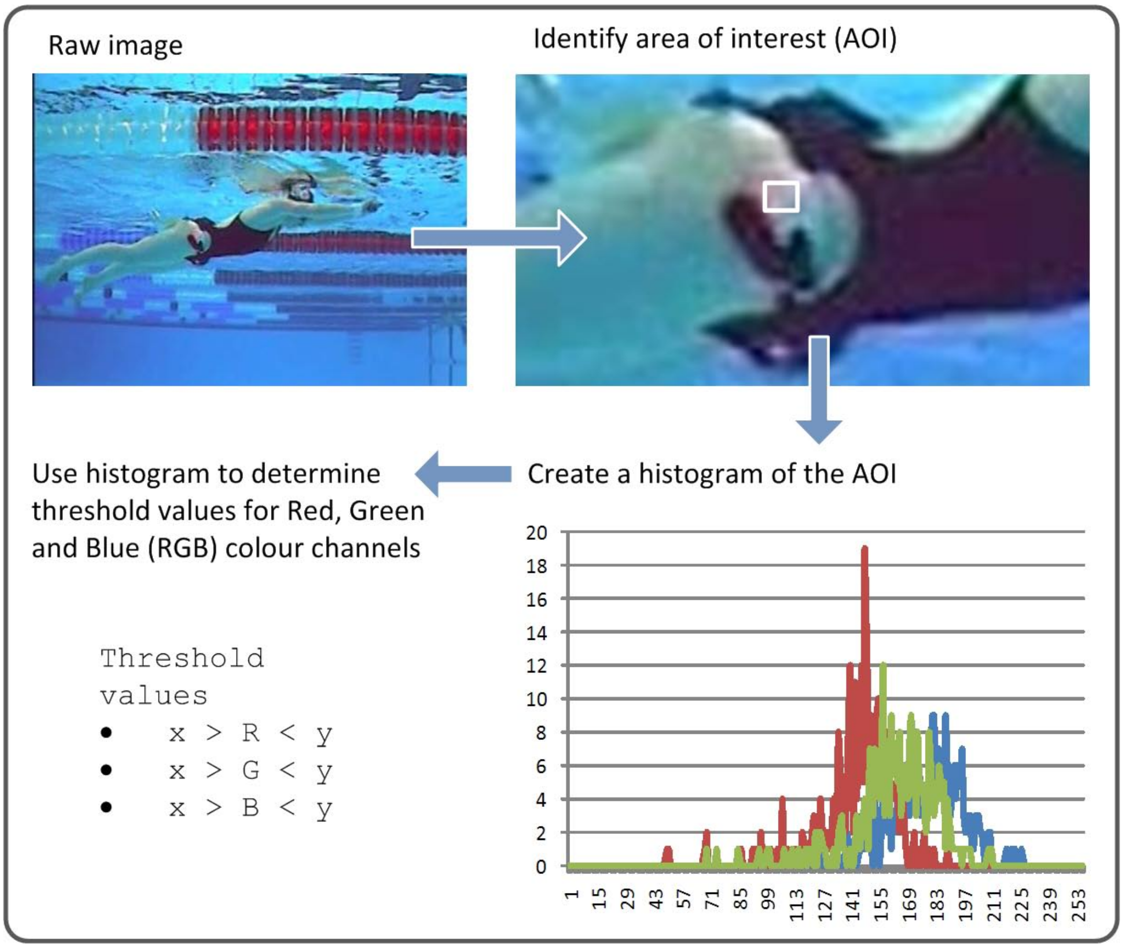


Figure 5-4: Process of using histograms to threshold LED markers

Testing of the LED markers, (developed and evaluated in starting analysis (see Chapter 4: Case Study - Starts), was carried out by attaching the marker to the hip of the athlete during filming using a waterproof CCTV camera. Histograms were generated in the RGB colour channel for the AOI, Figure 5-4. and threshold parameters determined such that the marker could be discriminated from the background.

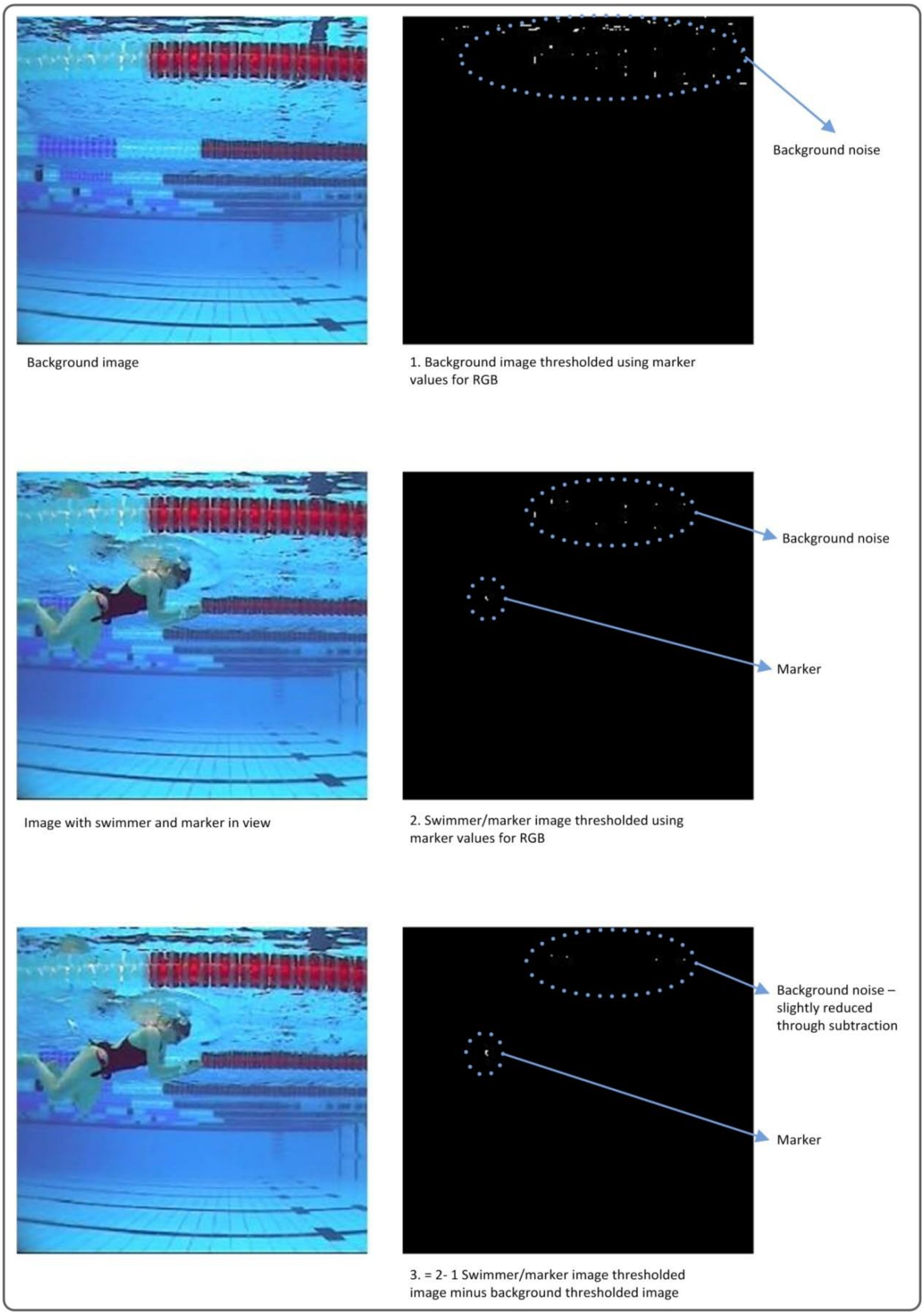


Figure 5-5: Techniques for noise removal in underwater thresholding

The LED could be readily differentiated from the background even though the red lane rope in the foreground created some noise, see Figure 5-5. Subtraction of sequential images did not completely remove the lane rope noise from the image, see *image 3* in

Figure 5-5. and hence the image was cropped to remove the noise and optimise segmentation. additionally reducing the size of the image and the noise also minimises the processing time of the software.

5.2.2.1 Understanding noise from lane ropes

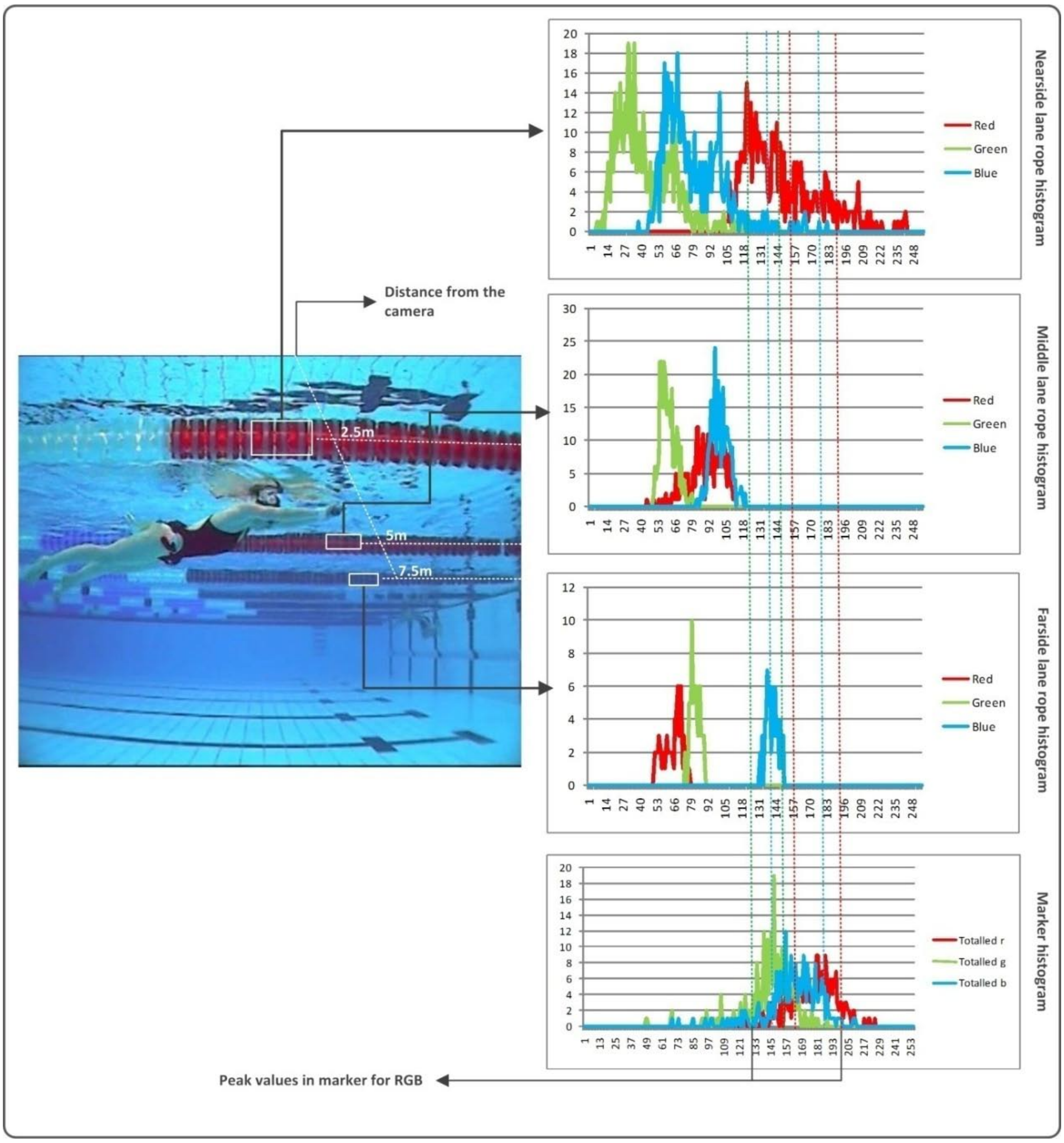


Figure 5-6: Looking at lane rope histograms to identify noise sources

Only the lane rope in the foreground of the image contributes to the noise in the image. The RGB colour histograms for both the marker and front lane rope are given in Figure 5-6. Lane ropes deeper within the field of view present do not contribute to this noise as their RGB colour properties are attenuated in the water outside the values of the marker.

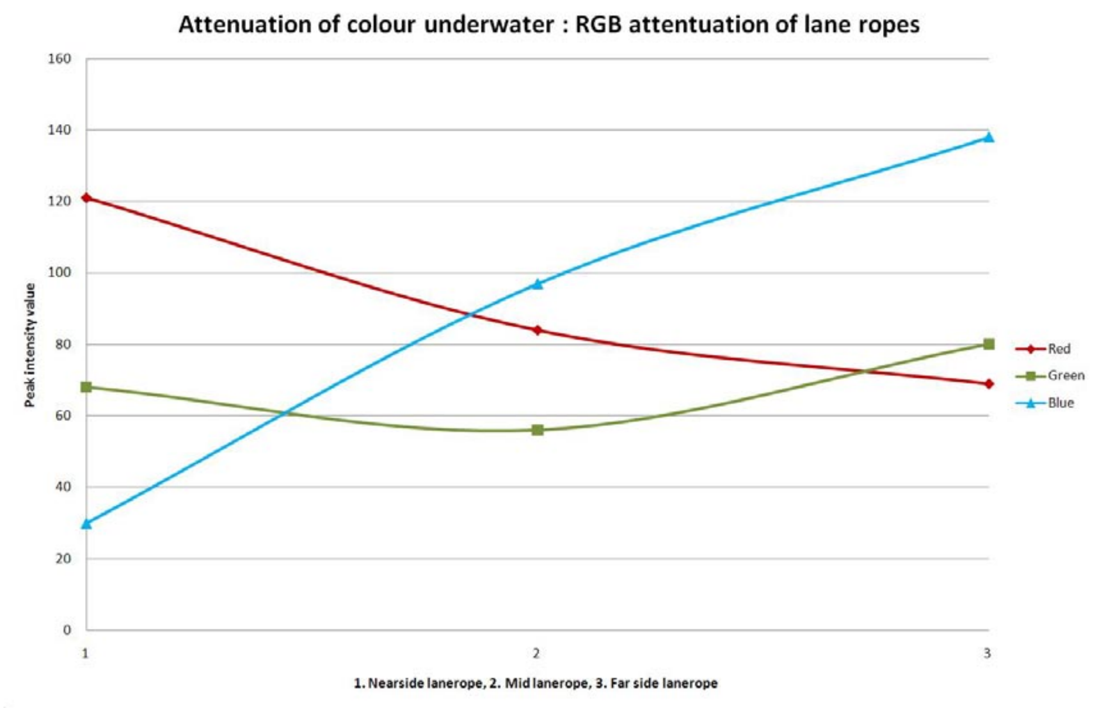


Figure 5-7: Attenuation of colour, from analysis in Figure 5-6

The intensity of each of the RGB channels for the three lane ropes (at distances of 2.5m, 5m and 7.5m from the camera) in the field of view see Figure 5-6 are illustrated in Figure 5-7. The red channel intensity decreases as a function of distance, the blue channel increases and the green channel remains roughly at a constant level. This is expected since shows red light is attenuated to a greater degree than blue or green light in water [Denny, 1993].

5.2.3 Example of underwater tracking using markers

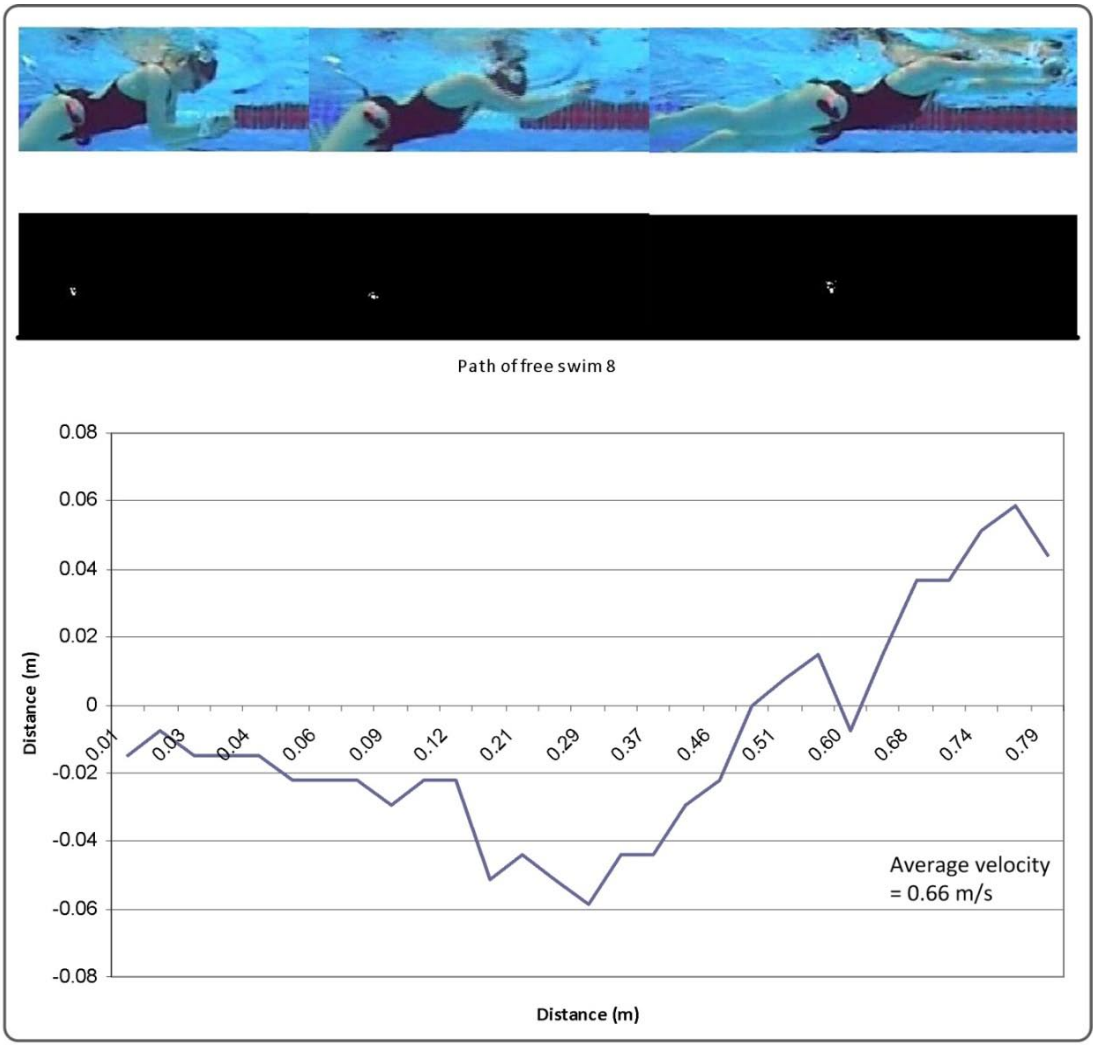


Figure 5-8: Tracking LED marker in free swimming

Free swimming performance was evaluated by tracking a marker placed on the hip of the swimmer (see Figure 5-8). This analysis was generated by tracking the marker at 25Hz, i.e. the frame rate of the camera and enabled the position of the hips of an amateur swimmer performing breaststroke swimming to be accurately determined (< 10cm). The average forward velocity was 0.66m/s. Unfortunately the field of view (~2m) limits the application of this technology to the analysis of a single stroke.

5.3 Free swim parameters derived from acceleration data

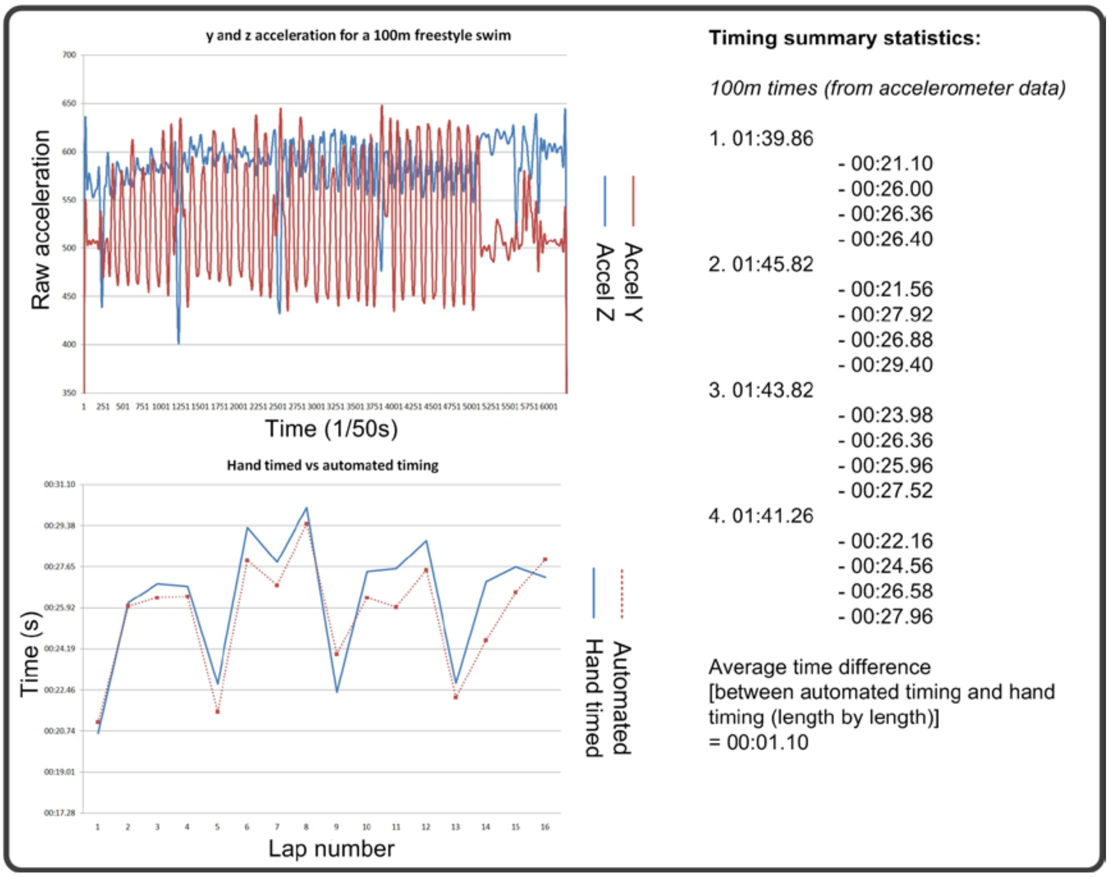


Figure 5-9: Example of timing using analysis of free swim acceleration data

Accelerometer data using the wireless node (see Chapter 3: Development of Component Technologies) was used to provide timing and stroke information in the free swimming event (e.g. parameters) (Figure 5-9). In these tests the node was located on the small of the swimmers back. Typical traces for the x, y and z components of acceleration throughout a freestyle trial are presented in Figure 5-9. Significant features represent the individual strokes and the turns at the end of each length. At the end of each length the downward peak in the z axis (blue line on the graph in Figure 5-9) represents the movement/rotation of the node axis as the swimmer turns onto their back and then returns to the prone position (further discussion of which can be found in Chapter 6: Case Study - Turns). This feature was used to establish split times for a number of 100m trials.

In addition to the times derived from the wireless node, manual timing (i.e. current practice) was recorded to allow comparison between the two methods. It was found that on average the timing derived via the wireless node was less than the equivalent manual timed measure. This may be due to either: (i) delays in judging the time at which the swimmer has reached the end of the lane in manual timing or (ii) by uncertainty in which part of the accelerometer trace identifies the end of one length and the start of the next.

Comparisons between the wireless node and manual split times are provide in Figure 5-10. The maximum range of differences varies from 0.72 seconds in trial one to 4.19 seconds in trial two. The differences appear to be systematic offsets and can occur throughout the 100m trial (i.e. sometimes occurring prior to the first split (Figure 5-10 (c)) others only evident after the first split (Figure 5-10 (b) and (d)). The differences do not increase linearly throughout each trial as would be expected if the wireless node clock was drifting.

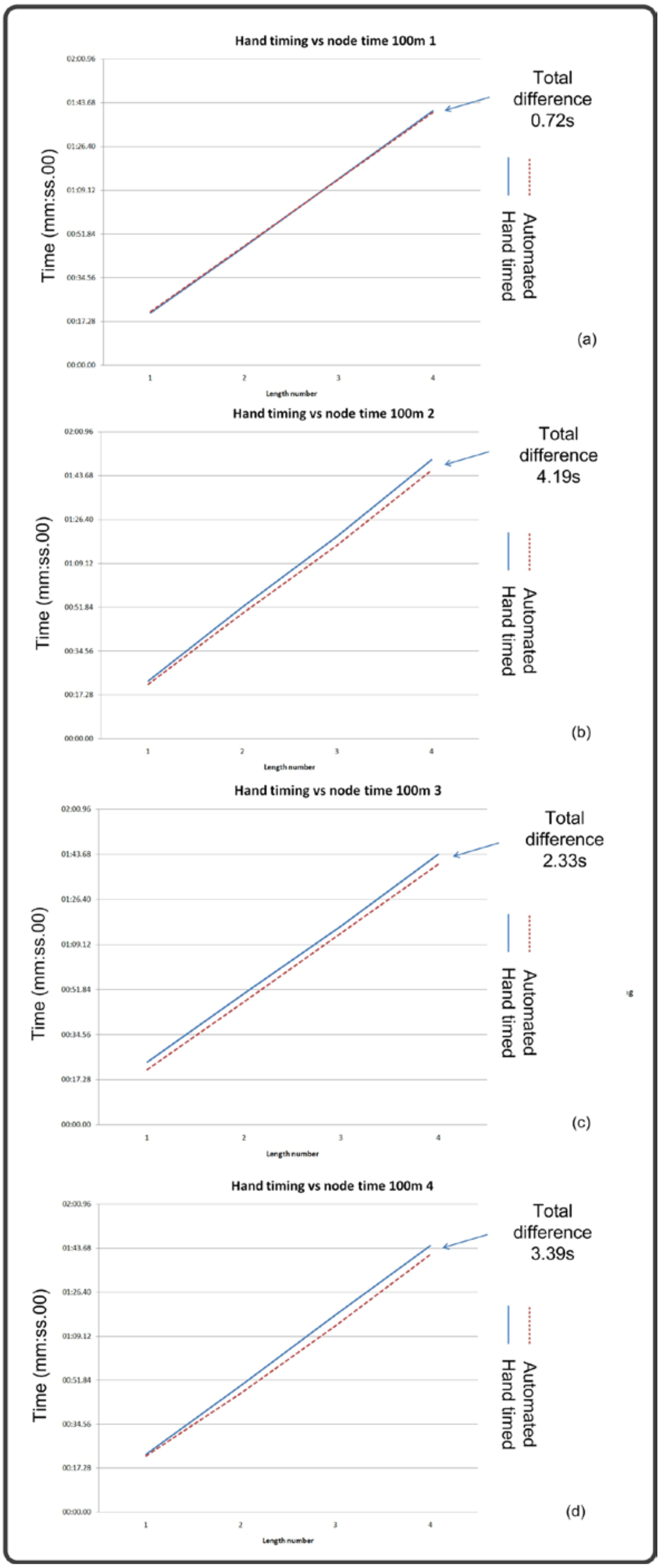


Figure 5-10: Timing comparison between hand and accelerometer methods of analysis

5.3.1 Pulse analysis

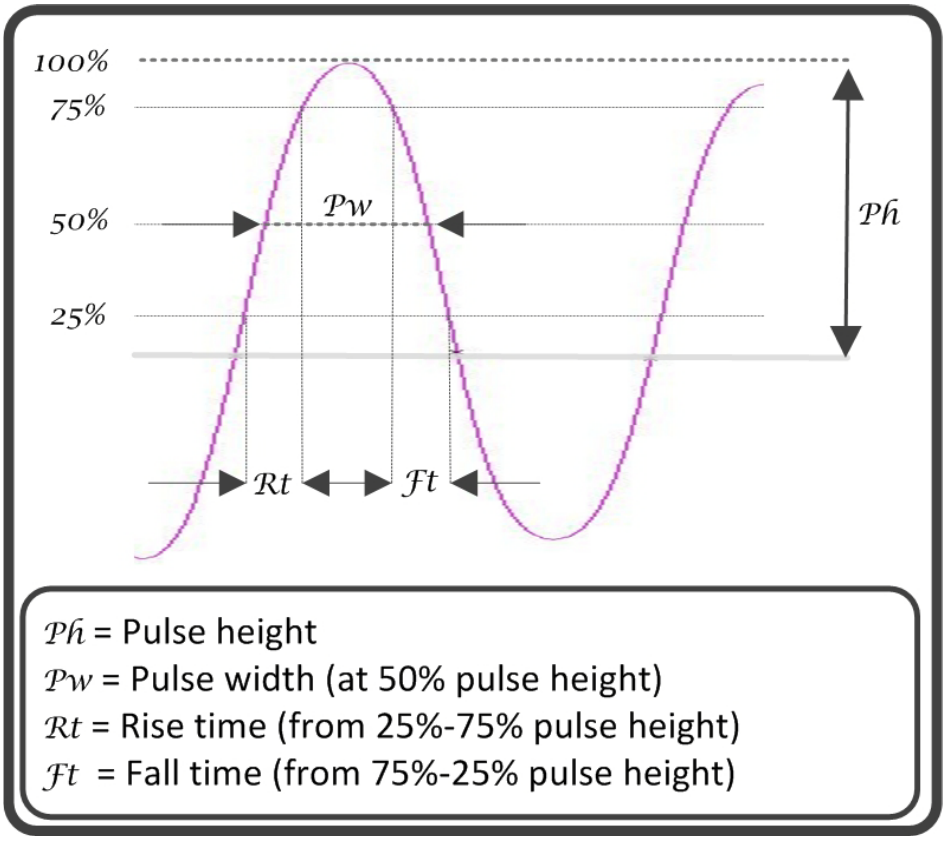


Figure 5-11: A summary of pulse analysis measurement parameters

The *shape* of the accelerometer traces during the free swimming phase provides an indication of the individual stroke characteristics of the swimmer. Detailed analysis of these signatures can be used to provide a record of variations in these characteristics which can in turn be related to changes in performance. Analysis of free swimming accelerometer signatures has included the measurement of parameters such as *pulse height*, *pulse width*, *rise time* and *fall time* for individual swimming strokes (see Figure 5-11). *Pulse height* was established as the maximum height of a given peak whereas *pulse width* was calculated as the time between the signal reaching 50% of the *pulse height*. *rise time* and *fall time* were calculated as the time the signal took to reach 75% *pulse height* from 25% *pulse height* and vice versa.

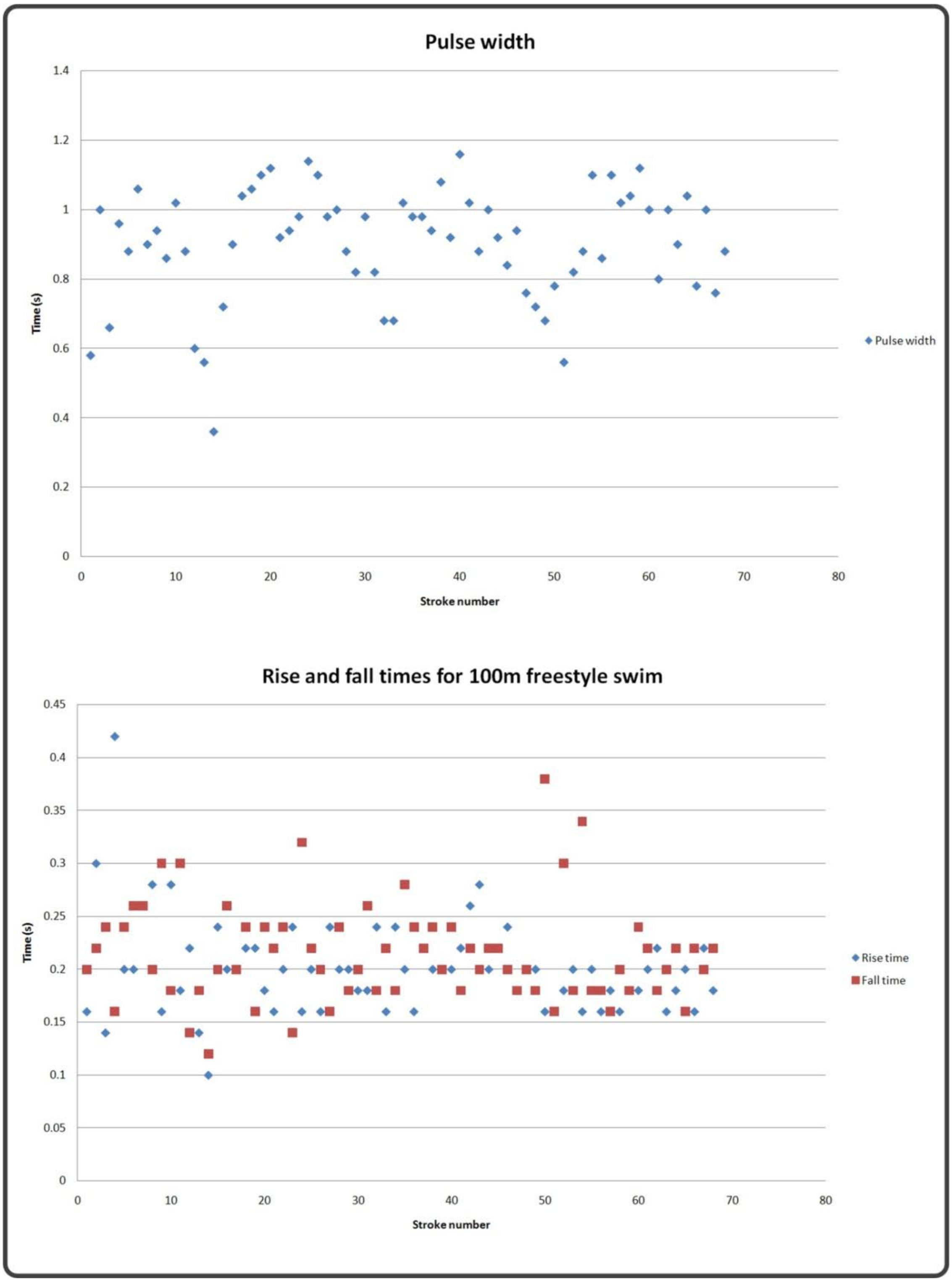


Figure 5-12: Example of pulse analysis for a 100m freestyle swim

The variation in, pulse width, rise-time and fall-time for a 100m freestyle trial are illustrated in Figure 5-12. The pulse width had an average value of 1.1 seconds with a variability of 0.16 seconds. For this athlete their last stroke into the turn and first stroke out of the turn tended to vary most significantly from this average. This trend can be seen where points drop below 0.6 seconds, all of which occur at the end of one length or the start of the next within this 100m swim. Rise and fall times have been plotted in Figure 5-12, these were averagely, 0.2 seconds, 0.21 seconds, respectively +/- 0.05 seconds or 25%. The athlete tested was of recreational standard and therefore it was expected that equivalent data collected for an elite athlete would demonstrate more consistent stroking parameters, i.e. with better control into and out of the turns. Similarly it was expected that for a different stroke, e.g. breaststroke, that the proportion of rise to fall time would not be so equally distributed or that there may not be a single rise and fall associated with each arm pull but multiple. These differences may provide a method from which stroke type could be distinguished automatically from raw data.

5.3.2 Time domain analysis

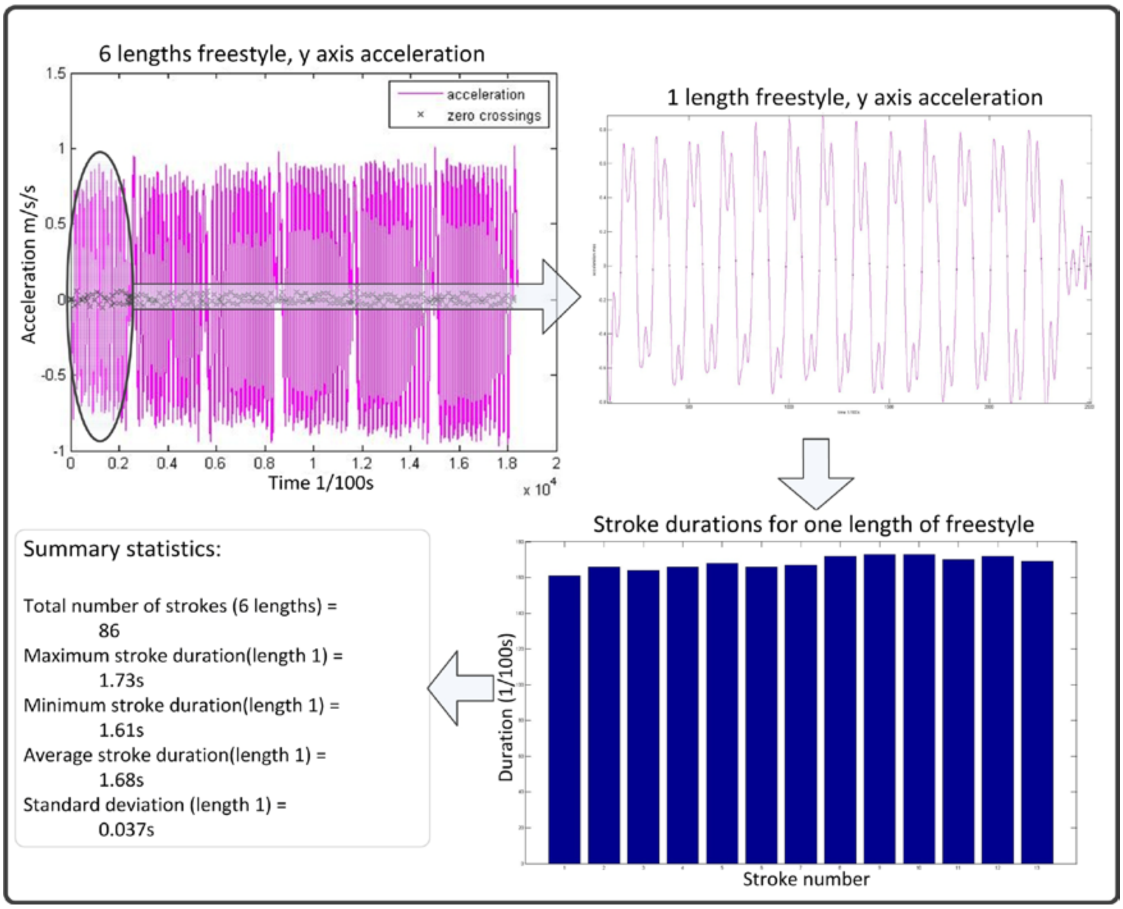


Figure 5-13: Analysis of free swimming using a zero crossings algorithm

The extraction of the number of strokes and stroke duration parameters (see Table 5-1) from freestyle swimming accelerometer data in the time domain is illustrated in Figure 5-13. The times at which the y-axis trace crosses the zero line (i.e. using a zero crossings algorithm) are used to establish the point at which one stroke starts and the other ends. In the zero crossings algorithm the data are initially normalised (i.e. biases are removed) so that values are centre on zero by subtracting the mean from every member of the data set. A zero crossing is identified by multiplying consecutive data points. If the result is negative then a zero crossing has occurred. A counter is incremented and the time of this crossing recorded. Differences between crossings provides information on stroke counts, stroke durations and variations.

Summary statistics taken during six consecutive lengths are illustrated in Figure 5-13. These statistics include the total number of strokes, maximum and minimum stroke durations, average stroke duration and their standard deviation. For example, over the six lengths 86 strokes were recorded. The average stroke length during the first length was 1.68s and varied between ranges of 1.73-1.61s. A histogram of the individual stroke lengths is given in Figure 5-13. In this way variations throughout trials can be monitored and indications of the onset of fatigue recognised. Average stroke distances and velocities are readily calculated from the summary statistics on number of strokes, times and distances covered (determined from the number of lengths swum).

The above features were all determined for the wireless node located in the small of the swimmers back. Coaches and athletes have indicated that it may be more practical to mount the node on the wrist, like a watch. Acceleration signatures will be significantly different for wrist mounted nodes. To understand these differences a node was mounted to the wrist of the swimmer and data was collected for a number of lengths of freestyle swimming.

Wrist mounted acceleration raw data exhibit more complex features (i.e. multiple cyclic peaks) than those observed when mounted on the small of the back (e.g. compare Figure 5-14(a) with Figure 5-14). However by using a low pass filter with a very low cut off frequency, i.e. 1hz, the signal can be filtered to a form similar to that seen in the small of the back, see Figure 5-14. It could then be analysed using the same techniques as described above, using zero crossings to identify strokes and their durations. It is noted that this low pass filter removes the features from the wrist data that represent the individual signature of the athlete’s performance/skill. Further analysis of the data with less extreme cut off frequencies are required to derive measures (e.g. pulse height, pulse width, rise-time, fall-time, number of secondary peaks) relevant to skill (see Figure 5-11 above).

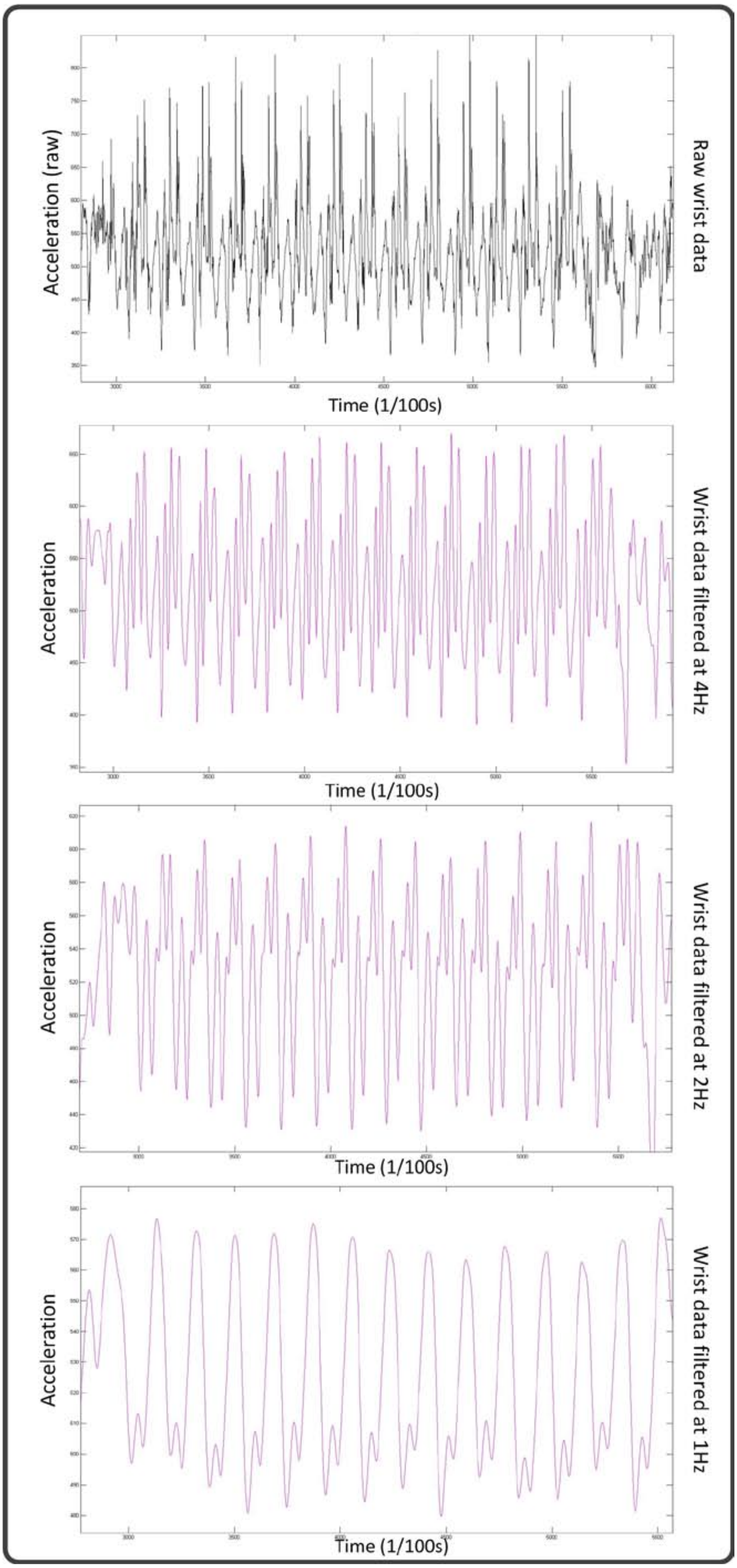


Figure 5-14: Example of filtering wrist data using varying cut off frequencies

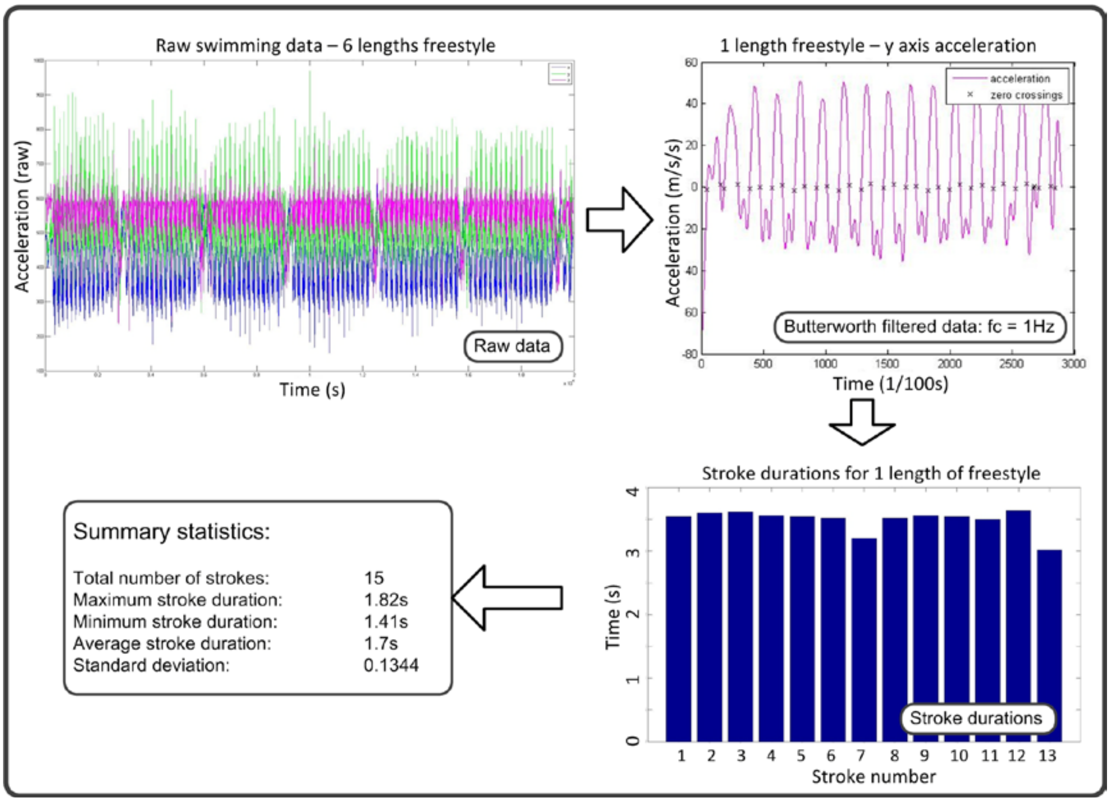


Figure 5-15: Applying zero crossings algorithm to wrist acceleration filtered at 1Hz cut off frequency

A summary of the analysis of the wrist mounted accelerometer data is presented in Figure 5-15. Although the raw data represent a much more complex signal than those recorded from the small of the back, filtering the data (i.e. using a Butterworth filter with a cut off frequency of 1hz) enables the same algorithms to be used to determine gross stroking parameters, see Figure 5-15. In the example given, 15 strokes were recorded with an average stroke duration of 1.7 seconds varying between ranges of 1.82-1.41s.

5.3.3 Frequency domain analysis

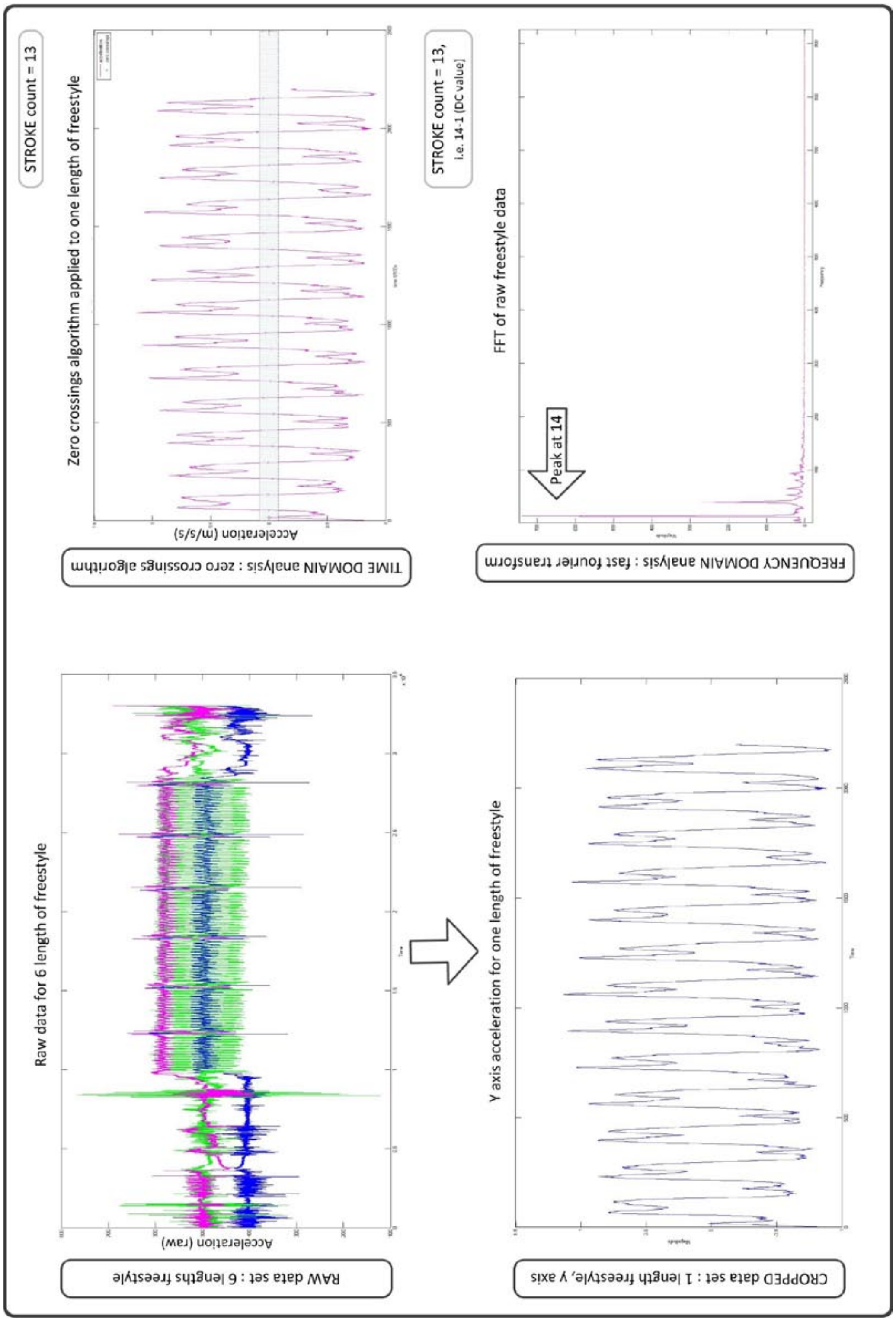


Figure 5-16: Comparing time and frequency domain methods for analysis of stroke rate

The use of time domain analysis has been proven as effective in the analysis of free swimming data. Frequency domain analysis has been explored to establish its potential use in deriving performance parameters from free swim data. The same set of data (cropped to cover a single length) was analysed using both time and frequency domain feature extraction, see Figure 5-16. It was anticipated that due to the cyclic nature of the free swimming accelerometer signal, the stroke rate may be readily derived using a Fast Fourier Transform (FFT) to determine the fundamental frequencies present in the signal. The Fourier Transform of the freestyle data returned one predominant peak (at f=14) and one secondary peak. The primary peak equates to the number of strokes in the data set (i.e. stroke count = ($f - dc_{value}$) = (14-1) = 13). The secondary peak indicates higher frequency present in each of the individual swimming strokes that could be used to indicate a measure of the individual athlete freestyle signature. It can be concluded that free swimming data stroke rate could be derived using either time or frequency domain characteristics. Note: the overhead in processing an fft and the relative simplicity and accuracy of the zero crossing algorithm supports the adoption of time domain analysis over frequency domain.

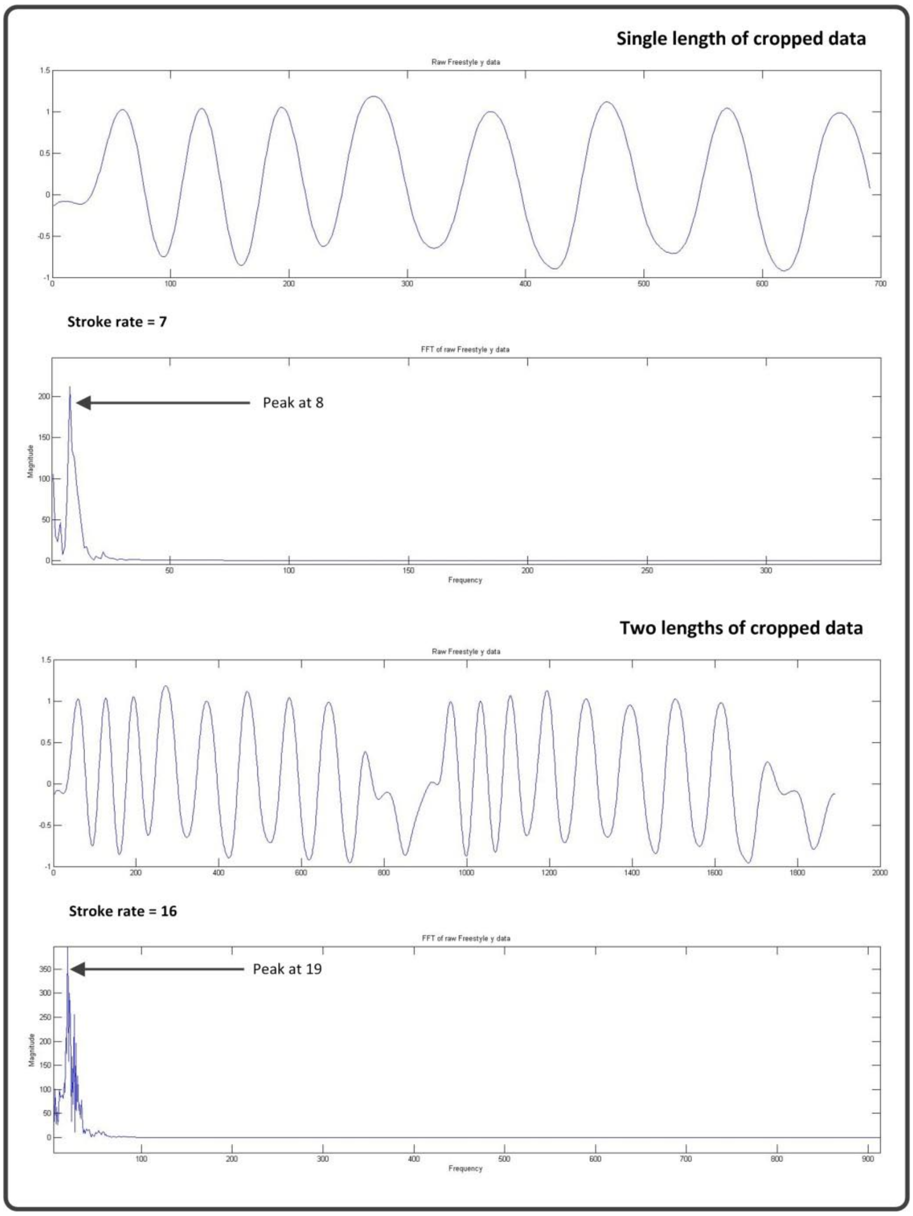


Figure 5-17: Using frequency domain methods to analyse stroke rate for data of a single length and for two lengths of swimming data

The use of an fft to determine stroke rate for multiple lengths rather than a cropped single length is illustrated in Figure 5-17. When tested on two consecutive lengths of data the fft was found to output the wrong stroke rate (i.e. returning values two stokes higher than actual), see Figure 5-17. This is attributed to the noise created by the turning phase, see Figure 5-17, where two peaks are evident in the data. This discrepancy arises because the FFT only analyses frequency components of a signal and cannot differentiate characteristics such as multiple amplitudes. In the time domain other features such as pulse height and pulse width can be used to determine whether the signature represents if a stroke or a turn has occurred. It is also important to note that the Fourier Transform is limited to outputting stroke duration and not more complex measures about the stroke, as is possible with pulse analysis in the time domain.

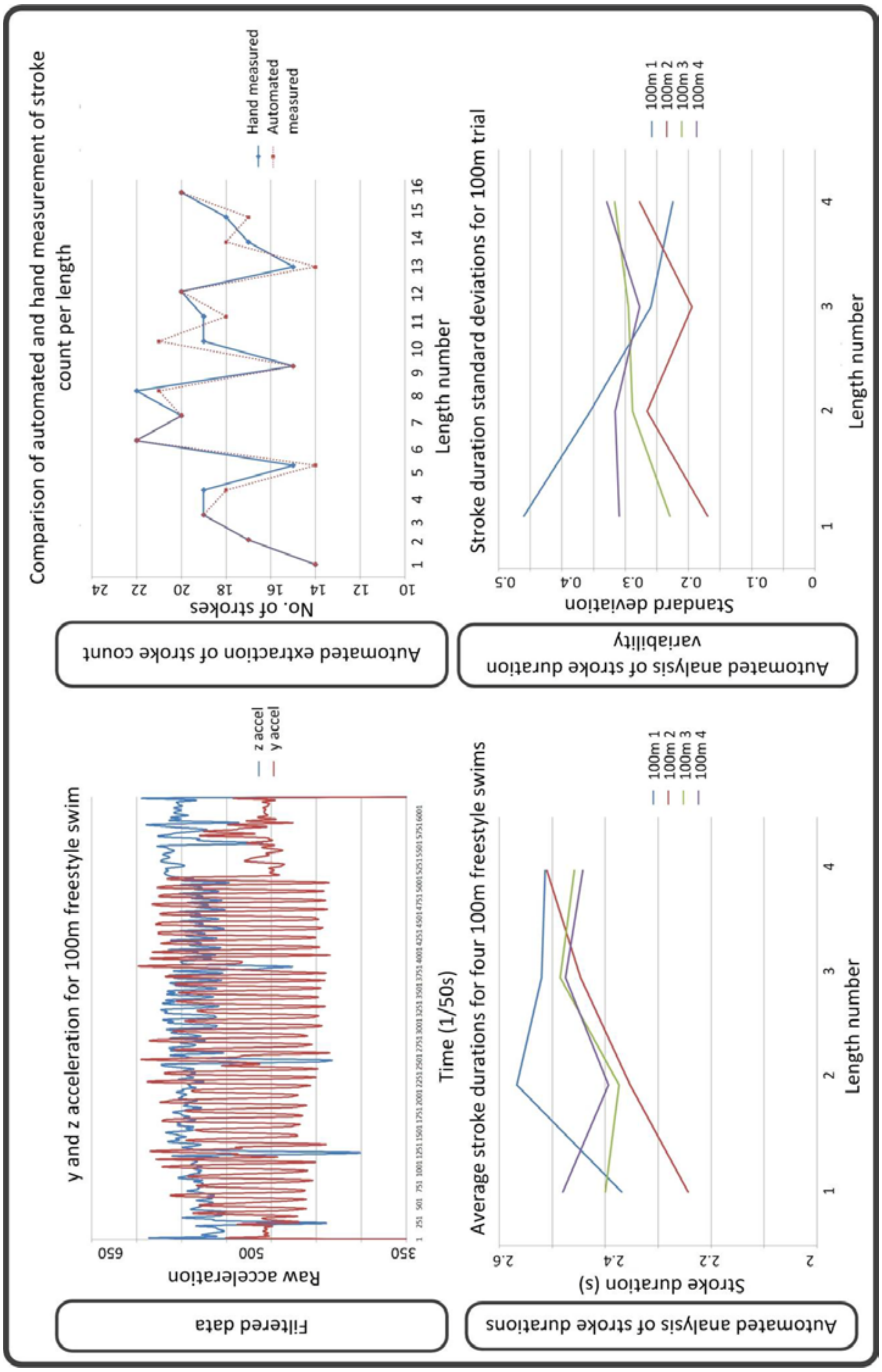


Figure 5-18: Summary of free swimming analysis from free swimming acceleration data

Time and frequency domain methods have been tested for the analysis of freestyle swimming acceleration data. It was found that data could be analysed to establish stroke count and timing information (e.g. stroke durations, rise times and fall times). This analysis can be collated to give an indication of the swimmers performance (see

Figure 5-18 for summary statistics). Automatic generation of split time was found to be on average within 1 second of manual timing. Given the average 1 minute 40 second split times of these trails, this equates to a difference of 1%. Note: manual timing is subject to human judgement and hence increased variability when compared with automated timing. Average stroke durations provide summaries of a swimmers typical stroke performance and therefore if their stroke duration increases from their average during a length, 100m trial or between each 100m then this may indicate fatigue or a pacing issue. The stroke duration standard deviation for each 100m trial is plotted in Figure 5-18. It is interesting to note that in the first trial the standard deviation (i.e. sd = 0.46s) is significantly higher than the other trials (sd = 0.17s, 0.23s, 0.31s). This could be attributed to the start up behaviour of the swimmer being more erratic than when they *settle* into the trial.

5.4 Summary

Two component technologies have been developed and their ability to add value to free swimming analysis evaluated in this chapter.

Table 5-2: Free swimming measurement parameter requirements

	Simple	Compound
Free swimming	• **Stroke count** • **Distance per stroke** • **Stroke duration** • Rotation during the stroke: longitudinal and vertical • **Variations in stroke cycles** • **Split times**	• **Stroke rate** • Swimming velocity • Variations in velocity throughout a stroke cycle • Indicators of skill

Measurement parameters that have been the focus within this chapter are highlighted in bold in Table 5-2 . It is noted that average values for the *distance per stroke* and *swimming velocity* can be derived from the timing and distance parameters outlined in the chapter. Measures of rotation are evident in the accelerometer traces (see Figure 5-9) where variations around the mean values of the stroke signatures can be used to provide an indication of how symmetrical the rotation of the swimmer's technique is. The variations in velocity during the stroke is perhaps the only parameter outstanding within the end user requirements. Since removal of drift and offset inherent in the integration of the accelerometer data (to obtain measures of velocity and distance) requires integrated accelerometer, gyroscope and magnetometer input, evaluation of this parameter is outside the scope of this thesis.

Stroke features within freestyle swimming have been illustrated via the *y component* of acceleration (see Figure 5-9), i.e. the medio-lateral axis of the swimmer. This axis exhibits a strong signature within the signal that is mainly an artefact of the swimmers rotation enhance by the contribution of gravity.

5.4.1 RQ1 Automated Vision

Vision based methods have been explored and their ability to provide performance analysis information about free swimming assessed. Two methods were explored, one to enable timing of a swimmer to a set point (i.e. 15m) and the other to track the swimmer.

An overhead camera was used to provide *timing-gate* information, whereby time was taken when a swimmer crossed a given point in the middle of the field of view (centred 15m from the end of the pool). Typically the head is used as the landmark for timing information. Using a skin thresholding algorithm other parts of the body (e.g. arms, hands, shoulders) and features within the image (i.e. wakes) triggered the system the majority of the time (i.e. 88% of the trials). By specifying swimmers wear swim hats of a predetermined colour a much more robust algorithm was developed. Wearing a red hat enabled successful segmentation of the head and robust timing information for every one of the trials investigated.

An attempt was made to track the swimmer in free swimming when viewed from under the water. This would enable investigation of elements of the performance (i.e. positions/velocities of the limbs) not possible from overhead camera positions. Attempts made to segment the swimmer using spatial thresholding using only the raw image data were unsuccessful. LED markers used to track landmarks throughout a field of view over time was applied successfully. However, given the small field of view, ~2m, only limited analysis could be undertaken. To overcome this limitation a number of integrated cameras or moving camera could be used but would be an impractical solution for monitoring free swimming.

5.4.2 RQ2 Wireless Node

A wireless node was used to provide acceleration data on free swimming performance. Features found in the data were analysed to provide information regarding lap counts, lap timing, stroke counts, stroke durations and variations in stroke cycle, i.e. stakeholder requirements.

Frequency and time domain algorithms have been investigated to determine the most robust analysis technique for accelerometer data. It is possible to determine lap and stroke counts for single laps using frequency analysis. However, for multiple lengths the signature of tumble turn cannot be distinguished from the strokes.

Time domain algorithms have been successfully applied to data collected for freestyle swimming to enable lap timing, stroke counts and stroke analysis. A zero crossings algorithm applied to filtered data enables individual strokes durations and counts to be derived. Individual pulses can be readily extracted from the data using this algorithm to enable a more complete evaluation of the stroke cycle (e.g. rise-time, fall-time, pulse width, peak height) that can be used to highlight changes in stroking technique due to for example fatigue, imbalance between arms or differences between athletes.

It is important to note that the analysis outlined in this chapter has been focussed on freestyle swimming as this is the most common stroke used in training for all athletes. Future work should look towards how these methods may be applied or adjusted to support analysis of other strokes.

Chapter 6

6. CASE STUDY – TURNS

6.1 Chapter Overview

Current turning performance parameters, highlighted in bold in Table 6-1, require manual vision analysis techniques to collect measurements. These incur high costs in terms of time, operator expertise and suffer from inherent variability due to their reliance on human judgement. The research outlined in this Chapter is focussed on the development of a solution/solutions capable of providing a more complete insight into turning performance, covering the range of specified measurement parameters listed in Table 6-1.

Table 6-1: Turn measurement parameter requirements (current measured parameters are listed in bold)

	Simple	Compound
Turns	• **Last stroke to wall timing** • Rotation information • **Time of wall contact** • Wall contact duration • Depth profile • Break out distance • First stroke timing	• Velocity into/out of the turn, also glide, start of initial swimming

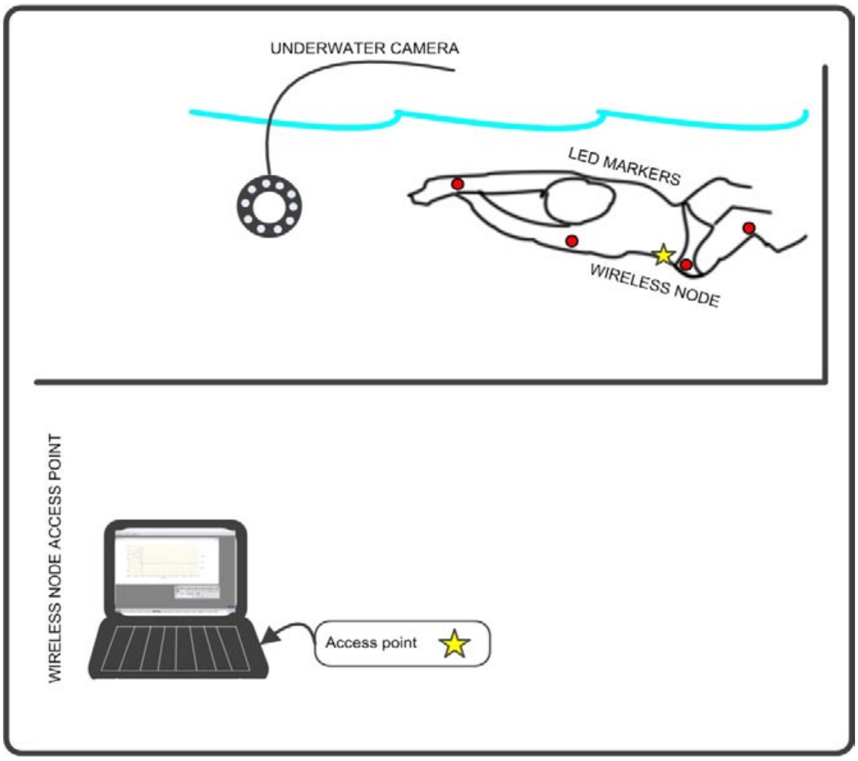


Figure 6-1: Component set up for swim turn testing

The research detailed in this chapter is concerned with the development of components for the analysis of swimming turns. Wireless acceleration data has been combined with image processing to form the integrated solution see Figure 6-1. Vision provides a reference medium that enables an understanding of the features observed in acceleration space. The aim was to generate a robust solution that would enrich the amount of information available regarding turning performance using time efficient methods.

6.1.1 Research Questions (RQs)

<u>RQ1 Automated Vision</u>

a. Are there any vision-based methods that can provide a robust and acceptable solution targeted analysis of swimming turn performance, pertaining to the requirements of the stakeholders?
b. What techniques are available to maximise the signal to noise ratio within an underwater environment to allow robust automated vision analysis?

RQ2 Wireless Node

a. What turn specific parameters are evident in accelerometer data?

b. How are these parameters best presented to monitor turning ability?

6.1.2 Chapter Structure

A vision-based method for automated analysis of turns is presented where LED markers are used to track body landmarks (see also Chapter 5: Case Study – Free Swimming, Section 5.2). Identifying and understanding turning phases in acceleration data is detailed. Phases of the turn are identified and classified to enable more complete understanding of the turn. Analysis results are presented using statistical process charts, which allow easy identification of outliers in performance.

6.2 Automated vision analysis of turns

The use of automated vision systems for performance analysis of start and free swim phases has been discussed in previous chapters (see Chapters 4: Case Study - Starts, Section 4.2, Chapter 5: Case Study – Free Swimming, Section 5.2). Visual information about the turn has to be collected using both over and underwater systems. Visual monitoring of tumble turn is complicated by the presence of bubbles that mask the swimmer. For this reason, a system of LED markers that create a readily distinguishable point on the swimmer and can be robustly segmented from the background image were adopted.

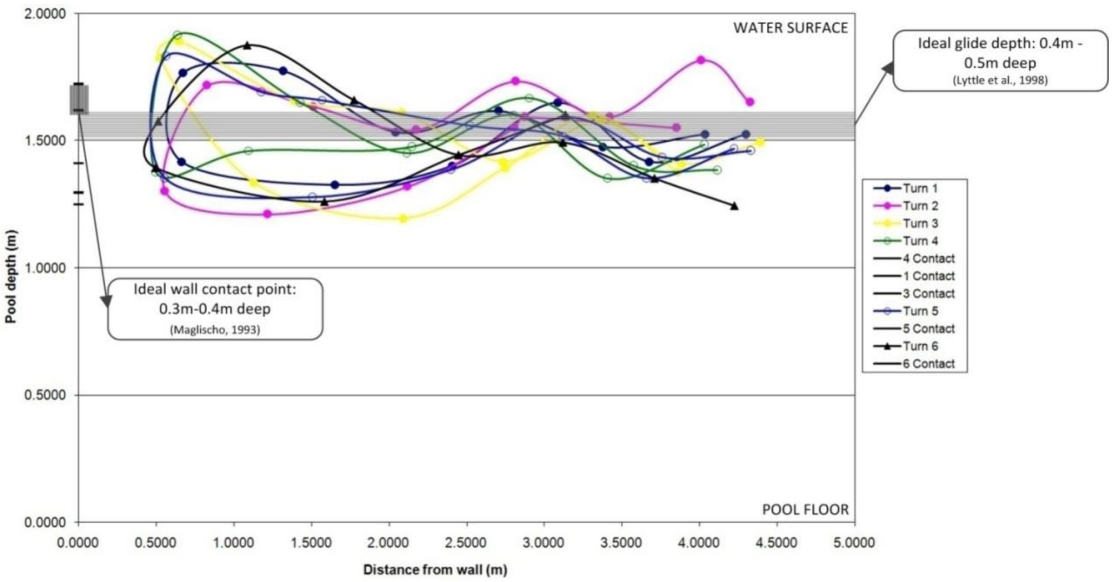


Figure 6-2: Analysis of turning using tracking of an LED marker using developed automated vision techniques

Turn analysis was undertaken for a number of turns performed by the same swimmer who was inexperienced in tumble turning. The swimmer was asked to wear an LED marker on each hip while they performed their turns, during which time underwater video was captured. Using automated vision analysis methods discussed previously (see Chapter 5: Case Study – Free Swimming, Section 5.2.2) the marker was tracked during each of the turns and each path was plotted on a single graph see Figure 6-2 . In addition the depth of foot contact was also plotted on the graph. It was observed that the swimmer was inconsistent in the position of foot contact (average depth – 1.46m, standard deviation 0.2m range from 1.25-1.72 m), which demonstrates their lack of experience in performing tumble turns.

The paths of the hips illustrated in Figure 6-2 enables the turn to be analysed with regards to identifying an optimal technique. From observations it was found that the ideal contact point of the feet on the wall has been reported as between 0.3m-0.4m deep [Maglischo, 1993, see Figure 6-2]. Data from the current turns analysis indicates that the swimmer is typically contacting the wall deeper than is considered ideal. Research has also been reported on the ideal depth of the glide after the turn (i.e. 0.4m-0.5m depth see Figure 6-2) [Lyttle, 1998] At this depth the level of drag from the water surface is minimised. For the data presented in Figure 6-2 it appears that the swimmer was a little too deep (typically 0.51 +/- 0.07m) during the initial turn and glide phases. There is also an indication that at the return to the surface is at an angle too steep to optimise the glide phase. Note: Increasing the field of view from 4m (via additional cameras or a track mounted camera) is required to provide information on the complete glide phase.

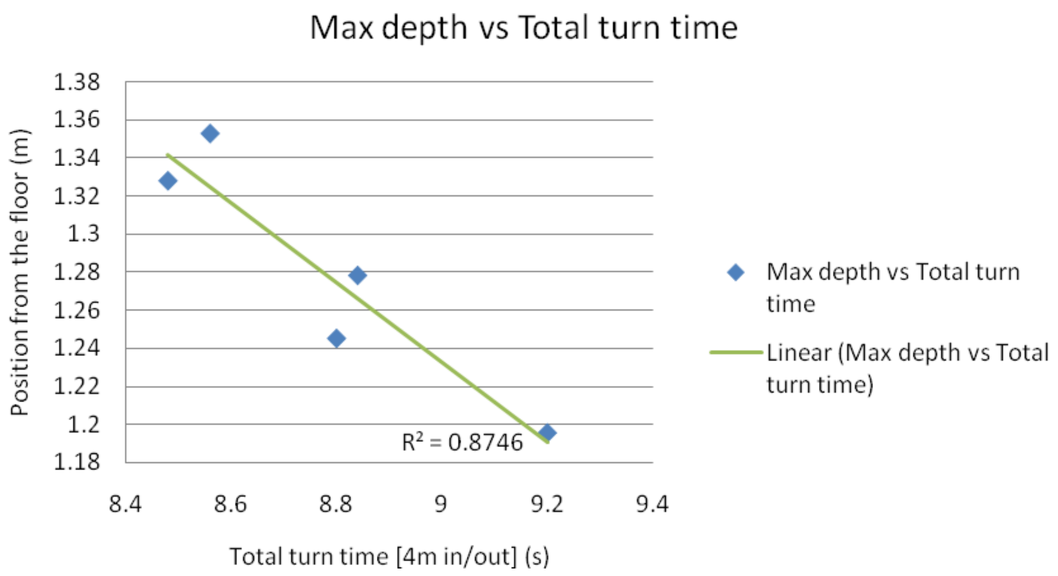


Figure 6-3: Maximum depth of the hip during turning plotted against total turn time

The maximum depth of the hip (in terms of position from the floor) during the turn is plotted against the total turn time (TTT) to 4m in Figure 6-3. A negative correlation is evident suggesting that a shallower turn results in a quicker 4m TTT for this athlete. These comparisons allow for more informed feedback to be given to an athlete during training. For this swimmer alone, the analysis outlined above would imply that they should aim to turn shallower and use a flatter profile swimming into and pushing out from the turn.

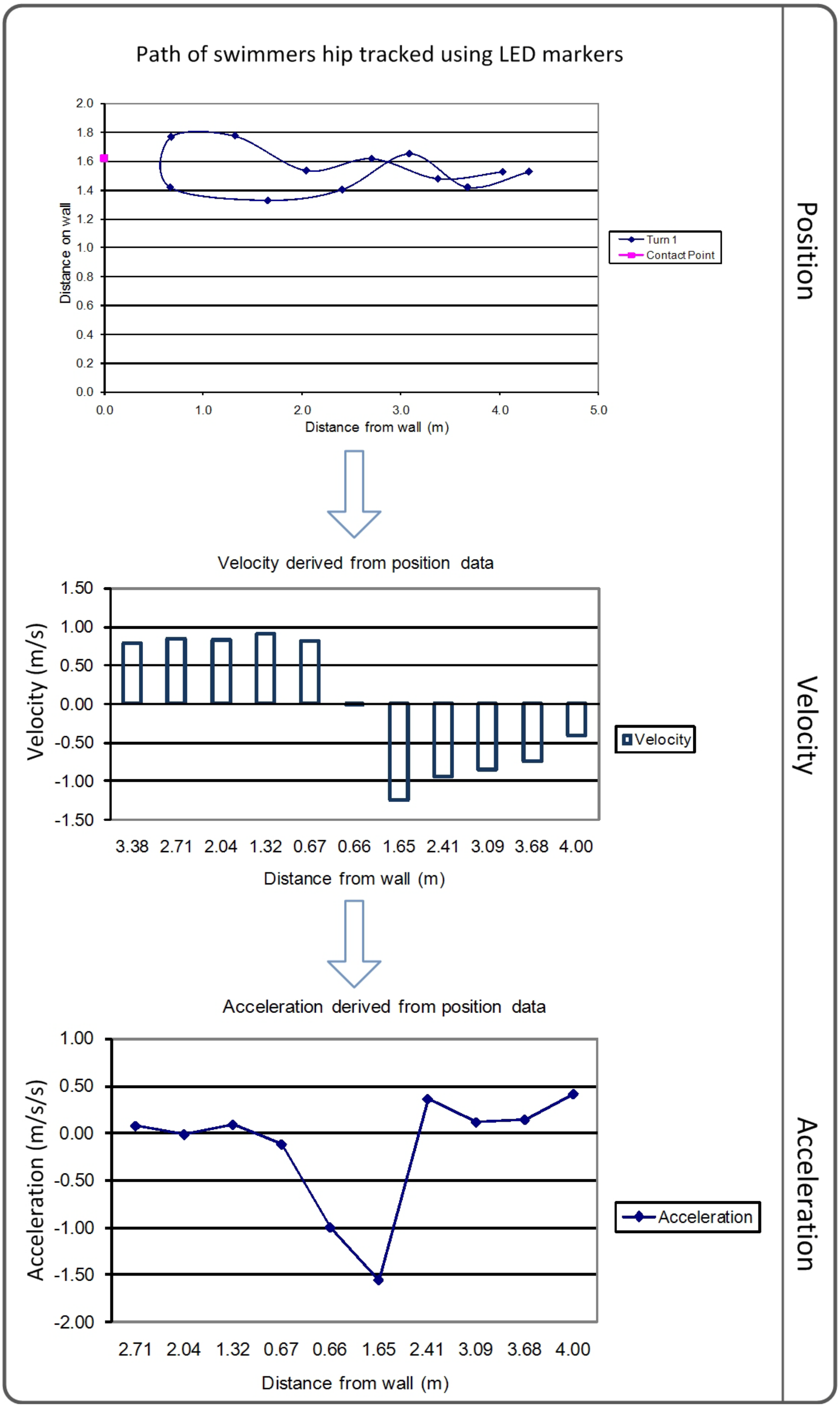


Figure 6-4: Performance parameters derived from tracking position of the hip during a tumble turn

Tracking the position of a marker on the hip during a tumble turn enables performance parameters such as: *Rotation information, Time of wall contact, Wall contact duration, Depth profile, Velocity into/out of the turn* (see Table 6-1) and accelerations of the swimmer in a given plane of motion. Typical velocities and accelerations for the swimmer's first turn (Figure 6-4(a)) are illustrated in Figures 6-4 (b) and (c). The average velocity into the turn was 0.84+/-0.1m/s. The maximum exit velocity was observed following the push off from the wall (1.35m/s) with an average decrease of ~0.6 m/s/m during the portion of the glide phase observed. The acceleration profile during the turn phase is to be noted for comparison with those observed in the accelerometer data (see below, Figure 6-5). In the approach phase the acceleration is zero representative of the constant velocity of approach. During the rotational phase the acceleration decreases rapidly (i.e. for dive one this was ~-1m/s/s) to its maximum negative value (~-1.5m/s/s) and then increases (i.e. for turn one this was ~2.4m/s/s, from the maximum negative acceleration to the resumption of positive acceleration away from the wall) during the push off phase (i.e. to +0.4 m/s/s). The decrease in velocity during the glide phase is evident in the decrease in the acceleration (i.e. for dive one this was a 60% degradation) between 2.4 and 3.7 m from the wall. The increase in acceleration was due to the initiation of a strokes and kicks by the swimmer after 3.7m.

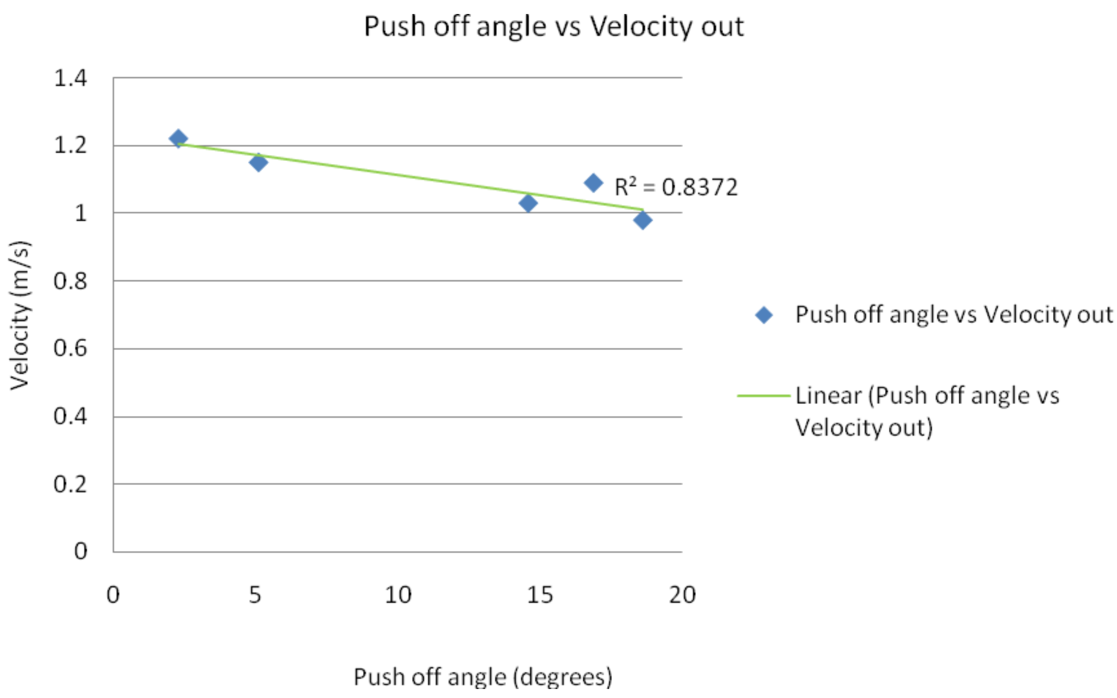


Figure 6-5: Push off angle plotted against velocity

The push off angle (representative of Rotation information) is plotted against the velocity out of the turn in Figure 6-5. The push off angle is defined as the angle the horizontal and a line between the foot contact point on the wall and the first LED marker position (on the hip) out of the turn. For this swimmer a negative correlation of push off angle with velocity immediately out of the turn is evident. Very shallow angles e.g. 5 degrees result in the largest exit velocities (i.e. ~1.2 m/s). The largest push off angles (i.e. 18 degrees) result in the slowest exit velocities (i.e. ~1.0 m/s). These differences are significant enough to focus the athlete on maintaining shallow push off angles. In addition this information provides valuable input into biomechanical and experiential knowledge of turning capability.

It has been proven in the analysis above that the use of markers to track a given landmark on the swimmer has the potential to provide useful information for providing feedback regarding turning performance. The LED system provides distinguishable markers that can be thresholded from the background in an underwater environment and therefore significantly enhance automated vision system analysis. Due to the nature of the turn, some parts of the swimmer inevitably are occluded at certain phases. These occlusions limit the use of vision techniques as markers will be lost and/or confused with other markers on the body.

6.3 Turning parameters derivable from acceleration data

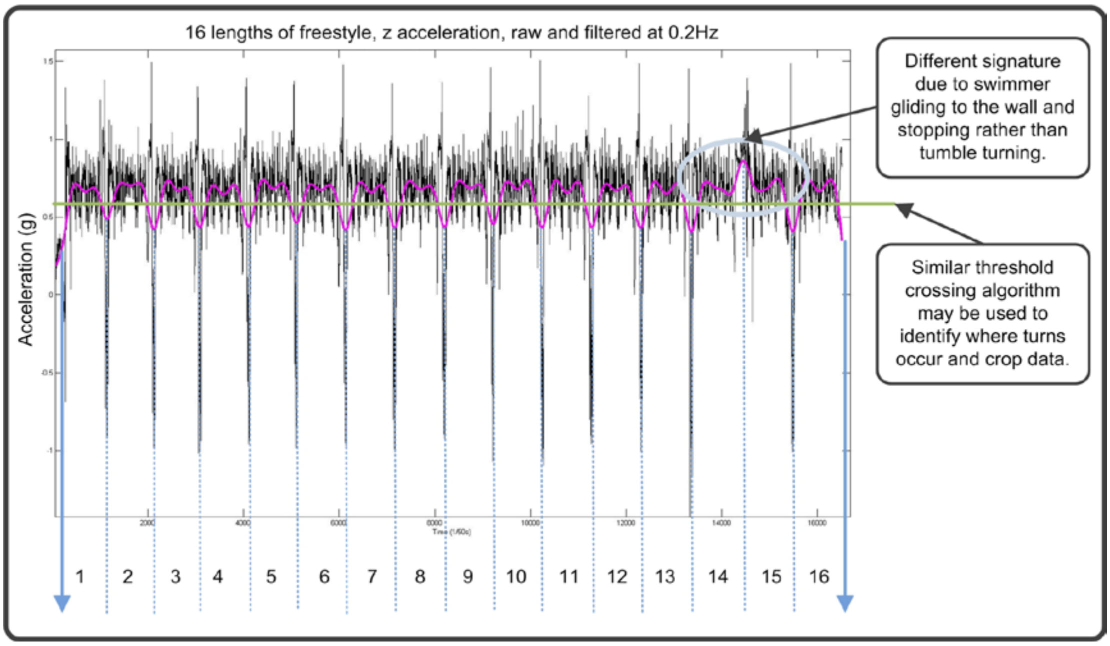


Figure 6-6: Filtering raw acceleration to identify turns in data

Tumble turning presents a unique signature in acceleration space that is distinctly different to that of free swimming (see Figure 6-7 and Figure 6-8). For the wireless node located on the small of the swimmers back, the z axis (vertical) of the turn experiences large positive and negative peaks that can be clearly differentiated from the free swimming signal (see Figure 6-6). A number of methods may be applied to the data to isolate these peaks. An example using low pass filtering at an appropriately low cut off frequency (corresponding to the frequency at which lengths occur in the data, i.e. 0.2 Hz) is given in Figure 6-6. The filtered data (the purple traces in Figure 6-6) represent a simple repeatable waveform, where the global minima correspond to the mid-point of the turn phase. Using the zero crossings or thresholding algorithms (see Chapter 5: Case Study – Free Swimming, Section 5.3.2) the number of lengths completed can be readily determined and appropriate timing points at which to crop the data in order to study each turn in more detail defined.

Between length 14 and 15 in Figure 6-6 an *upward peak* signature was evident rather than the downward peak seen in all other turns. This unique feature was the result of the swimmer gliding into the wall thinking they had finished their 400m swim. Two more lengths had to be completed before the end of the set. The uniqueness of the turning feature in this data set and also the potential discrimination of alternative actions are demonstrated in this example.

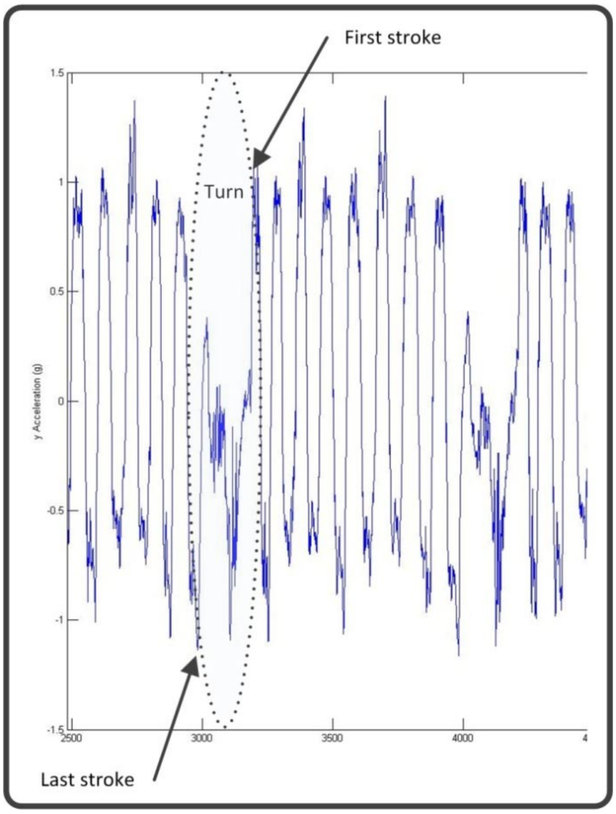


Figure 6-7: Identifying the turn from last stroke into the turn to first stroke after the turn

Turn features can be isolated by cropping the data from the last arm pull into the turn to the first arm pull following the turn as illustrated in Figure 6-7. Indeed timings associated with these limits are required parameters (e.g. *last stroke to wall timing, first stroke timing* see Table 6-1). For freestyle free swimming, acceleration in the y-axis (lateral) results in clear cycles corresponding to each arm pull. In Figure 6-7 it is clear how the last arm pull prior to the turn and the first arm pull after the turn can be determined in the data (i.e. the positions of the last minimum prior to the turn and the first maximum after. These points can then be used to crop the data to turns to be analysed in more detail using any of the three axes of acceleration.

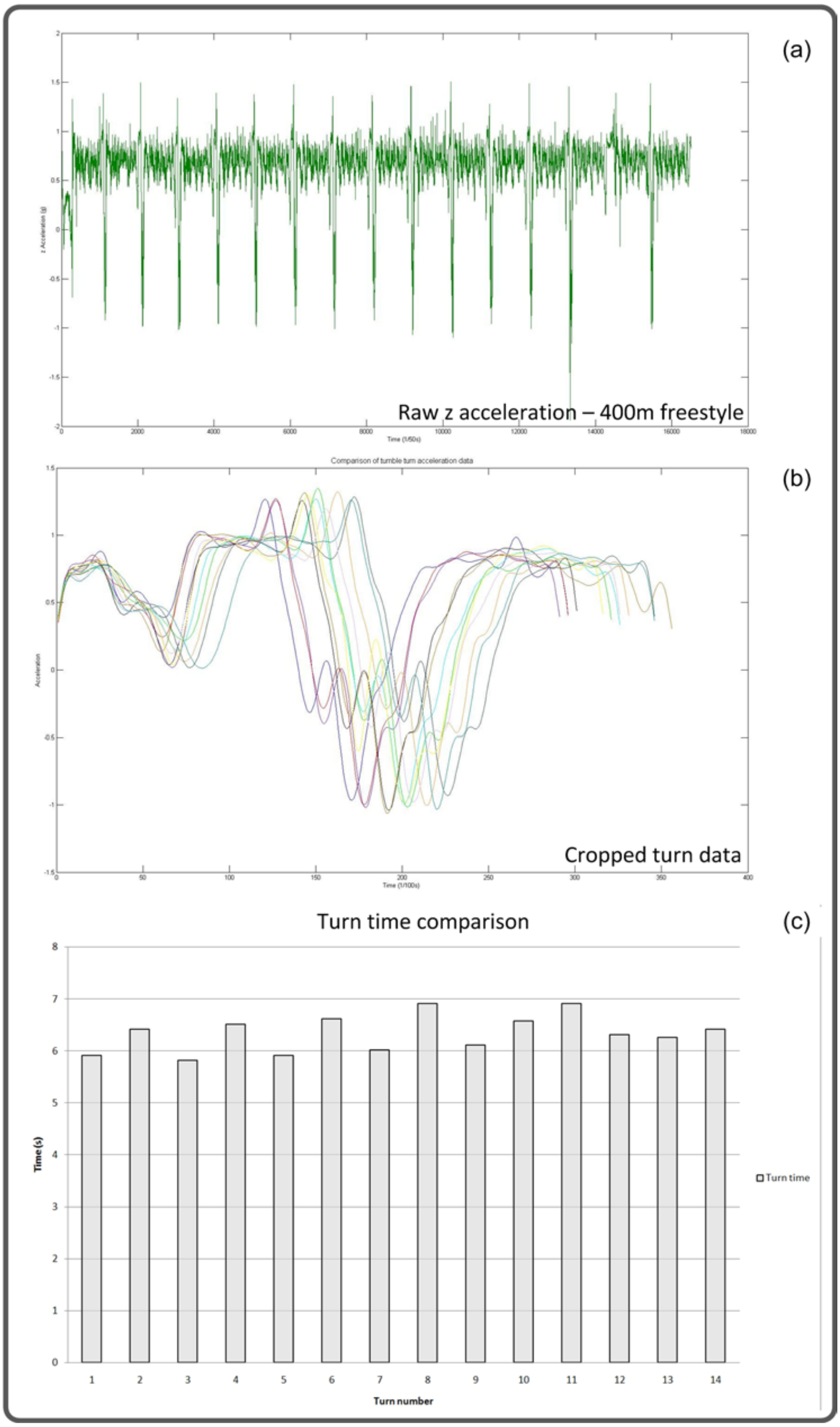


Figure 6-8: Analysis of turns performed in a 400m swim

Free swimming and turns data were collected for a 400m freestyle swim, i.e. 16 lengths of 25m swimming. The y-axis data were used to crop the turn profiles from the complete data stream and then the z-axis data used to analyse each of the turns in more detail, see Figure 6-8. Total turn times (TTT's) were defined as the time between the last arm pull before the turn and the first arm pull after the turn. The signature of the turn is discussed in more detail in the sections below but comparison with: (i) accelerations determined from digitised video of LED markers located on the athlete's hips (see Figure 6-4) and (ii) digitised video focussed on the position of the accelerometer on the small of the swimmer's back (see Figure 6-9) illustrate obvious similarities in profile.

The variation of each TTT throughout the trial is illustrated in the histogram in Figure 6-8(c). The average TTT is 3.21 +/- 0.22s with a range between 5.82s and 6.92s. Inspection of the data indicate a trend towards increased TTT as the trial progresses, a straight line fit produces an R^2 value of 0.3.Although not statistically significant, this trend could indicate the onset of fatigue and its effect on turning capability.

6.3.1 Understanding phases of the turn in acceleration space

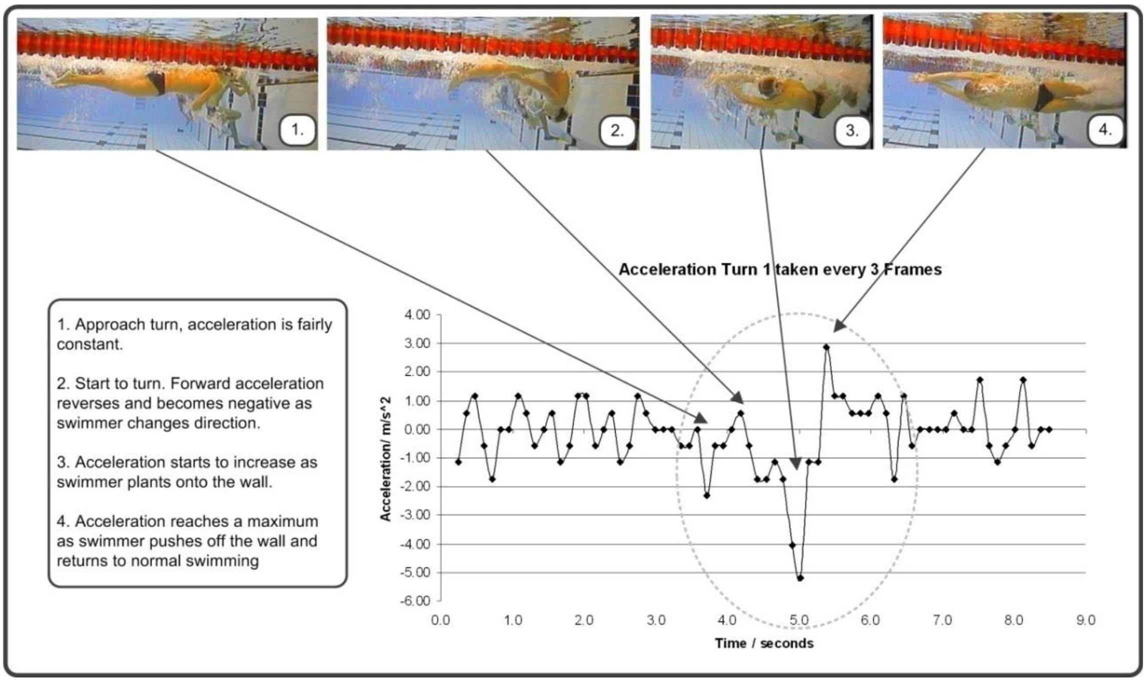


Figure 6-9: Digitisation of the hip during a tumble turn to derive acceleration

To gain an understanding of the physical meaning of the acceleration data recorded by the node, underwater video of a swimmer undertaking a tumble turn was digitised. Every three frames (i.e. n s) the x-y co-ordinate points approximating to the small of the back, i.e. where the node was mounted, were recorded. From this positional data the velocity and subsequently acceleration of this reference point were derived relating to the horizontal direction. Acceleration data are plotted in Figure 6-4. As the swimmer approaches the turn the acceleration was relatively constant (see also Figure 6-9), as would be expected for a free swimming approach at constant velocity with some undulations due the phases of the stroke (Figure 6-9 (1)). The swimmers acceleration then reduces significantly and becomes negative as the swimmer slows to rotate and change direction (Figure 6-9(2-3)). As the swimmer pushes of the wall they produce a higher acceleration than during the free swim phase (Figure 6-9 (4)). After the push off the swimmer glides and then returns to free swimming where their acceleration returns to fluctuating about zero (i.e. approximately constant velocity).

It is important to note that when digitising the image the coordinate origin was unchanged, i.e. + x was always left to right on the image as shown (Figure 6-10(1)). However the coordinate system on the node would rotate with the swimmer.

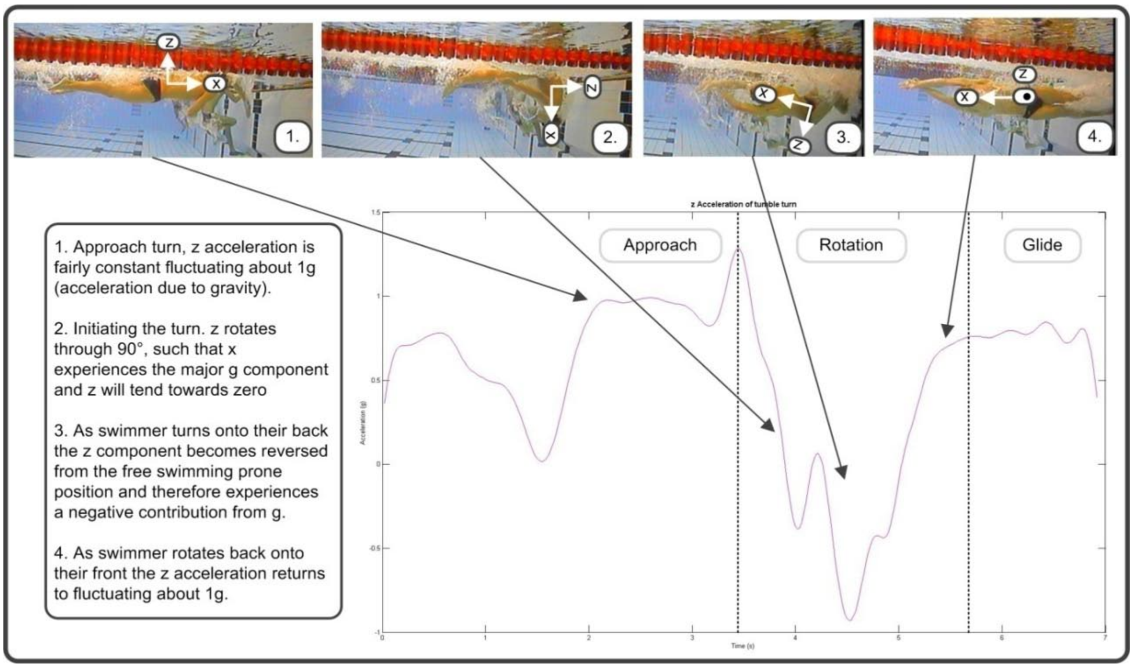


Figure 6-10: z axis (vertical) acceleration aligned with video data recorded during a tumble turn

Video and z-axis (vertical) acceleration data obtained during a tumble turn have been aligned in Figure 6-10. Coordinate axes are highlighted on the small of the back of the swimmer to illustrate how the contribution from gravity affects different node axes during the turn. Note: the contribution to acceleration due to gravity is larger than those generated during swimming. On the approach to the turn the z-axis experiences

+1g (Figure 6-10 (1)). At this point the orientation of the accelerometer is responsible for the overriding signal produced.

As the swimmer initiates the turn they rotate to where the node's axes have turned through 90 degrees clockwise (Figure 6-10 (2)). This means that the component of +1g is seen on the x-axis and the acceleration on the z-axis reduces to a figure close to zero. As the swimmer turns onto their back during the turn rotation (Figure 6-10 (3)), the contribution of gravity on the z-axis becomes -1g. Once the swimmer starts to rotate back to a prone position the acceleration returns toward +1g (Figure 6-10 (4)). The start of the positive gradient in the z-axis trace (i.e. from the minimum of -1g back to +1g) could be used to determine the point where the swimmer started to rotate off their back.

The x and z axes experience the most pronounced acceleration signatures during the turn, due to their orientation with relation to gravity. More detailed analysis of the signatures associated with these axes is illustrated in Figure 6-11.

In Figure 6-11, phases one to four illustrate the swimmer approaching the turn up to where they have rotated through 90 degrees such that their back is parallel to the wall. At the start of this phase the acceleration would approximate to +1g in the z axis and 0g in the x axis (Figure 6-11 (1)). After the approach to the wall and initial rotation the accelerations would approximate 0 g in the z axis and +1g in the x-axis. This can be seen in the acceleration traces in Figure 6-11(3) where the z and x axes cross. As the swimmer continues to rotate, i.e. phases five to seven (Figure 6-11 (5-7)), the accelerations would approximate -1 g in the z axis and 0 g in the x-axis (the swimmer is now on his back). As the swimmer pushes off from the wall they returned to a prone free swimming position where the accelerations would approximate +1g in the z axis and 0g in the x-axis. These phases are referred to as the *approach*, phases 1-4, *rotation*, phases 5-7 and the *glide*, phases 8-9.

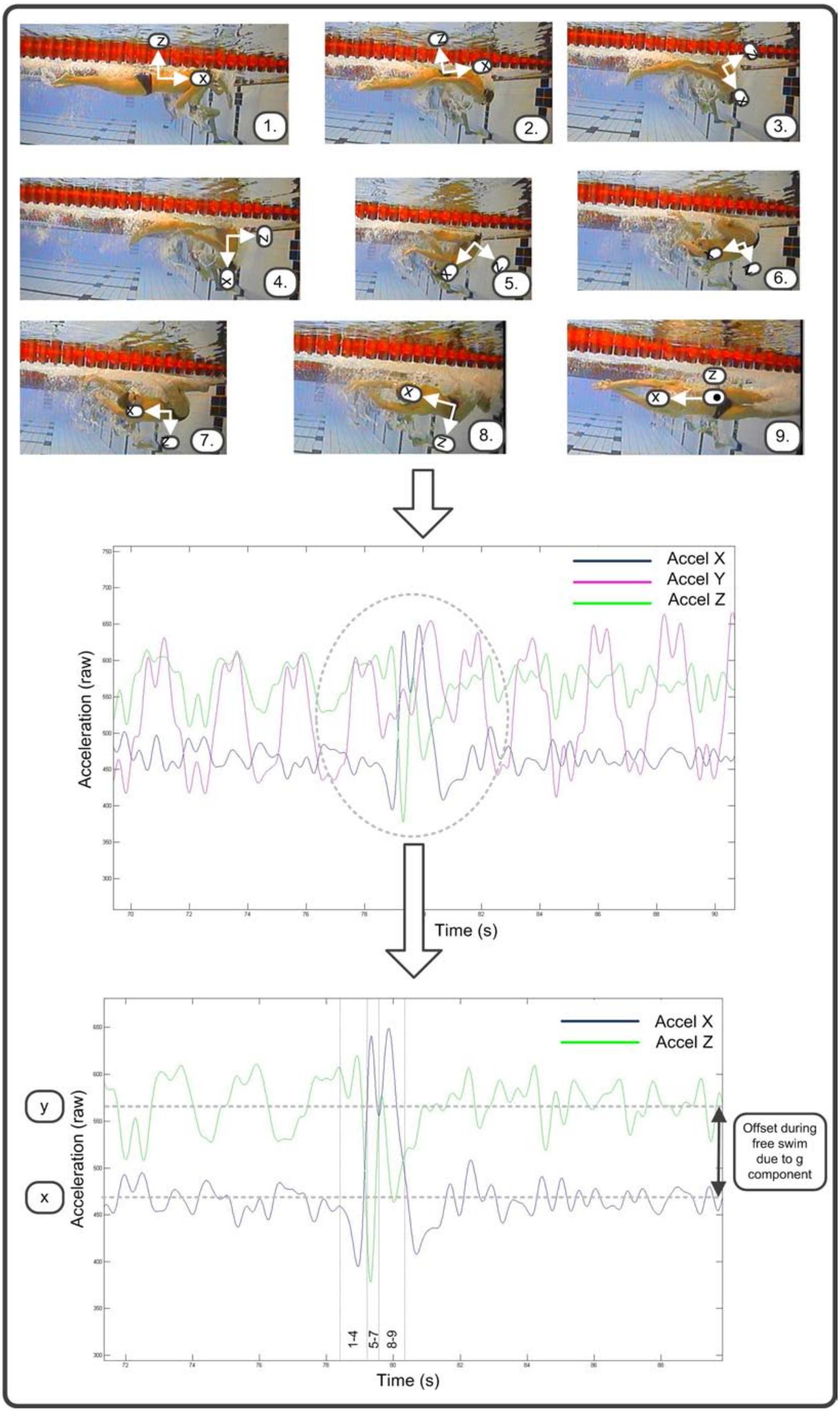


Figure 6-11: Acceleration data in x (horizontal) and z (vertical) axes during a tumble turn aligned with vision stills

6.3.2 Analysis of phases of the turns from acceleration data

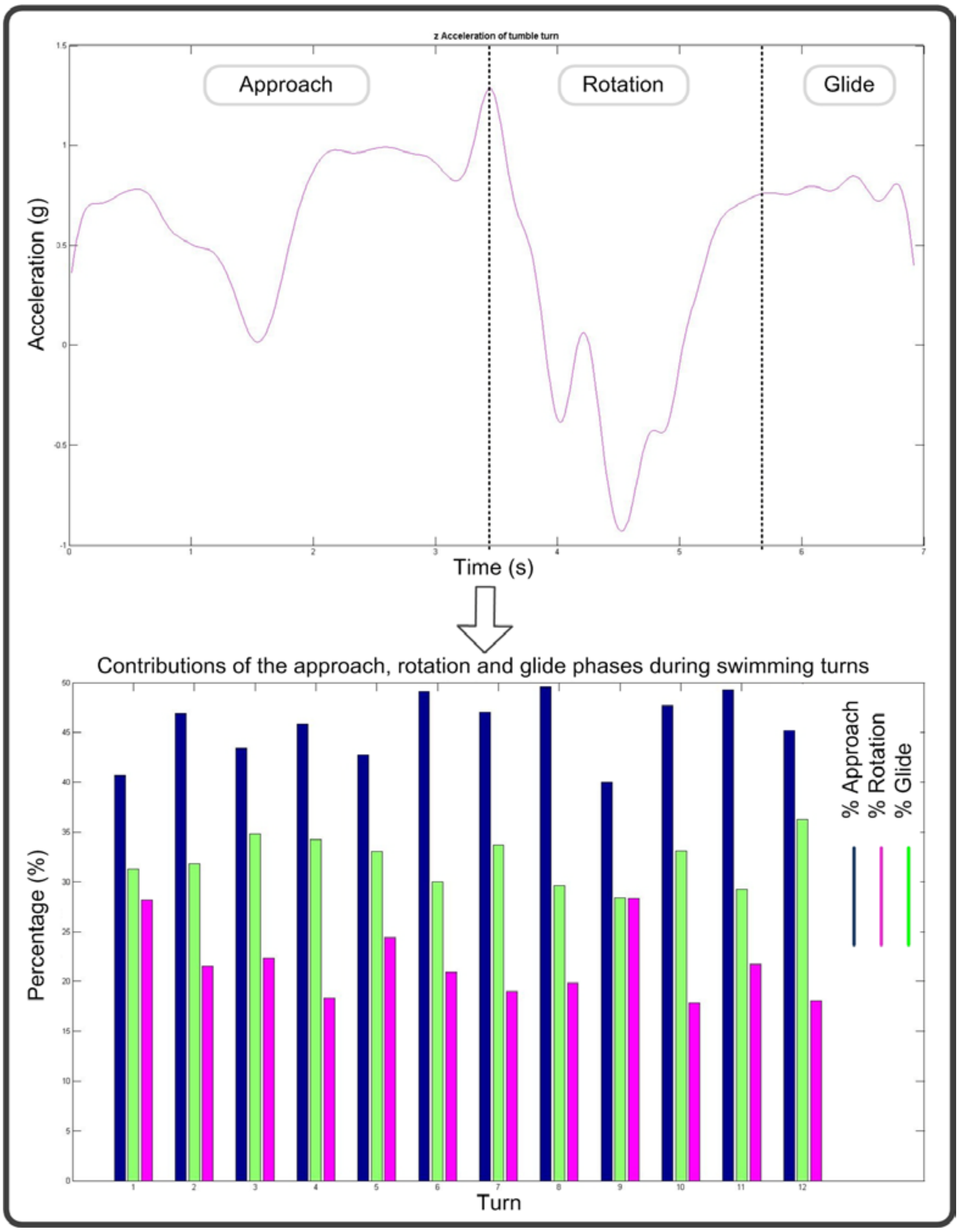


Figure 6-12: Analysis of turns using approach (blue), rotation (green) and glide (pink) phases identified in acceleration data

Detailed analysis of the different phases of the turn i.e. the *approach*, *rotation* and *glide* for a number of trials are presented in Figure 6-12 and Figure 6-13-15. Turns were cropped from last arm pull before the initiation of rotation to the first arm pull on completion of the turn. For the swimmer tested, on average, 46% of the turn was spent in the approach phase, 32% in the rotation and 22% in the glide.

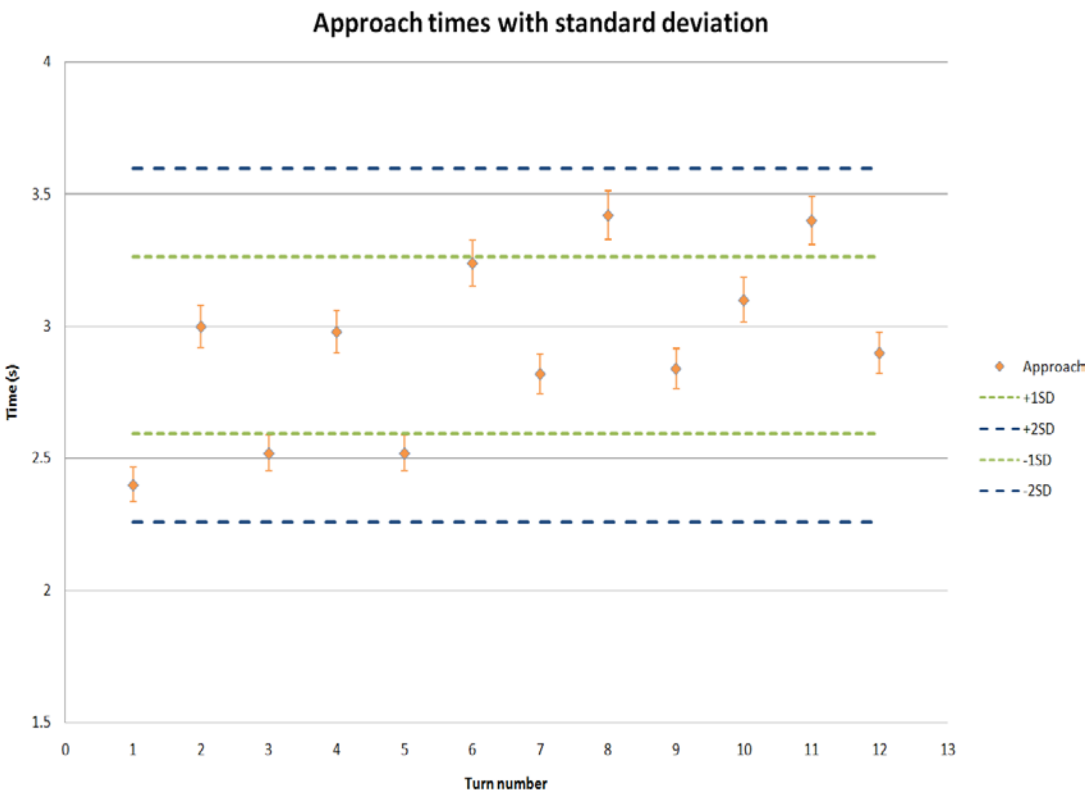


Figure 6-13: Approach time for turns plotted using an SPC

Statistical process control (SPC) charts have been used to illustrate the time sequence of each of the phases during the turn. The *approach time* sequence is illustrated in Figure 6-13. There are a number of interesting features within the data. Firstly there is a general trend towards increased approach times throughout the trial i.e. from 2.4 +/- 0.33 s at turn 1 to 3.4 +/- 0.33s at turn 11) possibly the result of fatigue. Secondly for the first 10 turns there is a significant variation in which the *approach times* of every *even* numbered turn (i.e. turns 2, 4, 6, 8 and 10) is on average 0.6+/- m s longer than the preceding *odd* numbered turn (i.e. turns 1, 3, 5 ,7 and 9). This behaviour is perhaps best explained by a preference of the swimmer when turning at one end of the pool than the other.

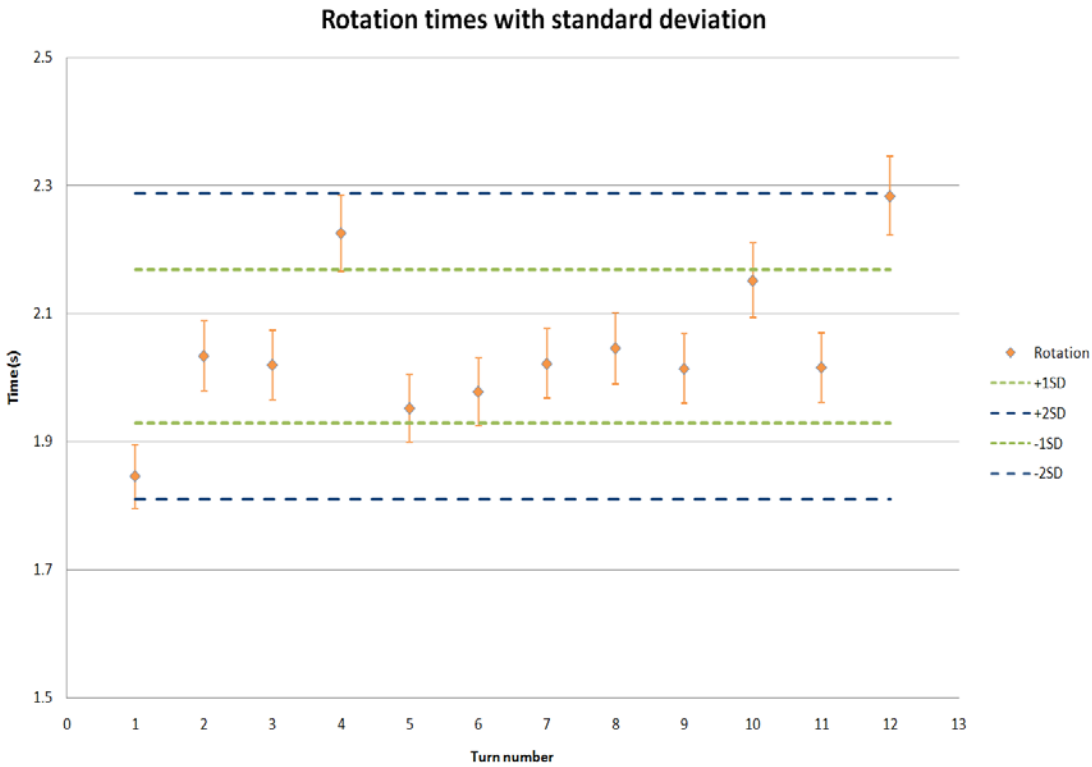


Figure 6-14: Rotation time for turns plotted using an SPC

An SPC chart for *rotation times* is presented in Figure 6-14. As with approach times there is a general trend towards increased rotation times throughout the trial (for a best fit line, R^2 = 0.26) although this conclusion is significantly influenced by the quick rotation of the first turn (i.e. 1.84+/- 0.12s) and the slow rotation of the last turn (i.e. 2.28 +/- 0.12s). Ignoring these outliers at that of turn 4 (i.e. 2.2 +/- 0.12s) the turning performance of the swimmer is remarkably consistent (i.e. average rotation time 2.05+/- 0.12s). Note: The fast *rotation time* for the first turn is correlated with a fast *approach time* for the first turn and could be attributed to the swimmer going off too fast for the first length. A longer final *rotation time* suggests either fatigue or the swimmer winding down on the last length.

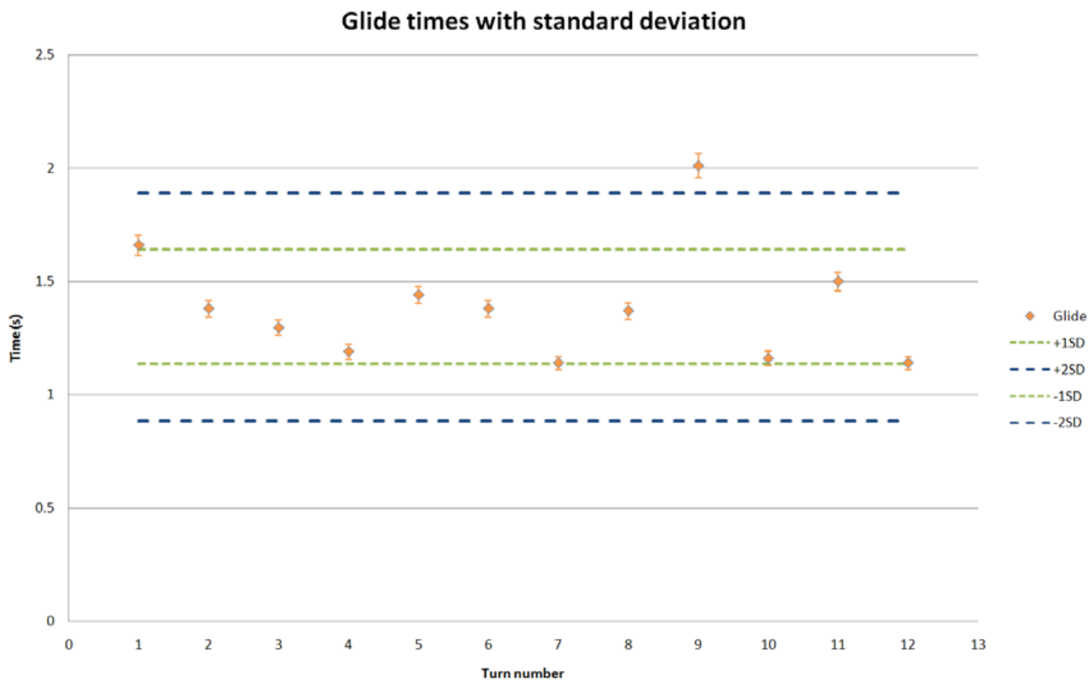


Figure 6-15: Glide time for turns plotted using SPC

The SPC chart for glide times is displayed in Figure 6-15: Glide time for turns plotted using SPC. With the exception of turn nine (and the first turn), all of the remaining *glide times* were closely distributed about the mean (i.e. 1.39 +/- 0.25s). It is difficult to determine what event caused the *glide time* of turn nine to fall outside of two standard deviations from the mean. This event illustrates the need for both integrated sensors and real-time feedback to support cause effect analyses of swimming training.

The use of SPC charts for swimming performance parameters is useful in highlighting both within and between athlete variations and forcing action to be taken to explain these events and subsequently implement changes. This kind of analysis may be particularly appropriate for long term monitoring of athlete performance and / or monitoring the performance of long distance swimmers to observe the effect of fatigue on turn capability and determining whether effects are prevalent in any particular phase (i.e. *approach, turn* or *glide*).

6.4 Summary

In this Chapter two monitoring component technologies (i.e. image processing using LED markers and a wireless 3-axis accelerometer node) have been developed for turns analysis and their ability to provide robust information on the phases of turns determined.

Table 6-2: Turn measurement parameter requirements

	Simple	Compound
Turns	• **Last stroke to wall timing** • **Rotation information** • Time of wall contact • Wall contact duration • **Depth profile** • Break out distance • **First stroke timing**	• **Velocity into/out of the turn, also glide, start of initial swimming**

The parameters (i.e. *last stroke to wall timing, rotation information, depth profile, first stroke timing and velocity (into, out, glide)*) that have been the focus this Chapter are highlighted in bold in Table 6-2. *Time to wall contact* and *wall contact duration* although not explicitly derived from the video or accelerometer data are inherent sub-components of the data that has been quantified. It is anticipated that integration of underwater high-speed video (using for example an LED marker on the swimmers ankle) and an underwater force plate would support the determination of *wall contact* signatures within the accelerometer data.

6.4.1 RQ1 Automated Vision

Vision based methods have been explored and their ability to provide performance analysis information about the swimming turn assessed. The development of wearable LED markers enabled landmarks (i.e. on the hip) to be tracked throughout the turn such that measurements including depths and velocities could be derived. Unlike free swimming the field of view was appropriate for complete analysis of the turn. Occlusions due to overlapping body parts were thought to limit a complete biomechanical analysis even with multiple cameras.

6.4.2 RQ2 Wireless Node

A wireless node was used to provide 3-axes of acceleration data regarding turning performance. Using integrated vision data it was possible to determine information on turning phases based on acceleration characteristics. This enabled more complete analysis of turning performance as the *approach, rotation* and *glide* could be individually identified. SPC charts were used to display results and were found to be useful in highlighting significant events such as glide phases that are substantially longer than in any other turn. This data representation is an easily understandable visualisation that enables users to be proactive to events, rather than the coach or biomechanist having to analyse every output in order to judge whether changes in performance are significant or not. The SPC charts also highlight the need for integrated monitoring in training to ensure that the causes of significant events can be traced in real-time.

Chapter 7

7. CONCLUSIONS AND FUTURE WORK

7.1 Research Summary

The objective of the research detailed within this thesis was to improve performance-related feedback in swimming. An evaluation of current methods of analysis identified a capability gap in real-time, quantitative feedback. A number of component technologies were developed to produce an integrated system for in-depth swim performance analysis in all phases of the swim, i.e. starts, free swimming and turns. These components were developed to satisfy two types of stakeholder requirements [detailed in Chapter 1: Quantification of Stakeholder Requirements]. Firstly, the measurement requirements, i.e. what did the end user want to measure. Secondly, the process requirements, i.e. how these measurements would be achieved. The components developed contributed towards new technologies and methods to facilitate a wide range of measurement parameters using automated methods and the application of technologies to facilitate automation of currently applied techniques.

It was concluded that a single component was not capable of providing information about all measurement parameters specified in the stakeholder requirements and, therefore, an integrated system would be required. It was important that all components could be centrally controlled to allow synchronised data capture. The developed prototype system included a wireless, swimmer-worn, accelerometer node, a starting block integrated with force transducers and an automated vision analysis system for both over and under water applications.

The automated vision system was developed to reduce the reliance on manual techniques to derive quantitative measurements from video data. The eventual solution used wearable LED markers to provide a distinguishable landmark for tracking in both under and over water video footage. The end user preferred the use of a marker as it was considered the least encumbering solution that had minimal impact on training sessions. The use of a marker also enabled more specific analysis to be undertaken, since explicit landmarks could be tracked in time and space.

An instrumented starting platform produced more in-depth data during the block phase of a swimming start and allowed automated analysis of timing, such as time to 1st movement or block time, which would have previously been established using manual techniques. In addition to this, the ability to predict flight parameters from force data was explored. Preliminary testing suggested that prediction techniques could be effective, however, these must be further refined before they can be confidently applied.

Finally, the feasibility of a wearable, wireless accelerometer node was explored. Examples of analysis using data collected from the node have been presented to demonstrate its capability to feedback useful information during starts, free swimming and turns.

The overall component-based system was able to provide enriched feedback to swimmers and coaches pertaining to specific aspects of swimming performance. A greater number of the specified stakeholder measurement requirements could be measured using this system, which complied with the original stakeholder process requirements. This resulted in a system capable of providing targeted feedback in a timely manner, whilst minimising input demands in terms of time and expertise. The automation of techniques also enabled the provision of more reliable/consistent results that would be comparable between system users, i.e. it would not be affected by the analysis being performed by different persons at different times.

7.2 Contributions to new knowledge

The development of an integrated, component-based system for in-training analysis of swimmers has not previously been presented in the literature. Rather, research reported in the literature presents specific interventions accompanied by appropriate testing protocols that are applied to analyse individual aspects of a swimmer's performance. This thesis has generated new knowledge via two research paths, i.e. *the* *development of component technologies* and *the application of component technologies* for analysis of swimming performance.

Manual vision analysis techniques were found to be the most prevalent methods applied in current swimming research. These demand significant resource in terms of operator time and expertise and suffered inherent variability as a result of a reliance on human judgement. One paper by Naemi et al 2008, looked at the development of an automated vision analysis system for analysis of the glide performance. Markers that were automatically tracked allowed real-time feedback on start performance. This example had been applied for the analysis of the underwater phase of the start and push off from turns. However, it was not proven for all aspects of swimming performance. This was the only paper reviewed that discussed an automated solution for digitisation of video data in this research domain.

This thesis presents an automated vision analysis component that has been applied in both under and over water applications for all aspects of swimming, i.e. starts, free swimming and turns. Red LED markers were used to improve the signal-to-noise ratio of the marker within the image, thus allowing robust image segmentation and tracking of the marker. It was noted that automated vision analysis in the start and turns were more effective than in free swimming, where a single camera limited the field of view and was not capable of analysis for both under and over water phases of a stroke cycle. The ability to synchronise data from the video with other components facilitated a more complete understanding of data captured from the force plate and accelerometers, allowing characteristics in the data sets to be aligned and better understood.

Within the literature reviewed it was concluded that the major drawback of using force plate data for the analysis of the start was the lack of knowledge and understanding of how best to use the resulting data. The addition of a force plate component allowed comparable data pertaining to forces associated with the block start to that presented in other research to be collected, thereby allowing further research to be added to this area. Additionally, the ability to predict subsequent flight parameters was explored. It was considered that with further refinement it might be possible to give an indication of flight characteristics from force data, a concept that has not been explored previously in this domain.

The use of accelerometer data for the analysis of swimming has been proven for free swim applications in work by Ohji et al 2003, 2005, James et al 2004 and Davey et al 2008. However, sensors in these applications operate in a data logging capacity, whereby data must be downloaded post-swim for subsequent analysis. This thesis describes the development of a wireless communications node solution that enables real-time capture and transmission of data for rapid poolside analysis of swimming performance. The challenges of wireless communications through an air-water interface were overcome with careful selection of radio transmission frequency and appropriate use of a buffer capability and robust communications protocol on the node. The system also enabled a wider network of nodes to transmit data simultaneously, providing the opportunity for analysis of a squad of swimmers, rather than an individual athlete, that is currently the situation with data logging solutions.

Data collection and analysis was not isolated to free swimming but also included start and turns. In free swimming, the analysis was capable of providing lap counts, split times, stroke counts, stroke durations and variability within strokes, by means of processing accelerometer data. Turns could be distinguished within the data by specific features in each of the three axes of acceleration. It was found that phases of the turn could be identified and subsequently analysed to provide more in depth understanding of turning performance. The start phase has not yet been completely characterised in acceleration space, however, acceleration data has been used to determine the time of the first stroke after entry and also free swim performance during the first length.

7.3 Recommendations for future work

The work presented in this thesis describes the development of a prototype system for the analysis of swimming performance. Future work should look towards the conversion of this system into a robust solution that can be used for daily monitoring of swimmers in training. The feasibility of the system has been presented for all aspects of swimming, but has focussed on block starts, freestyle swimming and tumble turns. It is essential that the functionality of the system is extended to address backstroke starts, all four competition strokes, i.e. freestyle, breaststroke, backstroke and butterfly, and all types of turning, i.e. tumble turning, backstroke tumble turning and the open turn used in butterfly and breaststroke. The development of data processing should work towards generating robust algorithms that can provide feedback using a set of performance indicators, i.e. presenting results to coaches as appropriate scales rather than in the format of raw or semi-processed data.

The synchronisation of data from each of the components has been implemented and is essential to provide effective feedback. Future work should look to extend this data collection into data storage. To ensure uptake of these technologies by end users, it is fundamental that data is stored and presented in a way in which they are able to readily understand, such that constructive, targeted feedback can be provided. The current system takes data from each of the components in a raw format that is then manipulated to derive results, however, this is not a desired format for the end user, as evident in the stakeholder requirements. It is important that a front-end interface is developed to allow the user to view simpler results that can be manipulated and stored as required. This defines the need for the development of a flexible, scalable human machine interface (HMI) that is designed specifically around the needs of the end user.
Further development of component technologies should be undertaken to optimise the solutions for use in day-to-day training. Within the automated vision analysis it is important that the second-generation LED markers are better packaged to ensure complete waterproofing, ruggedness to endure wear and tear from multiple uses and a mechanism to allow the battery to be charged or replaced as required. Algorithms should be tested to track multiple markers, especially for the turns, where markers will overlap or become occluded at times.

Current changes in competition standards mean that the form of the swimming start block has been altered; first use of these blocks in competition was in Summer 2009 at the World Championships in Rome. The major differentiating element of the new design is a wedge feature, similar to those used in athletics sprint starting blocks, mounted to the top plate that can be set in five different positions from the front of the block. A second generation start block should integrate the changes in design and also instrument both the top plate and the wedge feature of the block. Due to the infancy of the design implementation, little is understood about the best way to utilise the wedge to gain benefit. The limited understanding regarding force generated during the start and its subsequent impact on performance, using current instrumented starting blocks, mean that there little knowledge can be translated into understanding force profiles measured by the new block. It is important that testing using the new block is designed to address specific hypothesises to better understand the impact of force generation on dive performance.

Iterative steps should be taken to advance and optimise the wireless node design. Firstly, the current node should be redesigned to minimise its overall size. This node must then be packaged appropriately such that the swimmer can comfortably wear it, reconfigured if necessary and ensure it is sufficiently powered, either using rechargeable or replaceable batteries. A design should be pursued that includes a tri axis accelerometer, tri axis gyroscope and potentially additional sensors, such as a magnetometer and inclinometers. With such sensors, work could be undertaken towards implementing a Kalman filter to derive position from accelerometer data. This would facilitate the measurement of velocity, i.e. one of the measurement requirements that currently cannot be readily or accurately achieved.

The capability of embedding signal processing functionality onto the node hardware, i.e. onto the microcontroller, could also be explored, with a view to send only summary data across the limited bandwidth communications network, rather than raw data. There may be several levels of processing that could be embedded, such as filtering, cropping of data or derivation of performance parameters, such as stroke count per length. Embedding such analysis algorithms would reduce the bandwidth required per node to transmit data and therefore increase the capacity of the overall system in terms of networking more nodes or improving redundancy and robustness of the network. Independent of where the processing takes place, i.e. on the node or at the PC in software, it is important to work towards processing that outputs simple measures of performance that can be interpreted easily by coaches and athletes, rather than the less understandable, raw data.

Future iterations of work arising from this thesis should continue to address technologies and processing requirements with a scalable and expandable approach. It is essential that as understanding is furthered, the system is able to adapt appropriately such that data is captured, processed and presented in the way that adds most value to the end-user. The ongoing development of the system should look towards satisfying the remaining stakeholder measurement requirements while continuing to comply with stakeholder process requirements.

Reference List

Acharya, T., Ray, A.K., (2005) 'Image Processing – Principles and Applications'. Chapter 1, pp 1-9, Wiley-InterScience. Hoboken, New Jersey

Actigraph, http://www.theactigraph.com/, viewed January 2010

Alberty M et al. (2005) 'Stroking Parameters in Exhaustion in Swimming'. International Journal of Sports Medicine, 26, pp 471–475

Alberty, M., Sidney, M., Huot-Marchand, F., Hespel, J., Pelayo, P., (2005) ' Intracyclic Velocity Variations and Arm Coordination during Exhaustive Exercise in Front Crawl Stroke'. *International Journal of Sports Medicine*, **26**, pp 471-475

Amat, J., Casals, A., Frigola, M., (1999) ' Stereoscopic System for Human Body Tracking in Natural Sciences'. International Workshop on Modelling People, Corfu, Greece

Anderson, M., Hopkins, W., Roberts, A., Pyne, D., (2006) ' Monitoring Seasonal and Long-Term Changes in Test Performance in Elite Swimmers'. *European Journal of Sports Sciences*, **6:3**, pp 145-154

Arellano, R., Llana, S., Tella, V., Morales, E., Mercade, J., (2005) ' A Comparison CMJ, Simulated and Swimming Grab-Start Force Recordings ad their Relationships with the Start Performance'. *Proceedings of XXI International Society of Biomechanics in Sport*, China, pp 923-926

Berio, G. and Vernadat, F. (2001) 'Enterprise modelling with CIMOSA: functional and organizational aspects'. *Production Planning & Control*, **12: 2**, pp 128 — 136

Betke, M., Gips, J., Fleming, P., (2002) ' The Camera Mouse: Visual Tracking of Body Features to Provide Computer Access for People with Severe Disabilities'. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* Vol **10**, No 1, pp 1-10

Bharatkumar, A., Daigle, K., Pandy, M., Cai, Q., Aggarwal, J., (1994) ' Lower Limb Kinematics of Human Walking with the Medial Axis Transformation'. *IEEE Workshop on Motion of Non-Rigid and Articulated Objects*, Austin, TX, USA, pp 70-76

Blanksby, B., Nicholson, L., Elliot, B., (2002) ' Biomechanical Analysis of the Grab, Track and Handle Swimming Starts: An Intervention Study'. *Sports Biomechanics*, **1:1**, pp 11-24

Blanksby, B., Skender, S., Elliot, B., McElroy, K., Landers, G., (2004) 'An Analysis of the Rollover Backstroke Turn by Age Group Swimmers'. *Journal of Sports Biomechanics*, Jan **3 (1)**, pp 1-14

Bobick, A., Johnson, A., (2001) ' Gait Recognition using Static, Activity Specific Parameters'. *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp 423-430

Bobick, A., Davis, J., (2001) ' The Recognition of Human Movement using Temporal Templates'. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol **23**, No 3, pp 257-267

Breed, R., Young, W., (2003) ' The Effect of a Resistance Training Programme on the Grab, Track and Swing Starts in Swimming'. *Journal of Sports Sciences*, **21:3**, pp 213-220

Callaway, A., Cobb, J., Jones, I., (2009) ' A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming'. *International Journal of Sports Sciences and Coaching*, Vol **4**, No 1, pp 139-152

Campbell, L., Bobick, A., (1998) ' Recognition of Human Body Motion using Phase Space Constraints'. *5th International Conference on Computer Vision, Cambridge*, MA, USA, pp 624-630

Chai, J., Xiao, J., Hodgins, J., (2003) ' Vision Based Control of 3D Facial Animation'. *Eurographics/SIGGRAPH Symposium on Computer Animation*, San Diego, CA, pp 193-206

Cho, K., Jang, J., Hong, K., (2001) ' Adaptive Skin Colour Filter'. *The Journal of Pattern Recognition Society*, **34**, pp 1067-1073

Chollet, D., Seifert, L., LeBlanc, H., Boulesteix, L., Carter, M., (2004) ' Evaluation of Arm-Leg in Flat Breaststroke'. *International Journal of Sports Medicine*, **25**, pp 486-495

Chollet, D., Seifert, L., Boulesteix, L., Carter, M., (2006) ' Arm to Leg Coordination in Elite Butterfly Swimmers'. *International Journal of Sports Medicine*, **27**, pp 322-329

Coifman, B., Beymer, D., McLauchlan, P., Malik, J., (1998) ' A Real-time Computer Vision System for Vehicle Tracking and Traffic Surveillance'. *Transportation Research*, Part C **6**, pp 271-288

Cossor, J., Mason, B., (2001) ' Swim Start Performances at the Sydney 2000 Olympic Games'. *XIX International Symposium on Biomechanics in Sports*, San Francisco, pp 70-74

Cossor, J., Blanksby, B., Elliot, B.C., (1999) 'The Influence of Plyometric Training on the Freestyle Tumble Turn'. *Journal of Science and Medicine in Sport 2*, (**2**), pp 106-116

Cronin, J., Jones, J., Frost, D., (2007) 'The Relationship Between Dry-Land Power Measures and Tumble Turn Velocity in Elite Swimmers'. *Journal of Swimming Research*, Vol **17**, pp 17-23

Dalsa Boa Smart Camera:
http://www.dalsa.com/ipd/products/boa.aspx, viewed 11th January 2010

Davey, N., Anderson, M., James, D., (2008) ' Validation Trial of an Accelerometer-Based Sensor Platform for Swimming'. *Sports Technology*, **1**, No 4-5, pp 202-207

Dempster, W., (1955) 'Space Requirements of the Seated Operator: Geometrical, Kinematic and Mechanical Aspects of the Body with Special Reference to the Limbs'. WADC Technical Report, Wright-Patterson Air Force Base, OH, pp 55-159

Denny, M., W., (1993) 'Air and Water: The Biology and Physics of Life's Media'. Princeton University Press, New Jersey, USA. Chapter 11

Dekerle, J., Sidney, M., Hespel, J., Pelayo, P., (2002), 'Validity and Reliability of Critical Speed, Critical Stroke Rate, and Anaerobic Capacity in Relation to Front Crawl Swimming Performances'. *International Journal of Sports Medicine*, **23**, pp 93-98

Ely, M.R., Cheuvront, S.N., Roberts, W.O., Montain, S.J., (2007) 'Impact of Weather on Marathon Running Performance'. *Medicine and Science in Sports and Exercise*, **39(3),** pp 487-493

ESPRIT Consortium AMICE CIMOSA: Open System Architecture for CIM, Vol. 1, 2nd edition, 1993, pp. 233 (Springer-Verlag, Berlin)

Figuero, P., Leite, N., Barros, M., (2003) ' A Flexible Software for Tracking of Markers used in Human Motion Analysis'. *Computer Methods and Programs in Biomedicine*, **72**, pp 153-165

Fina regulations,
http://www.fina.org/project/index.php?option=com_content&task=view&id=51&Itemid=119#fr2, FR 2, viewed January 22nd 2010

Fong, D., Wong, J., Lam, A., Lam, R., Li, W., (2004) ' A Wireless Motion Sensing System using ADXL MEMS Accelerometer for Sports Science Applications'. *Proceedings of the 5th World Congress on Intelligent Control and Automation*, China, pp 5635-5640

Fritzdorf, S., Hibbs, A., Kleshnev, V., (2009) ' Analysis of Speed, Stroke Rate and Stroke Distance for World-Class Breaststroke Swimming'. *Journal of Sports Sciences*, **27(4),** pp 373-378

Fuentes, L., Velastin, S., (2006) ‘ People Tracking in Surveillance Applications’. *Image and Vision Computing*, **24**, pp 1165-1171

Galbraith, H., Scurr, J., Wood, L., Graham-Smith, P., (2008) ‘Biomechanical Comparison of the Track Start and the Modified One-Handed Track Start in Competitive Swimming: An Intervention Study’. *Journal of Applied Biomechanics*, **24**, pp 307-315

Goncalves, L., Bernardo, E., Perona, P., (1998) ‘ Reach Out and Touch Space (Motion Learning)’. *3rd IEEE International Conference on Automatic Face and Gesture Recognition*, Nora, Japan, pp 234-239

Gopalai, A., Senanayake, A., (2008) ‘ 2D Human Motion Regeneration with Stick Figure Animation using Accelerometers’. *World Academy of Science, Engineering and Technology*, **29**, pp 55-60

Haritaoglu, I., Harwood, D., Davis, L., (1998) ‘ W^4: Who? When? Where? What? A Real-time System for Detecting and Tracking People’. *International Conference on Face and Gesture Recognition*, Nara, Japan, pp 222-227

Hellard. P., Dekerle, J., Avalos, M., Caudal, N., Knopp, M., Huasswirth, C., (2008) ‘Kinematic Measures and Stroke Rate Variability in Elite Female 200m Swimmers in the Four Swimming Techniques: Athens 2004 Olympic Semi-Finalists and French National 2004 Championship Semi-Finalists’. *Journal of Sports Sciences*, **26(1)**, pp 35-46

Holger, K (2005), ‘Protocols and Architectures for Wireless Sensor Networks’, Chapter 3, pp 59 , Chichester, Wiley

Hosand, heart rate monitor, http://www.hosand.com/prodotti_scheda.asp?pid=7, viewed 22nd January 2010

Hu, C., Yu, Q., Li, Y., Ma, S., (2000) ‘ Extraction of Parametric Human Model for Posture Recognition using Generic Algorithm’. *4th IEEE International Conference on Automatic Face and Gesture Recognition*, Grenoble, France, pp 518-523

Hume P. (2005), "Visual feedback to change rowing technique", Brian Mackenzie's Successful Coaching (ISSN 1745-7513), Issue 19

IFAC-IFIP Task Force (1999). GERAM:Generalized Enterprise Reference Architecture and Methodology, Version 1.6.3, IFAC-IFIP Task Force on Architecture for Enterprise Integration

Issurin, V., Veribitsky, O., (2002) ‘ Track Start vs. Grab Start: Evidence of the Sydney Olympic Games’. *Proceedings of the IXth Symposium of Biomechanics in Swimming IX*, France, pp 21213-218

Iwase, S., Saito, H., (2004) ‘ Parallel Tracking of all Soccer Players by Integrating Detected Positions in Multiple View Images’. *Proceedings of the 17th International Conference on Pattern Recognition*, Vol **4,** Surrey, UK, pp 751-754

James, D., Davey, N., Rice, T., (2004) ‘ An Accelerometer Based Sensor Platform for Insitu Elite Athlete Performance Analysis’. *Proceedings of IEEE Sensors*, Austria, Vol **3**, pp 1373-1376

Justham, L.M., Slawson, S.E., West, A.A., Conway, P.P., Smith, J.D., Caine, M.P., Harrison, R., (2008) ‘Business Process Modelling and its use within an Elite Training Environment’. *Proceedings of the International Sports Engineering Association (ISEA) 7th International Conference*, June 3 - 6, 2008, Biarritz, France, Vol.**1**, pp 73-80

Kerrison, T, Cossor, J, Renshaw, K. (2007) Stakeholder requirements, Personal correspondence

KinetiSense, http://www.clevemed.com/products/kinetisense_overview.shtml, viewed January 2010

Kirby, R., (2009) ‘Development of a real-time performance measurement and feedback system for alpine skiers’. *Sports Technology*, **2**, No. 1–2, pp 43–52

Kong, T., Rosenfeld, A., (1996) ‘Topological Algorithms for Digitial Image Processing’. Elsevier Science B V. Printed in Netherlands. Chapter 1

Kruger, T., Wick, D., Hohmann, A., El-Bahrawi, M., Koth, A., (2002) ‘ Biomechanics of the Grab and Track Start Technique’. *Proceedings of the IXth Symposium of Biomechanics in Swimming IX*, France, pp 219-224

Landabaso, J., Xu, L., Pardas, M., (2004) ‘ Robust Tracking and Object Classification towards Automated Video Surveillance’. Lecture Notes in Computer Science, Springer.

LeBlanc, H., Seifert, L., Baudry, L., Chollet, D., (2005) ‘Arm-Leg Coordination in Flat Breaststroke: A Comparative Study Between Elite and Non-Elite Swimmers’. *International Journal of Sports Medicine*, **26**, pp 787-797

Little, J., Boyd, J., (1998) ‘ Recognizing People by their Gait: The Shape of Motion’. *Videre: Journal of Computer Vision Research*, Winter 1998, Vol **1**, No 2

Liu, Q., Hay, J., Andrews, J., (1993) ‘ Body Roll and Handpath in Freestyle Swimming: An Experimental Study’. *Journal of Applied Biomechanics*, **9**, pp 238-253

Liu, Z., Sarkar, S., (2004) ‘ Simplest Representation yet for Gait Recognition: Averaged Silhouette’. *17th International Conference on Pattern Recognition*

Luinge, H., Veltink, P., (2005) ' Measuring Orientation of Human Body Segments using Miniature Gyroscopes and Accelerometers'. *Medical and Biological Engineering and Computing*, Vol **43**, pp 273-282

Lyttle, A.D., Blanksby, B., Elliot, B.C., Lloyd, D.G., (1999) ' Investigating Kinetics in the Freestyle Flip Turn Push-Off'. *Journal of Applied Biomechanics*, **15**, pp 242-252

Lyttle, A.D., Blanksby, B., Elliot, B., Lloyd, D., (2000) ' Net Forces During Tethered Simulation of Underwater Streamlined Gliding and Kicking Techniques of the Freestyle Turn'. *Journal of Sports Sciences*, **18**, pp 801-807

Lyttle, A.D. (1998) 'The effect of depth and velocity on drag during the streamlined glide'. *The Journal of Swimming Research*, vol. **13**, issue 13, pp 15-22

Maglischo, E.W. (1993). Swimming Even Faster. Palo Alto, California: Mayfield Publishing Co.

Mason, B., Alcock, A., Fowlie, J., (2007) ' A Kinematic Analysis and Recommendations for Elite Swimmers Performing the Sprint Start'. *Proceedings of XXV International Society of Biomechanics in Sport*, Brazil, pp 192-195

McArdle, W., Katch, F., Katch, V., (2001) 'Exercise Physiology: Energy, Nutrition and Human Performance, 5th Edition'. Lippincott Williams and Wilkins, Maryland, USA
McKenna, S., Jabri, S., Duric, Z., Wechsler, H., (2000) ' Tracking Interacting People'. *4th IEEE International Conference on Automatic Face and Gesture Recognition*, pp 148-153

Millet, G., Chollet, D., Chalies, S., Chatard, J., (2002) ' Coordination in Front Crawl in Elite Triathletes and Elite Swimmers'. *International Journal of Sports Medicine*, **23**, pp 99-104

Mintel, (2009) 'Top Ten Participation Sports in the UK – UK – May 2009', Regular participants in sports, by demographics, Figure 44, http://academic.mintel.com/sinatra/oxygen_academic/search_results/show&/display/id=395152/display/id=460797#hit1, viewed 30th March 2010

Misu, T., Naemura, M., Zheng, W., Izumi, Y., Fukui, K., (2002) ' Robust Tracking of Soccer Players based on Data Fusion'. *16th International Conference on Pattern recognition*, Quebec City, Canada, Vol 1, pp 556-561

Moeslund, T., Granum, E., (2001) ' A Survey of Computer Vision Based Human Motion Capture'. *Computer Vision and Image Understanding*, **81**, pp 231-268

Molina, A., Sánchez, J., Kusiak, A., (1998) 'Handbook of life cycle engineering: concepts, models, and technologies'. Kluwer academic publishers, printed in GB, Chapter 7

Monfared, R.P, West, A.A., Harrison, R., Weston, R.H., (2002), 'An implementation of the business process modelling approach in the automotive industry'. *Proceedings Institution Mechanical Engineers*, Vol **216**, Part B: J Engineering Manufacture, pp 1413-1427

Munkelt, O., Ridder, C., Hansel, D., Hafner, W., (1998) ' A Model Driven 3D Image Interpretation System Applied to Person Detection in Video Images'. *4th International Conference on Pattern Recognition*, pp 70-73

Naemi, R., Artitan, S., Goodwill, S., Haake, S., Sanders, R., (2008) ' Development of Immediate Feedback Software for Optimising Glide Performance and Time of Initiating Post-Glide Actions'. *The Engineering of Sport 7*, Springer Paris, pp 291-300

Nakazawa, A., Kato, H., Inokuchi, S., (1998) ' Human Tracking using Distributed Vision Systems'. *IEEE International Conference on Pattern Recognition*, pp 593-596

Narayanan, P., Rander, P., Kanade, T., (1998) ' Constructing Virtual Worlds using Dense Stereo'. *6th International Conference on Computer Vision*, Bombay, India, pp 3-10

Niyogi, S., Adelson, E., (1994) ' Analyzing and Recognizing Walking Figures in XYT'. *Proceedings of Computer Vision and Pattern Recognition*, Seattle, pp 469-474

Nokia Step Counter, http://betalabs.nokia.com/betas/view/nokia-step-counter, viewed January 2010

Ohji, Y, (2006) ' MEMS Sensor Application for the Motion Analysis in Sports Science'. *ABCM Symposium Series in Mechantronics*, Vol **2**, pp 501-508

Ohji, Y., Ichikawa, H., Homma, M., Miyaji, C., (2003) ' Stroke Phase Discrimination in Breaststroke Swimming using a Tri-Axial Acceleration Device'. *Sports Engineering*, **6**, pp 113-123

Omega OSB11 Block, http://www.swisstiming.com/Detail.559.0.html?&tx_stproducts_pi1%5Buid%5D=29&tx_stproducts_pi1%5BcurrentSport%5D=1&tx_stproducts_pi1%5BcurrentType%5D=1&cHash=a56523a707, viewed 21st January 2010

Omron, http://www.omron-healthcare.com/sitepreview.php?SiteID=275, viewed January 2010

Payton, C., Bartlett, R., Baltzopoulos, Coombs, R., (1999) 'Upper Extremity Kinematics and Body Roll during preferred-side Breathing and Breath-Holding Front Crawl Swimming'. *Journal of Sports Sciences*, **17**, pp 689-696

Pearson, C.T., McElroy, G.K., Blitvich, J.D., Subic, A. and Blanksby, B.A. (1998) 'A Comparison of the Swimming Start using Traditional and Modified Starting Blocks.' *Journal of Human Movement Studies*, **34**, 49 - 66

Pers, J., Kovacic, S., (2000) ' A System for Tracking Players in Sports Games by Computer Vision'. *Electrotechnical Review - Journal for Electrical Engineering and Computer Science*, **67(5),** pp 281-288

Polana, R., Nelson, R., (1994) ' Low Level Recognition of Human Motion (Or How to get your Man without finding his Body Parts)'. *IEEE Workshop on Motion of Non-Rigid and Articulated Objects*, Austin, TX, USA, pp 77-82

Potdevin, F., Bril, B., Sidney, M., Pelayo, P., (2006) ' Stroke Frequency and Arm Coordination in Front Crawl Swimming'. *International Journal of Sports Medicine*, **27**, pp 193-198

Prins, J., Patz, A., (2006) ' The Influence of Tuck Index, Depth of Foot-Plant, and Wall Contact Time on the Velocity of Push-Off in the Freestyle Flip Turn'. *Xth International Symposium on Biomechanics and Medicine in Swimming*, pp 82-85

Rahimifard, A., Weston, R., (2007) 'The enhanced use of enterprise and simulation modelling techniques to support factory changeability'. *International Journal of Computer Integrated Manufacturing*, Vol. **20**, No. 4, pp 307 – 328

Rigoll, G., Eickeler, S., Muller, S., (2000) ' Person Tracking in Real World Scenarios using Statistical Methods'. *4th IEEE International Conference on Automatic Face and gesture Recognition*, pp 342-347

Rodriguez, D., Brown, A., Troped, P., (2005) ' Portable Global Positioning units to Complement Accelerometry-Based Physical Activity Monitors'. *Medicine and Science in Sports and Exercise*, Supplement pp 572-581

Rohr, K., (1997) ' Human Movement Analysis Based on Explicit Motion Models'. Motion Based Recognition, M. Shah amd R.Jain (Eds), Kluwer Academic Publishers Dordrecht, Boston, pp 171-198

Ruschel, C., Araujo, L., Pereira, S., Roesler, H., (2007) ' Kinematical Analysis of the Swimming start: Block, Flight and Underwater Phases'. *Proceedings of XXV International Society of Biomechanics in Sport*, Brazil, pp 385-388

Sanders, R.H., (1995) 'Can skilled performers readily change technique? An example, conventional to wave action breaststroke'. *Human Movement Science*, **14(6)**, pp 665-679

Saunders, P. U., Telford, R. D. , Pyne, D. B., Cunningham, R. B., Gore, C. J. , Hahn, A. G., Hawley, J. A., (2004) 'Improved running economy in elite runners after 20 days of simulated moderate-altitude exposure'. *Journal of Applied Physiology*, **96**, pp 931–937

Schiele, B., (2006) ' Model Free Tracking of Cars and People Based on Color Regions'. *Image and Vision Computing*, **24**, pp 1172-1178
Seifert, L., Vantorre, J., Chollet, D., (2007) ' Biomechanical Analysis of the Breaststroke Start'*. International Journal of Sports Medicine*, **28**, pp 970-976

Seifert, L., Delingnieres, D., Boulesteix, L., Chollet, D., (2007) ' Effect of Expertise on Butterfly Stroke Coordination'. *Journal of Sports Sciences*, **25(2)**, pp 131-141

Smith, D., Norris, S., Hogg, J., (2002) ' Performance Evaluation of Swimmers'. *Sports Medicine*, **32(9),** pp 539-554

Speedo LZR suit, http://www.speedo.co.uk/en_uk/aqualab_technologies/aqualab/fastskin_lzr_racer/index.html, viewed 21st January 2010

Takagi, H., Sugimoto, S., Nishijima, N., Wilson, B., (2004) 'Differences in Stroke Phases, Arm-Leg Coordination and Velocity Fluctuation due to Event, Gender and Performance Level in Breaststroke'. *Sports Biomechanics*, **3: 1**, pp 15-27

Takeda, T., Ichikawa, H., Takagi, H., Tsubakimoto, S., (2009) ' Do Differences in Initial Speed Persist to the Stroke Phase in Front-Crawl Swimming?'. *Journal of Sports Sciences*, **27(13),** pp 1449-1454

Thompson, K., MacLaren, D., Lees, A., Atkinson, G., (2004) ' The Effects of Changing Pace on Metabolism and Stroke Characteristics during High –Speed Breaststroke Swimming'. *Journal of Sports Sciences*, **22**, pp 149-157

Toumaz Sensium, http://www.toumaz.com/, viewed January 2010

Toubekis, A., Peyrebrune, M., Lakomy, H., Nevill, M., (2008) ' Effects of Active and Passive Recovery on Performance During Repeated Sprint Swimming'. *Journal of Sports Sciences*, Vol **26**, 14, pp 1497-1505

Tourny-Chollet, C., Chollet, D., Hogie, S., Papparodopolous, C., (2002) ' Kinematic Analysis of Butterfly Turns of International and National Swimmers'. *Journal of Sports Sciences*, **20**, pp 383-390

Trewin, C., Hopkins, W., Pyne, D., (2004) 'Relationship Between World-Ranking and Olympic Performance of Swimmers'. *Journal of Sports Sciences*, **22**, pp 339-345

Tzetzis, G., et al., (1999) 'The effect of modeling and verbal feedback on skill learning'. *Journal of Human Movement Studies*, **36(3),** pp 137-151

Vasa ergometer, http://www.vasatrainer.com/, viewed 21st January 2010

Vezhnevets, V., Sazonov, V., Andreeva, A., (2007) ' A Survey on Pixel-Based Skin Color Detection Techniques'. Pattern Recognition, Vol 40, Issue 3, pp 1106-1122

Vezos, N., Gourgoulis, V., Aggeloussis, N., Kasimatis, P., Christoforidis, C., Mavromatis, G., (2007) ' Underwater Stroke Kinematics during Breathing and Breath-Holding Front Crawl Swimming'. Journal of Sports Science and Medicine, 6, pp 58-62

Weba ergometer, http://www.weba-sport.com/weba/swim_ergo.html, viewed 21st January 2010

Welcher, R., Hinrichs, R., George, T., (2008) ' Front of Rear-Weighted Track Start or Grab Start: Which is the Best for Female Swimmers'. Sports Biomechanics, 7(1), pp 100-113

Welk, G., Schaben, J., Morrow, J., (2004) ' Reliability of Accelerometry-Based Activity Monitors: A Generalizability Study'. Medicine and Science in Sports and Exercise, pp 1637-1645

Welk, G., (2005) ' Principles of Design and Analyses for the Calibration of Accelerometry Based Activity Monitors'. *Medicine and Science in Sports and Exercise*, Supplement pp 501-511

West, A, A., Smith J, D., Monfared, R, P. & Harrison, R. (Accepted) 'Formalised requirements documentation of a novel exercise system using enterprise modelling concepts', *Proceedings of Asia-Pacific Congress on Sports Technology*, Singapore, pp 93-98

Williams, T., Li, H., (1998) 'PERA and GERAM—Enterprise reference architectures in enterprise integration'. *Proc. IFIP Information Infrastructure Systems Manufacturing II*, Forth Worth, TX, pp 3–30

Wixted, A., Thiel, D., Hahn, A., Gore, C., Pyne, D., James, D., (2007) ' Measurement of Energy Expenditure in Elite Athletes using MEMS Based Triaxial Accelerometers'. *IEEE Sensors Journal*, Vol **7**, No 4, pp 481-488

Wren, C., Clarkson, B., Pentland, A., (2000) ' Understanding Purposeful Human Motion'. *4th IEEE International Conference on Automatic Face and Gesture Recognition*, pp 378-383

Yamamoto, M., Ohta, Y., Yamagiwa, T., Yagishita, K., Yamanaka, H., Ohkubo, N., (2000) ' Human Action Tracking Guided by Key Frames'. *4th IEEE International Conference on Automatic Face and Gesture Recognition*, pp 354-361

Yang, G., (2006) 'Body Sensor Networks'. Springer-Verlag, London, pp 146, 375, 404

Yoo, J., Nixon, M., (2003) 'Markerless Human Gait Analysis via Image Sequences'. *Proceedings XIXth Congress of the International Society of Biomechanics*, Dunedin, New Zealand

Zelm, M., Vernadat, F.B. , Kosanke, K., (1995) 'The CIMOSA business modelling process'. *Computers in Industry*, **21(2)**, Special Issue: Validation of CIMOSA.