



**Quantification of performance analysis factors in front
crawl swimming using micro electronics: A data-rich
system for swimming**

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A thesis submitted in partial fulfillment of the requirements of Bournemouth
University for the degree of Doctor of Philosophy

September 2014

Bournemouth University

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Abstract

The aim of this study is to increase the depth of data available to swimming coaches in order to allow them to make more informed coaching decisions for their athletes in front crawl swimming. A coach's job is to assist with various factors of an individual athlete to allow them to perform at an optimum level. The demands of the swimming coach require objective data on the swim performance in order to offer efficient solutions (Burkett and Mellifont, 2008). The main tools available to a coach are their observation and perceptions, however it is known that these used alone can often result in poor judgment. Technological progress has allowed video cameras to become an established technology for swim coaching and more recently when combined with software, for quantitative measurement of changes in technique. This has allowed assessment of swimming technique to be included in the more general discipline of sports performance analysis.

Within swimming, coaches tend to observe from the pool edge, limiting vision of technique, but some employ underwater cameras to combat this limitation. Video cameras are a reliable and established technology for the measurement of kinematic parameters in sport, however, accelerometers are increasingly being employed due to their ease of use, performance, and comparatively low cost. Previous accelerometer based studies in swimming have tended to focus on easily observable factors such as stroke count, stroke rate and lap times.

To create a coaching focused system, a solution to the problem of synchronising multiple accelerometers was developed using a maxima detection method. Results demonstrated the effectiveness of the method with 52 of 54 recorded data sets showing no time lag error and two tests showing an error of 0.04s. Inter-instrument and instrument-video correlations are all greater than $r = .90$ ($p < .01$), with inter-instrument precision (Root Mean Square Error; RMSE) $\approx .1\text{ms}^{-2}$, demonstrating the efficacy of the technique.

To ensure the design was in line with coaches' expectations and with the ASA coaching guidelines, interviews were conducted with four ASA swim coaches. Results from this process identified the factors deemed important: *lap time, velocity, stroke count, stroke rate, distance per stroke, body roll angle and the temporal aspects of the phases of the stroke*. These factors generally agreed with the swimming literature but extended upon the general accelerometer system literature. Methods to measure these factors were then designed and recorded from swimmers.

The data recorded from the multi-channel system was processed using software to extract and calculate temporal maxima and minima from the signal to calculate the factors deemed important to the coach. These factors were compared to video derived data to determine the validity and reliability of the system, all results were valid and reliable. From these validated factors additional factors were calculated, including, distance per stroke and index of coordination and the symmetry of these factors.

The system was used to generate individual profiles for 12 front crawl swimmers. The system produced eight full profiles with no issues. Four profiles required individualisation in the processing algorithm for the phases of the stroke. This was found to be due to the way in which these particular swimmers varied in the way they fatigued.

The outputs from previous systems have tended to be either too complicated for a coach to understand and interpret e.g. raw data (Ohgi et al. 2000), or quite basic in terms of output e.g. stroke rate and counts (Le Sage et al. 2011). This study has added to the current literature by developing a system capable of calculating and displaying a breadth of factors to a coach.

The creation of this system has also created a biomechanical research tool for swimming, but the process and principles can be applied to other sports. The use of accelerometers was also shown to be particularly useful at recording temporal activities within sports activities. Using PC based processing allows for quick turnaround times in the processing of detailed results of performance.

There has been substantial development of scientific knowledge in swimming, however, the exchange of knowledge between sport science and coaches still requires development (Reade et al. 2008; Williams and Kendall 2007). This system has started to help bridge the gap between science and coaching, however there is still substantial work needed. This includes a better understanding of the types of data needed, how these can be displayed and level of detail required by the coach to allow them to enact meaningful coaching programmes for their athletes.

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Authors Declaration

Parts of this thesis have been published in the following papers:

Callaway, A., Cobb, J. E., & Jones, I. (2009). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *International Journal of Sports Science and Coaching*, 4, 139-153.

Callaway, A., & Cobb, J. E. (2012). Linear acceleration measurement utilising inter-instrument synchronisation: A comparison between accelerometers and motion based tracking approaches. *Measurement in Physical Education and Exercise Science*, 16, 151-163

Except where indicated, I certify that I am the sole author of the thesis submitted today entitled:

Quantification of performance analysis factors in front crawl swimming using micro electronics: A data-rich system for swimming

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Andrew Callaway

September 2014

Acknowledgements

Upon completion of this thesis, I am pleased to take this opportunity to acknowledge the following people, without whose help, collaboration and support this thesis would not have been possible.

First of all I would like to express my gratitude to my supervisors Dr Jon Cobb and Dr Ian Jones for their continued guidance and support.

I would also like to thank all of the swimmers and coaches who assisted with the development of the work, without whom this just would not have been possible.

A big thank you to Shelley Broomfield for helping develop and challenge my knowledge of performance analysis. From this we developed a great unit to run at the University which is growing in strength each year.

But most of all to my family, and my better half Megan, for their unwavering support, patience and love. Thank you!

Chapter 1 - Introduction

Parts of this chapter have been published in the following papers:

Callaway, A., Cobb, J. E., & Jones, I. (2009). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *International Journal of Sports Science and Coaching*, 4, 139-153.

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1. Introduction

A key responsibility of sports' coaches is to optimise the coaching environment for their athletes to allow them to improve (Knudson 2007). Coaching can take one of two roles as Lyle (1999) discusses. One is focused on increasing/maintaining participation; the second is concerned with maximising performance in sport. With sports performance being at the heart of the coaching process (Coleman 1998), the process of trying to improve performance is often ongoing (Hay 1993), particularly with the need to perform consistently within sport now being a regular expectation of individuals and teams, leading to a more pressurized environment (Meyers 2006).

The primary tool available to a coach are their observation and perceptions (Coleman 1998; Hynes et al. 2013) which are qualitative by nature. The need for feedback on a technique is vitally important as minor improvements could provide the difference between a win and a loss. Feedback is considered one of the most important variables affecting learning and future performances (Maslovat and Franks 2008). Feedback can include all information which results from an action or response (McMorris and Hale 2006) and it needs to be delivered to the athlete at the correct time, which is a key factor to improving performance (Harding and James 2010). Maslovat and Franks (2008) state that feeding information back during an activity can divert the athlete's attention by not allowing them to process and evaluate the intrinsic feedback. However, feedback immediately after the skill or performance may also not always produce the best results (Maslovat and Franks 2008). This view is also shared by McMorris and Hale (2006) who found that although the delay between a performance and providing feedback had little effect; the feedback should still be delivered before another activity to avoid impeding the learning process. It was found, that the time between feedback and the next performance was more important, whereas activity between feedback and the next performance could also impede learning. It is also suggested that if the feedback to next performance time is too short, then there is insufficient time for the athlete to assimilate an appropriate intrinsic response. Based on the coaches observations, they will generate different training programmes or implement technique changes based on these observations of a performance, which will always depend on the specific

circumstances at the time, and will involve either a qualitative or quantitative observation depending on location and equipment used. The effectiveness of any required changes will be determined by how a coach implements such changes. Rushall (1985) and Cross (1999) describe several principles that are necessary for good coaching and development of these interventions. One of these, generally unutilized by many coaches (Cross 1999; Rushall 1985), is the individualization of the intervention and the coaching process to that individual athlete, in order to maximise their output. Swimmers can have "highly individual" combinations of stroke length and stroke rate (Toussaint et al. 2006) further pointing towards the need for coaches to coach the individual rather than focus on changes or improvement programmes for groups of swimmers (Cross 1999; Rushall 1985).

Using their observational skills, coaches in general could be looking for a gross action, for example, a corner kick in football, or finer details to develop a part of a technique, for example, the specific foot placement of the plant foot for a corner kick. However, studies by Franks and Miller (1986) and Laird and Waters (2008) which respectively show that Physical Education students can recall around 42% of sporting actions in a football match, and experienced coaches can recall around 60% of a football match; prove that observation alone cannot be wholly beneficial. Without objective knowledge of performance and results (Maslovat and Franks 2008), leading to the evaluation and assessment of various sport-specific performance measures (Anderson et al. 2006; Smith et al. 2002), the athlete, coach and analyst cannot correctly create or define appropriate techniques for improvement or revised training programmes in response to the athlete's required technique change or training programme.

One method that a coach can use to assist with observation error is video analysis which has the ability, when correctly interpreted, to produce objective performance information (Lyons 2005). Video recording information during sporting events is essential to developing our understanding of performance and can also provide a permanent objective measure. In an event, practice or competition, coaches can use video for either immediate or post event analysis (Bartlett 1997; Coleman 1998; Hay

1993). This analysis then allows the potential for qualitative and quantitative biomechanical analysis, including the notation of technique variances in different situations to track the progress of an athlete in various situations. This does require a coach to have some biomechanical knowledge, but as noted by Coleman (1998, p.131),

"...an understanding and awareness of the application of biomechanical principles to sports performance is an important part of the coach's technical repertoire".

Sport science in general has been viewed as inaccessible, too technical or not applicable by many coaches (Meyers 2006) and video analysis can often be very time consuming for the coach (Le Sage et al. 2011), which problematises Coleman's assertion. Moreover, biomechanical measurement tools are generally expensive, and as with the cameras, the processes involved in obtaining data from them are time consuming (Lees 1999). This is further supported by Bishop (2008, p.253) who states that the *"translation of sport science research to practice is poor"*.

Performance analysis principles, in part, can assist in resolving the challenge. Performance Analysis is an amalgamation of multiple disciplines within sports science with the direct aim of collecting and reporting objective information for coaches. Starting in the late 1990's with the initiation of the Performance Analysis Steering Group (PASG) by the British Olympic Association, the disciplines of Notational Analysis and Biomechanics were brought together (Bartlett 2001, 2012). This was later expanded to include Motor Learning and Sports Technology specialists (Bartlett 2001, 2012). The purpose of performance analysis, therefore, is to provide objective information to help feedback towards the coaching process (Brackenridge and Alderson 1985) where feedback systems for sport can improve the quality of training (Ghasemzadeh et al. 2009). Bartlett (2012) demonstrates how Performance Analysis fits into this spectrum of movement based analysis and sport biomechanics (Figure 1).

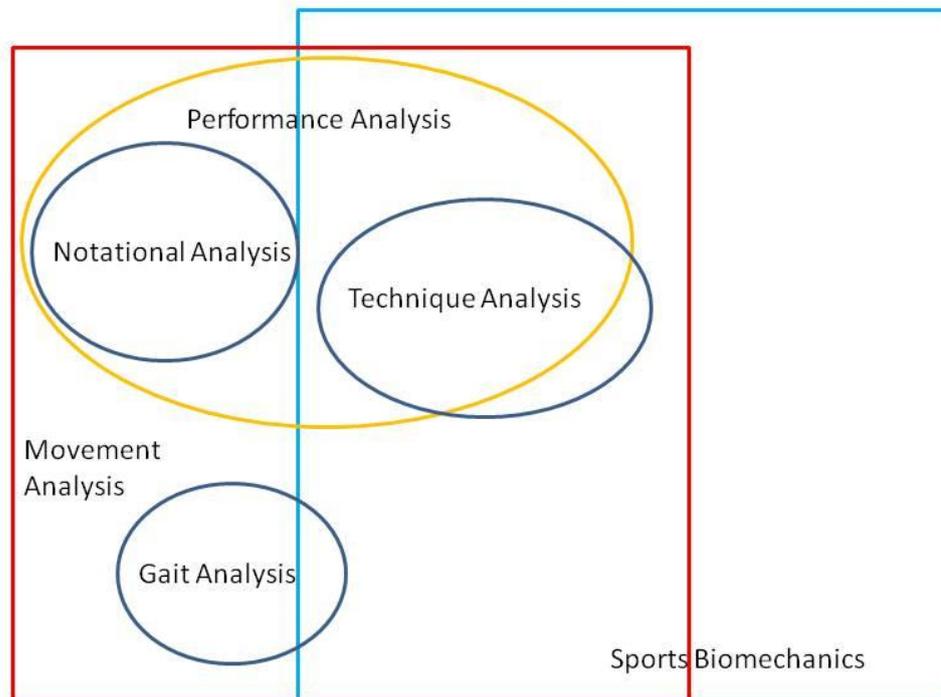


Figure 1: Schematic representation of the union of performance analysis, movement analysis and sports biomechanics. Based on work by Bartlett (2012)

Burkett and Mellifont (2008, p.110) state that for,

"...the demands of the swimming coach and athlete, objective data on the swim performance is required"

yet the technical aspects of the front crawl stroke occur under water, for which the coaches would primarily attempt to use their visual observation skills. The coach and sports scientist now need to be open to new ideas to help develop performance (Burkett and Mellifont 2008) and require the ability to coordinate sport science support so that it is integrated into the coaching process to facilitate performance enhancement (Wright et al. 2012). One method of achieving this is through the use of sports technology, Hughes and Bartlett (2008, p.9) state that,

"further development of IT- and AI-based coaching tools by performance analysts is a high priority"

and with the advances and miniturisation of sensors, these can now often be unobtrusively attached to the body (Bonato 2005) which could record data directly and be processed in '*real time*' to present information to the coach.

Wearable sensor technologies hold the key to unlocking novel performance assessment (Harding and James 2010) and there is interest in the development of sports technology (Baca et al. 2009). This technology plays an increasing role, particularly in elite performances where equipment design changes have had significant impact on records (Davison and Williams 2009; Haake 2009).

This also coincides with the assessment of performances now focusing on shifting from the laboratory setting into the field (Burkett and Mellifont 2008; Harding and James 2010; Lyons 2005). In swimming, where there is a need for ease of testing, and where laboratory settings are hard to replicate at times (Anderson et al. 2006), the need for developing field based assessment methods for the coach is paramount.

1.1 Thesis Research Rationale

The literature has identified that objective data on swimmers' technique is required for the coach to better develop their athletes (Coleman, 1998; Burkett and Mellifont, 2008). The observational skills used by coaches can be unreliable (Franks and Miller, 1986; Laird and Waters, 2008; Maslovat and Franks 2008). Video technology has aided with this using specialised software to derive kinematic data (Mayagotia, Nene, and Veltink, 2002). For a coach however, this video digitisation can often be too time consuming to warrant its use (Le Sage et al. 2011; Stamm et al. 2009).

A solution to this problem is to use an alternative method to capture performance data, based on acceleration data captured directly from the swimmer. Accelerometer based data loggers are gaining widespread use in many areas of sports science ranging from personal activity measurement to weightlifting performance (Sato,

Smith, and Sands, 2009; Silva, Mota, Esliger, and Welk, 2010). Placing an accelerometer data logger on each limb allows the measurement of multiple factors directly from the athlete. As noted by Coleman (1998), swimming requires a technique focus, so analysing various components of technique which are created using various limbs of the swimmer will therefore play a key role in identification of weaknesses (Mason and Portus 2005) offering a solution to the time requirements of video analysis.

Current accelerometer based systems for swimming are, however, lacking in the depth of factors in which they present, for example current studies focus on the limited areas of stroke rate, stroke count and lap time (Davey et al. 2008; Le Sage et al. 2011; Ohgi 2002), with one study extending this to include body roll angles (Bächlin and Tröster 2012). These systems allude to factors such as arm coordination (IdC) and the symmetry of phases within the stroke, which Chollet et al. (2000b) and Seifert et al. (2005b) have deemed important.

The current accelerometer systems are directed towards the swimmer for feedback, however the details presented generally surround raw acceleration (Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002) and basic factors (stroke count, rate and lap times), but should be directed to the coach to be able to make correct, individualised, long term and informed decisions to the training programmes (Cross 1999; Rushall 1985). The translation of information from sports science to practice has generally been poor (Bishop, 2008) demonstrating a lack of appropriate feedback methods used from science to coaches. This project will therefore develop an accelerometer based system which will extend the amount of data which can be recorded and presented, producing an output which is useable by a coach to inform training programmes.

1.2 Thesis Aim

This thesis has a primary aim which is to:

Increase the level of data available to swimming coaches through the use of sports technology

To complete this aim, multiple objectives were outlined,

- To design a system that records performance factors of importance to the coach
- To develop a method to synchronise multiple non-wireless accelerometer based data-loggers
- To determine whether an on-the-body sensor system can record stroke characteristics of a swimmers stroke in a valid and reliable manner
- to present the recorded information in a way that coaches can then use the data
- to demonstrate the future potential of the system for future biomechanical research, demonstrating a potential dual use

1.3 Thesis Outline

This thesis is presented in two phases. Chapter two provides a literature review of the biomechanics of swimming and introduces Performance Analysis and Sports Technology and outlines involvement in coaching.

Chapter three discusses the method for the current system design. This starts with results of interviews with coaches identifying the factors they record in swimming, which were used to inform the system design. This chapter includes the discussion of key issues in design and analysis, and also covers the presentation of the hardware and set up to allow cameras as a validation system including data collection protocols and setup.

Chapter four presents the results of the system. This starts with the validation of a synchronisation method for devices. The validation and reliability of the swimming

system is then shown. The last part of the chapter demonstrates a selection of individual swimmers' results to highlight the use of the output.

Chapter five discusses the results of the system through the various stages in reference to current literature. The end of this chapter concludes with limitation of this work and presents possible future directions.

Chapter 2 - Review of Literature

Parts of this chapter have been published in the following papers:

Callaway, A., Cobb, J. E., & Jones, I. (2009). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *International Journal of Sports Science and Coaching*, 4, 139-153.

Callaway, A., & Cobb, J. E. (2012). Linear acceleration measurement utilising inter-instrument synchronisation: A comparison between accelerometers and motion based tracking approaches. *Measurement in Physical Education and Exercise Science*, 16, 151-163

2 Performance Analysis in Swimming

Within the coaching environment, there are many assessment techniques and types of data available to the coach; from physiological assessment (and other motor control) through to psychological assessment. As shown (Figure 2) by Hughes (2004a, 2004b), given the different avenues that data can come from, the coach needs to understand and interpret the data from each source. In addition the data should be interpretable by other scientists due to the potential implications this could have on their suggestions to the coach.

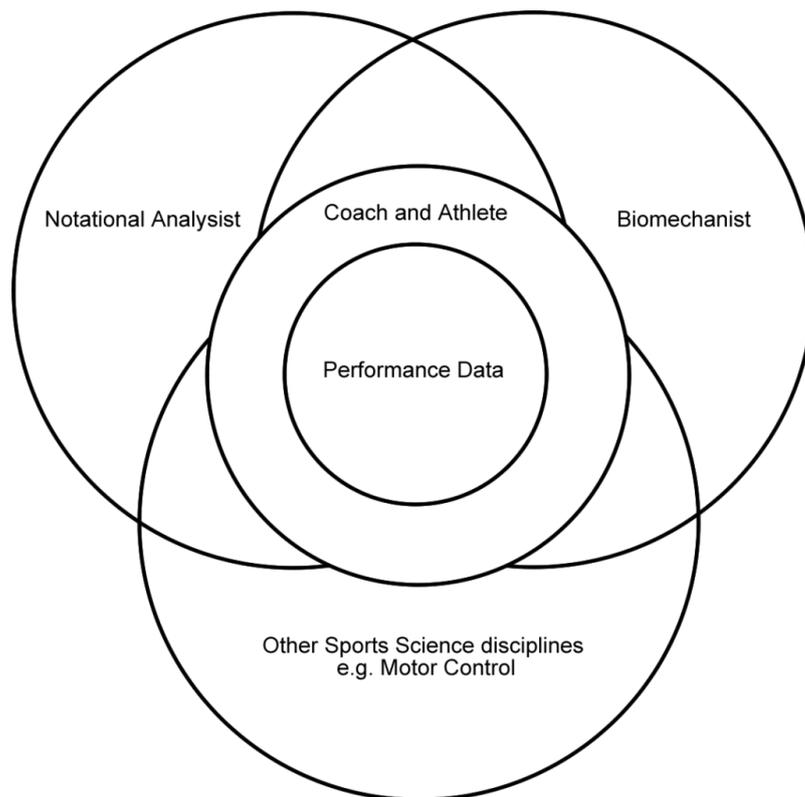


Figure 2: A digital systems diagram showing the interactions of the data collected with various other team members. Developed from work by Hughes (2004a, 2004b)

Performance analysis is the investigation of sporting performance, with the aim being to develop an understanding of sports that can inform decision-making, enhance performance and inform the coaching process, through the means of objective data collection and feedback (Hodges and Franks 2002; Hughes 2004b; Hughes and Bartlett 2008; O'Donoghue 2009). This is used by both biomechanists

and notational analysts who are concerned with the improvement of sports performance (Hughes and Bartlett 2002). Whilst biomechanics and notational analysis have similar goals they also differ; biomechanics looks at the fine detail of sports techniques based around mechanics and anatomy, where notational analysis studies the gross movements and strategy, typically of team sports (Hughes and Bartlett 2008). Each method, however, uses deterministic models which are constructed around performance indicators and their relationships with each other (Hughes and Bartlett 2008). A performance indicator is a selection, or combination of variables that aim to define some (or all) aspects of a performance (Hughes and Bartlett 2002). A deterministic model (Figure 3) starts with the goal of the sport; so for swimming, the fastest time wins and so time is therefore at the top of the model. At each subsequent level are the factors which make up the preceding level, as shown in Figure 3.

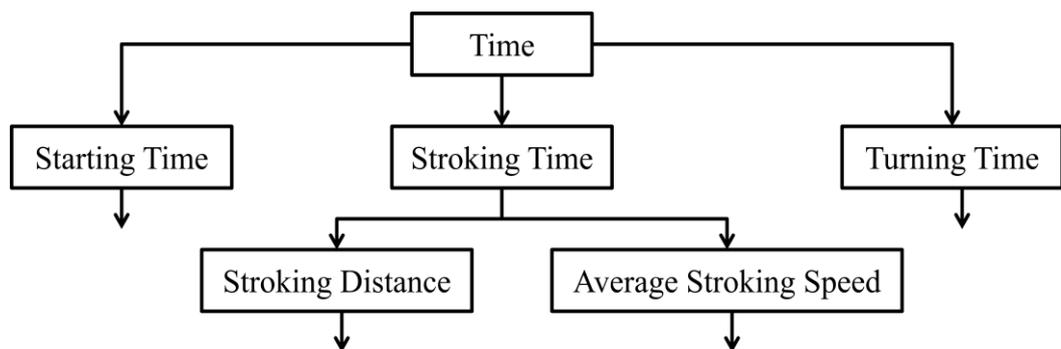


Figure 3: An example of the start of a deterministic model, based on work by Hay (1993)

Using factors highlighted by Hay (1993), scientists and researchers have measured swimmers to establish what top level swimmers do so that their techniques can be understood by coaches. They use various techniques including biomechanical, notational and technique analysis. Bartlett (2012) demonstrates where performance analysis fits into this spectrum of movement based analysis with its overlap into

many areas of this spectrum (Figure 4).

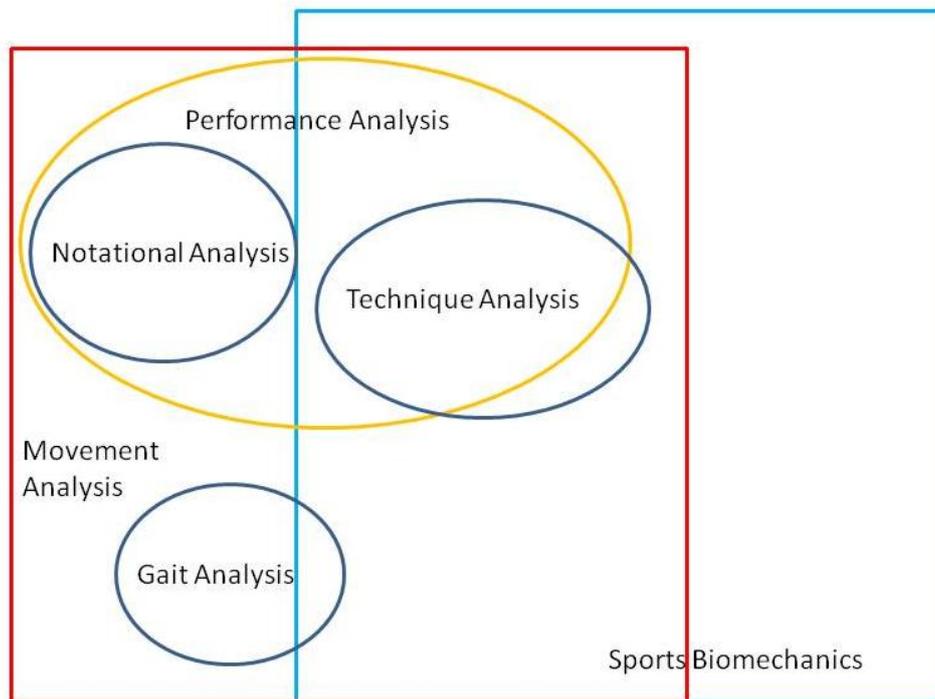


Figure 4: Schematic representation of the performance analysis and sports biomechanics overlaps. Based on work by Bartlett (2012)

This chapter reviews general background and relevant theory of front crawl swimming and identifies performance factors of swimming. Front crawl swimming was chosen because it is the fastest of all the stroking techniques used in competition (Seifert et al. 2005a). Aiding a coach in understanding these fast underwater phases will allow them to develop swimmers' performance. Also, by choosing an asymmetric swimming style the development of the system is challenged further than by developing a system to measure a symmetrical stroke (breaststroke and butterfly). An asymmetric swimming stroke such as front crawl tests the creation of the system due to the complex nature of the coordination between various body segments to create forward movement patterns. Designing with this in mind will allow future developments to add in other strokes for analysis.

The first section describes Performance analysis and its use in front crawl swimming. The second section describes front crawl technique with the

identification of some critical factors identified in the literature. The third section then looks at whether these factors have helped coaches.

2.1 Front Crawl - An Introduction

Previous work in Biomechanics has tended to break into two sections, focusing on Kinematic and Kinetic factors of the stroke, which also forms the structure for the review (Barbosa et al. 2011; Toussaint and Truijens 2005), this work will focus on the Kinematic properties of the stroke.

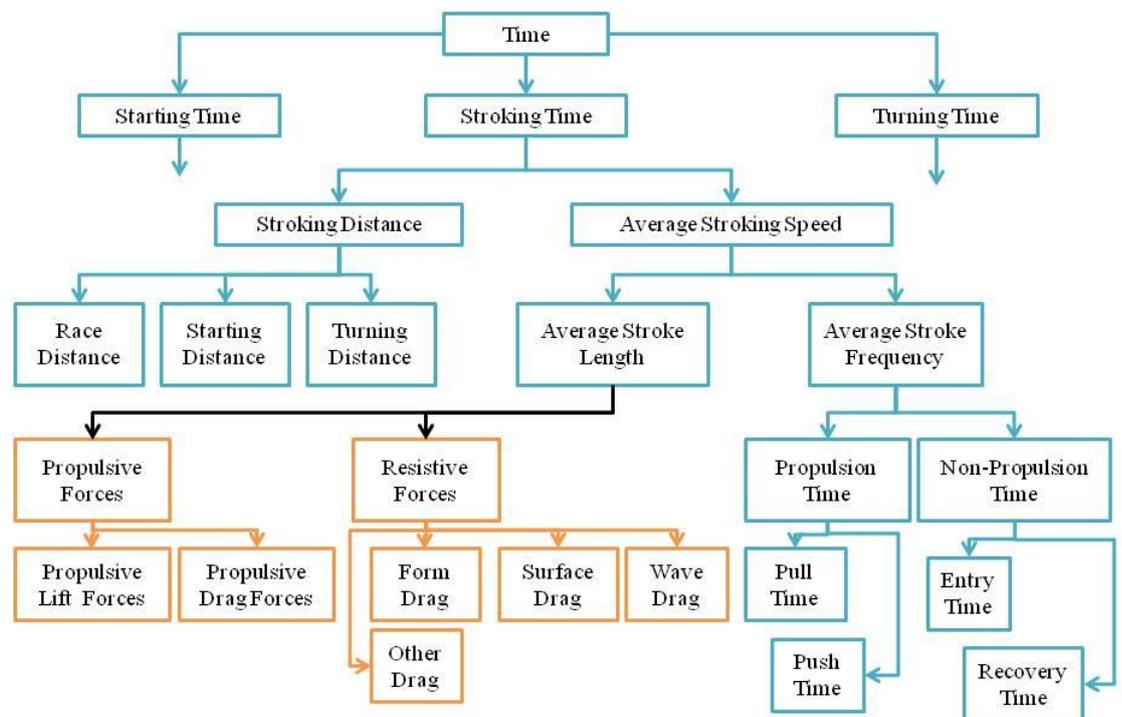


Figure 5: An example of the start of a deterministic model, adapted from work by Hay (1993). Blue represents Kinematic elements. Orange represents Kinetics.

Using factors highlighted (Figure 5) by Hay (1993), scientists and researchers have measured swimmers to establish what swimmers 'do' during the stroke to make them faster.

The arms contribute more to propulsion than the legs in front crawl swimming, with reports of up to 90%, but generally agreed at 85% (Counsilman 1968; Deschodt et al. 1999; Di Prampero et al. 1974; Hollander et al. 1988; Holmér 1978; Maglischo 2003; Toussaint 1990b; Zamparo et al. 2008). Counsilman (1968) extended this stating that;

“the arm stroke in the crawl is the main source of propulsion and, in the case of most swimmers, the only source of propulsion”.

In addition to this, the swimmer's arm motions, and the coordination of them, are of importance in relation to performance (Seifert et al. 2005a). Developing, and refining the large contributions offered by the upper body element of the stroke could aid in the development of the swimmer. Better understanding these underwater processes will be of benefit to the coach to offer better training and technique improvements. This review will consider the upper body mechanics of the front crawl stroke following the factors shown in Figure 3. This also covers the methods used to measure these factors. The review and study will progress to a consideration of the electronic measurement studies conducted in swimming.

2.1.1 Front Crawl Kinematics

The competitive swimmers objective is to swim the full distance in as short a time as possible where the time will consist of the time starting, time stroking and time turning (Hay 1993) EQ[1].

$$t_{TOTAL} = t_{STARTING} + t_{STROKING} + t_{TURNING}$$

[1]

During any event the swimmer will spend most of their time in the stroking phase. For this reason, although start and turn are important, it is the stroking phase which is the most critical movement of the swimming performance (Barbosa et al. 2011). Stroking time is determined by two factors: the distance of the race and the average speed of the swimmer (Hay 1993). The average speed (average velocity) is

calculated as the product of Average Stroke Length (\overline{SL}) and Average Stroke Frequency (\overline{SF}) EQ[2,3,4].

$$\bar{v} = \overline{SL} \cdot \overline{SF}$$

[2]

Where:

$$\overline{SL} = \frac{\text{Distance stroked}}{\text{number of complete arm cycles}}$$

[3]

And,

$$\overline{SF} = \frac{\text{number of complete arm cycles}}{\text{time spent stroking}}$$

[4]

Stroke length and stroke frequency have been the focus of much research due to their importance in producing maximal speed (Toussaint et al. 2006). Stroke rate and length are independent of each other (Hay 1993). Whilst stroke length has been identified as the “*single best predictor of swimming performance*” (Costill et al. 1985). Craig et al. (1985) compared finalists in the 1976 and 1984 Olympic games and showed that there were improvements in performance due to stroke length increase. This has been further verified by Chollet et al. (1997) who state that skilled swimmers are better able to maintain stroke length over the course of a race. The swimmer with the fastest velocity will win the race (Barbosa et al., 2011) and Arellano et al. (1994) found that there was no relationship with the stroke frequency and velocity, but there were significant results for stroke length (Table 1).

	Male	Female	Male	Female
	SF vs V		SL vs V	
50m	-0.22	-0.04	0.63*	0.42*
100m	-0.06	-0.22	0.59*	0.61*
200m	-0.03	-0.27	0.53*	0.58*

Table 1: Relationships between SF & V and SL & V. (* = $p < 0.05$) (Arellano et al, 1994)

As stroke length increases, swimmers will tend to find they need longer to complete the stroke, leading to a decrease in stroke rate (Hay 1993; Sanders, 2002). This has been confirmed by Arellano et al. (1994) who found strong negative relationships between stroke length and stroke frequency (Table 2).

	Male	Female
50m	-0.89	-0.92
100m	-0.83	-0.90
200m	-0.86	-0.94

Table 2: Correlations between Stroke Length and Stroke Frequency (all results $p < 0.05$) (Arellano et al, 1994)

There are also alternative methods to these equations shown by Fritzdorf et al. (2009) EQ[5].

$$\bar{v} = \bar{SL} \cdot \frac{\bar{SF}}{60}$$

[5]

Where this can also be rewritten for average distance per stroke (SL), EQ[6].

$$\begin{aligned}\overline{SL} &= V \cdot T \\ &= 60 \cdot \frac{\bar{v}}{SF}\end{aligned}$$

[6]

The product of Speed and Stroke Length (SL) have also been used to create a Stroke Index (SI) as a method of measuring stroke efficiency (Fritzdorf et al. 2009) EQ[7].

$$\begin{aligned}SI &= \bar{v} \cdot \overline{SL} \\ &= 60 \cdot \frac{v^2}{SF} \\ &= \overline{SL}^2 \cdot \frac{SF}{60}\end{aligned}$$

[7]

Where SI is then expressed as $\text{m}^2 \cdot \text{s}^{-1}$. Fritzdorf et al. (2009) has stated that the SI has limited practical application as with an increase in the stroke rate the output will always decrease, adding support to similar points made by Hay (1993). Yet, with this statement from Fritzdorf et al. (2009) there have been studies which show that elite level swimmers have a higher Stroke Index, suggesting it could be a useful performance indicator (Jesus et al. 2011; Sánchez and Arellano 2002).

2.1.1.1 Arm Path

Front crawl stroke mechanics have long been debated. Counsilman (1977) initially found that a significant number of top level swimmers which he videoed and

observed, employed an ‘inverted question mark’ stroke as part of their natural technique Figure 6.



Figure 6: Pulling pattern relative to body from underneath. Reproduced with permission (Counsilman 1981).

Subsequent studies led to the proposal of a fundamental relationship between forward motion and the curvilinear path of the hand during the stroke, which allows the swimmer to push against ‘still’ water. As Counsilman (1977) states, if the hand were to remain in a straight path then the water will naturally start to move in that direction, meaning that little propulsion can be generated from already moving water. Using a curving path results in the swimmers arm moving a greater distance per stroke, allowing a greater volume of still water to be displaced, resulting in forward propulsion being generated (Counsilman 1977). The curving path is known as a ‘sculling’ motion (Counsilman 1981), sometimes referred to as an elliptical pull. The finding was confirmed in subsequent work by Toussaint and Beek (1992) and Maglischo (2003). Psycharakis and Sanders (2010) suggest that body roll also has a relationship to the curvilinear hand path with a 'better' body roll creating a more

pronounced curve of the hand's path, which can increase forward propulsion.

Toussaint and Truijens (2005) discuss that the methods by which this propulsion is generated involves the hand acting as a hydrofoil generating both lift and drag. By curving the arm path allows for easier positioning of the hand pitch (angle of attack) which contributes to the lift forces generated, resulting in greater forward propulsion to the swimmer (Maglischo, 2003).

This curved hand path also allows the swimmer to have a slower stroke rate which in turn leads to lower rates of energy expenditure (Counsilman 1977), which is known to be a limiting factor of performance (Toussaint *et al.*, 2006). Consequently sculling has come to be regarded as a highly desirable feature in front crawl swimming (Hay *et al.* 1993).

Despite substantial evidence suggesting the use of the curved hand paths, contemporary swimmers seem to lack this S-shaped pull and defined movement paths of the hand (Rushall *et al.*, 2009). Brown and Counsilman (1971) started the discussion on this before the identification of the sculling methods. They argued that the arm should be kept straight (the elbow should not be bent) and the arm and hand should be pulled in a straight line directly under the body. This leads to the principle that efficient propulsion would consist of pushing a large amount of mass a short distance with little acceleration, which has since been reiterated using Computational Fluid Dynamics principles by Bixler (2005a). Rushall *et al.* (2009) identified the reduction in the use of the S-shaped pull, however, subsequent papers have not seemed to confirm this. This has also not effected the definitions of the phases of the stroke which have been measured as kinematics in relation to performance. Knowing that the arms contribute 85%-90% of propulsion (Counsilman 1968; Deschodt *et al.* 1999; Di Prampero *et al.* 1974; Hollander *et al.* 1988; Holmér 1978; Maglischo 2003; Toussaint 1990b; Zamparo *et al.* 2008), demonstrates the current importance of the curving path.

2.1.1.2 Stroke Phases

The definitions of the stroke phases vary throughout the literature ranging from five phases (Maglischo 2003) and two definitions of four phases by Hogarth (1998) and Chollet et al. (2000a). Hogarth (1998); writing for coaches; has identified four key phases being, Entry, Catch (which is a point in time, rather than a phase), Propulsion phase and Recovery. The phase definitions according to Chollet et al. (2000a) are shown in equivalent terms to other literature (Figure 7).

Entry: *Entry and catch of the hand in the water. This phase correspond to the time from the hand's entry into the water to the beginning of its backwards movement. [Blue in Figure 7 and throughout document]*

Pull: *This phase correspond to the time from the beginning of the hand's backwards movement to the hand's arrival in the vertical plane to the shoulder. This phase is the beginning of propulsion. [Yellow in Figure 7 and throughout document]*

Push: *This phase corresponds to the time from the hand's position below the shoulder to its release from the water. [Purple in Figure 7 and throughout document]*

Recovery: *This phase corresponds to the time from the hand's release from the water to its following entry into the water. [Black in Figure 7 and throughout document]*

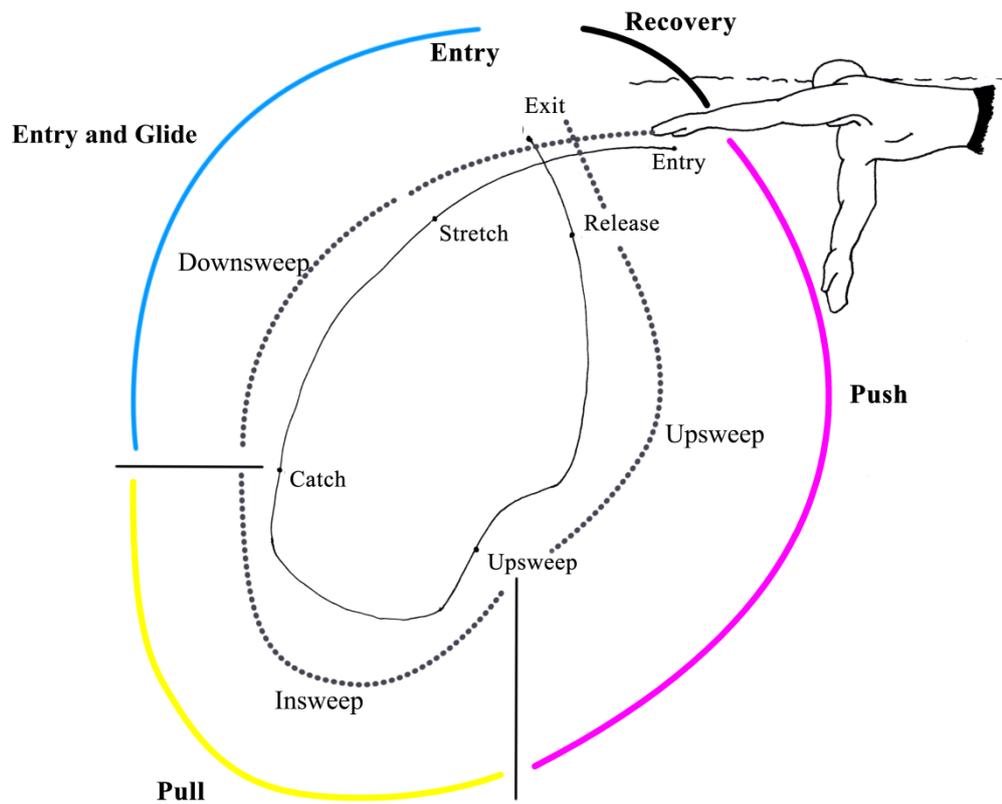


Figure 7: Stroke Phase Terminology: Solid black line: Maglisco (2003); Dashed line: Hogarth (1998); Coloured lines: Chollet et al. (2000a).

Using these defined parameters for the stroke, research has been conducted measuring these through various conditions including level of athlete, speed and distance covered. A summary of these studies is given in Table 3.

Author(s)	Notes	Entry-Catch (%)	Pull (%)	Push (%)	Recovery (%)	
		Elite	Elite	Elite	Elite	
Chollet et al. (2000a)	Highest Performance Group	800m (1.49ms ⁻¹)	30.3 ±6.5	21.3 ±4.2	22.9 ±2.7	25.5 ±2.4
		100m (1.76ms ⁻¹)	25.2 ±5	23.4 ±2.4	25.2 ±3.5	26.2 ±2.7
		50m (1.81ms ⁻¹)	22.1 ±3.9	26.7 ±3.7	26.3 ±2.7	24.9 ±1.9
	Middle Performance Group	800m (1.4ms ⁻¹)	31.3 ±4.9	20.9 ±2.6	23 ±1.1	24.8 ±2.9
		100m (1.65ms ⁻¹)	27.4 ±4.1	22.7 ±3.2	23.8 ±2.6	26.1 ±3
		50m (1.75ms ⁻¹)	24.7 ±6	24.1 ±3	24.6 ±4.4	26.6 ±1.9
	Lowest Performance Group	800m (1.3ms ⁻¹)	34.3 ±8	19.4 ±5.2	21.5 ±3.8	24.8 ±3.4
		100m (1.6ms ⁻¹)	28.6 ±4.3	21.6 ±3.4	22.9 ±3	26.8 ±3.5
		50m (1.7ms ⁻¹)	26.7 ±4.1	22.8 ±3.3	23.1 ±3.1	27.4 ±4
Seifert et al. (2004)	3000m (1.43ms ⁻¹)	35.8 ±6.3	19.5 ±4.7	19.6 ±1.9	25.1 ±3.6	
	1500m (1.50ms ⁻¹)	34.3 ±6.2	20.7 ±4.1	19.7 ±2.2	25.3 ±3.4	
	800m (1.53ms ⁻¹)	32.7 ±6.7	21.3 ±4.4	19.9 ±1.8	26.1 ±4.2	
	400m (1.61ms ⁻¹)	31.8 ±5.8	22.5 ±3.5	20.0 ±2.0	25.8 ±4.0	
	200m (1.71ms ⁻¹)	28.3 ±6.4	23.8 ±3.5	20.4 ±1.8	27.5 ±3.9	
	100m (1.80ms ⁻¹)	23.4 ±5.3	26.7 ±3.6	22.1 ±2.8	27.8 ±3.4	
	50m (1.85ms ⁻¹)	20.0 ±6.7	28.7 ±4.5	22.5 ±3.1	28.8 ±2.6	
	Maximal Velocity (1.93ms ⁻¹)	18.5 ±6.3	28.8 ±5.1	23.6 ±2.8	29.1 ±3.6	
Seifert et al. (2007a)	Male 100m (1.89ms ⁻¹)	18.9	32.6	21.4	27.3	
	Male 100m (1.73ms ⁻¹)	21.5	30.4	20.6	27.5	
	Female 100m (1.55ms ⁻¹)	25.5	27.9	21.9	24.7	
	Female 100m (1.58ms ⁻¹)	19.6	33.5	21.2	26.3	
Schnitzler et al. (2008)	50m (1.35ms ⁻¹)	41.8 ±3.6	14.7 ±2.4	19.7 ±1.2	23.9 ±2.6	
	100m (1.25ms ⁻¹)	44.1 ±3.3	14.3 ±2.2	19.9 ±1.5	21.7 ±2.5	
	150m (1.25ms ⁻¹)	43.7 ±4	14.4 ±3	19.8 ±1.6	22.2 ±2.5	
	200m (1.24ms ⁻¹)	44.2 ±3.2	14.1 ±2.6	20.0 ±1.8	21.7 ±2.3	
	250m (1.25ms ⁻¹)	43.8 ±3.5	14.6 ±2.6	20.1 ±2	21.5 ±2.7	
	300m (1.24ms ⁻¹)	44.3 ±3.4	14.0 ±2.4	20.3 ±1.7	21.4 ±2.3	
	350m (1.25ms ⁻¹)	43.6 ±3.7	14.9 ±2.9	20.2 ±2	21.3 ±2.5	
	400m (1.25ms ⁻¹)	44.0 ±4	14.5 ±2.9	20.0 ±1.7	21.5 ±2.4	
	Average Men 400m (1.29ms ⁻¹)	42.6 ±0.4	15.9 ±0.2	19.8 ±0.2	21.7 ±0.3	
Average Women 400m (1.22ms ⁻¹)	44.8 ±0.5	13.0 ±0.4	20.2 ±0.2	22.1 ±0.4		
Seifert et al. (2010)	National Swimmers ~60-65% effort	42.9	13.3	19.1	24.7	

		~70	42.2	13.7	19.3	24.8
		~75	41.4	14.4	20.4	23.8
		~80	35.9	16.1	22.1	25.9
		~85	31.1	16.8	25.6	26.5
		~90	28.4	18.6	25.2	27.8
		~95	25.0	20.0	26.8	28.2
		100% - Maximal	24.5	20.5	27.3	27.7
		Regional Swimmers				
		~60-65% effort	43.3	13.4	17.4	25.9
		~70	43.0	14.1	17.8	25.1
		~75	41.8	14.7	18.5	25.0
		~80	40.4	14.8	19.1	25.7
		~85	38.4	15.7	20.1	25.8
		~90	33.2	18.8	21.5	26.5
		~95	29.1	20.3	22.3	28.3
		100% - Maximal	27.7	21.3	22.7	28.3
Figueiredo et al. (2010)		50m (1.64ms ⁻¹)	37.7 ±4.9	23.1 ±1.4	14.1 ±1.2	25.1 ±3.7
		100m (1.48ms ⁻¹)	39.0 ±5.1	12.4 ±1.6	24.3 ±3.4	24.4 ±3.1
		150m (1.46ms ⁻¹)	39.3 ±5.1	12.4 ±2.1	23.8 ±1.9	24.5 ±3.1
		200m (1.40ms ⁻¹)	37.8 ±5.2	13.5 ±2.9	24.9 ±4.7	23.8 ±2.4
Telles et al. (2011)	Right Arm	Free Swimming (1.83ms ⁻¹)	14.0 ±3.8	34.1 ±4.4	24.8 ±4.2	27.2 ±3.9
		Hand Paddles (1.87ms ⁻¹)	12.3 ±4.6	34.4 ±4.1	25.0 ±3.7	28.3 ±3.6
		Parachute (1.25ms ⁻¹)	15.1 ±6.1	33.1 ±3.9	26.6 ±4.4	25.2 ±4.8
		Paddles + Parachute (1.29ms ⁻¹)	12.5 ±5.6	35.5 ±4.7	26.8 ±3.3	25.2 ±2.2
	Left Arm	Free Swimming (1.83ms ⁻¹)	14.0 ±4.7	33.9 ±5.6	21.3 ±2.7	29.3 ±4.3
		Hand Paddles (1.87ms ⁻¹)	11.5 ±4.3	35.6 ±4.9	21.7 ±3.8	32.9 ±3.1
		Parachute (1.25ms ⁻¹)	13.1 ±4	32.6 ±6.9	24.8 ±4.6	28.3 ±3.5
		Paddles + Parachute (1.29ms ⁻¹)	12.3 ±4.3	33.8 ±2.9	24.7 ±2.9	29.0 ±4.4

Table 3: Summary of previous works showing percentage of time per phase of the stroke

The results here show varying percentages for each phase. Under first inspection it could appear that there is a considerable difference between measurements of these factors with results ranging from 14% to 40%, for the entry phase during free

swimming. However, there is a relationship between the speed of the swimmer and this percentage.

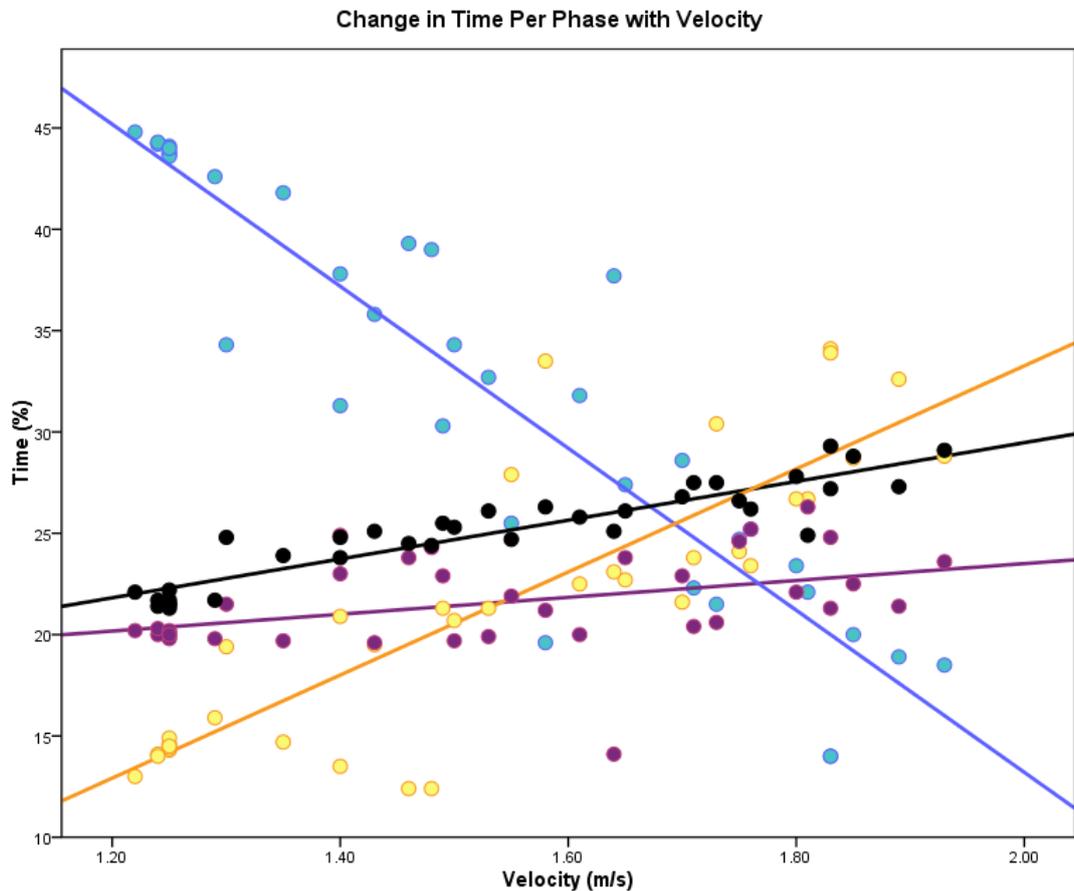


Figure 8: Change in time per phase with respect to velocity. Blue = Entry, Yellow = Pull, Purple = Push, Black = Recovery.

Using the previous works shown in Table 3, a Pearson correlation was performed showing significant results ($r = -0.92$, $n = 36$, $p = .00$) for each phase to velocity. Velocity was chosen, regardless of swimming distance, due to the principle that the fastest swimmer will win a race (Toussaint 1990a).

As speed increases, the entry phase duration decreases ($r = -0.92$, $n = 36$, $p = .00$), which then allows for an increase in the pull and push times, the times which generate forward propulsion. The pull phase duration significantly increases with a

strong positive correlation ($r = .851$, $n = 36$, $p = .00$) as speed increases. The push phase does show a positive increase in duration, but to a moderate extent ($r = .406$, $n = 36$, $p = .014$), which would be expected to be stronger yet previous results by Chollet et al. (2000a) have shown that the pull increases more than the push. However, the results show that as speed increases, the recovery time also strongly increases ($r = .92$, $n = 36$, $p = .00$), in contrary to the principles outlined, as this shows an increase in non propulsion time for this element of the stroke. This has been accepted as a longer recovery time (Chollet et al. 2000a).

Chollet et al. (1997) have stated that long stroke lengths characterise high expertise, and Costill et al. (1985) have expressed that stroke length is the best indicator of performance. With the results shown here, swimmers at a higher velocity spend less time in the entry phase of the stroke by moving the catch point (the start of the pull) earlier in the stroke. This may suggest that longer stroke lengths could be created by reducing the entry time of the stroke, resulting in the swimmer benefiting from two aspects which would enhance performance (Chollet et al. 2000a). However, the results show that the recovery phase also increases in duration with this speed increase. The push phase, whilst it does increase in duration, does not increase strongly. This could be due to the fact that the pull phase starts when the arm is directly below the shoulder and finishes when the hand exits the water. Whilst the distance of this will change from swimmer to swimmer due to their individual anthropometrics, the swimmer cannot physically change this length without making alterations to other aspects of the stroke, such as body roll.

2.1.1.3 Body Roll

The swimmer needs to maximise their propulsive forces, and has to breathe by integrating this into the stroke cycle without increasing the resistive forces, for example, by lifting the head to breath (Payton et al. 1999; Yanai 2001). Maglischo (2003) suggests that to achieve this, the swimmer should roll further on the breathing side. In addition to this, the body roll also contributes to the curvilinear hand path

creating a more pronounced curve of the hand's path, which can increase forward propulsion (Payton et al. 2002; Psycharakis and Sanders 2010).

Several previous studies, (Hay et al. 1993; Liu et al. 1993; Payton et al. 1999; Payton and Bartlett 1995) have treated the hip and shoulder rolls in a combined state of the trunk using a balsa wood fin attached to the swimmers back. Whilst these provided interesting findings, demonstrating contributions to hand path and breathing, hip roll and shoulder roll are usually taken as single units and should be considered separately (Psycharakis and Sanders 2008; Psycharakis and Sanders 2010). Cappaert et al. (1995) demonstrated this early need for separation when analysing the mens 100m front crawl event at the 1992 Olympics. Their findings showed that the hips rolled significantly less than the shoulders. The sub-elite group (from heats) presented shoulder rolls of $34.4^{\circ} \pm 1.7^{\circ}$ and hip roll of $-17.8^{\circ} \pm 1.5^{\circ}$, the negative values show an opposite hip to shoulder roll. The elite group showed $35.4^{\circ} \pm 2.5^{\circ}$ for shoulder roll and $8.5^{\circ} \pm 1.5^{\circ}$ for hip roll, with two gold medalists showing equal levels of hip and body roll. Since this work there have been studies with varying conditions and speeds, where body roll has been estimated using simulation, 2D and 3D camera techniques (Psycharakis and Sanders 2010), summarised in Table 4. The results indicate that over varying conditions and with different swimmers, the hips roll significantly less than the shoulders.

Author(s)	Hip Roll Angle	Shoulder Roll Angle	Notes
Liu et al. (1993)	60.8° ±4.4°		Found that the medio-lateral distance of hand to mid trunk is linked, in part, to the body roll of the swimmer. Trunk measured.
Cappaert et al. (1995)	8.5° ±1.5°	35.4° ±2.5°	2.01ms ⁻¹ Elite, 1992 Olympics
	-17.8° ±1.5°	34.4° ±1.7°	1.87ms ⁻¹ Sub-Elite, 1992 Olympics
Payton et al. (1999)	62° ±4°		Breathing Side. Trunk measured. 1.52ms ⁻¹
	55° ±4°		Non-Breathing Side. Trunk measured.
Yanai (2001)	36°	58°	1.6ms ⁻¹
Yanai (2003)	41° - 33°	75° - 66°	Speed increase from 1.3ms ⁻¹ to 1.6ms ⁻¹ to generate fatigue
	74° ±3°	65° ±4°	1.27ms ⁻¹ . Breathing/ 1.33ms ⁻¹ Non-Breathing. Trunk measured
Castro et al. (2003)	71° ±6°	62° ±4°	1.5ms ⁻¹ . Breathing/ 1.61ms ⁻¹ Non-Breathing. Trunk measured
	63° ±6°	50° ±7°	1.88ms ⁻¹ . Breathing/ 1.94ms ⁻¹ Non-Breathing. Trunk measured
Psycharakis and Sanders (2008)	~25° ±12°	~53°	200m, speeds ranging from 1.45ms ⁻¹ to 1.68ms ⁻¹ . Angles halved from full range reported.
	(Left) 24.6° / 25.7° (Right)	(Left) 57.1° / 49.6° (Right)	Asymmetry identification
		57°	Non-Breathing Side. Trunk measured
Psycharakis and McCabe (2011)	24.5°	59.9°	Breathing Trial, Breathing Side. 1.76ms ⁻¹
	20.4°	51.9°	Breathing Trial, Non-Breathing Side. 1.76ms ⁻¹
	19.1°	50.4°	Non-Breathing Trial, Breathing Side. 1.81ms ⁻¹
	19.5°	53.3°	Non-Breathing Trial, Non-Breathing Side. 1.81ms ⁻¹

Table 4: A summary of research demonstrating the variation in body roll

Using this data (Table 4), a Pearson correlation was performed, the results show a negative correlation between shoulder roll (including Trunk) and velocity ($r = -.777$, $n = 15$, $p = 0.001$), Figure 9. This has also been found by (Psycharakis and Sanders 2008) stating that for 200m, swimmers tend to roll their shoulders less than slower swimmers. There was no significant relationship with the hip roll and velocity ($r = -.667$, $n = 7$, $p = 0.102$), probably due to a lack of data presented and outlying data presented by Cappaert et al. (1995) showing negative hip roll, which is the only study to show this. Although, Psycharakis and Sanders (2008) did find that as swimmers got faster, they rolled their hips less.

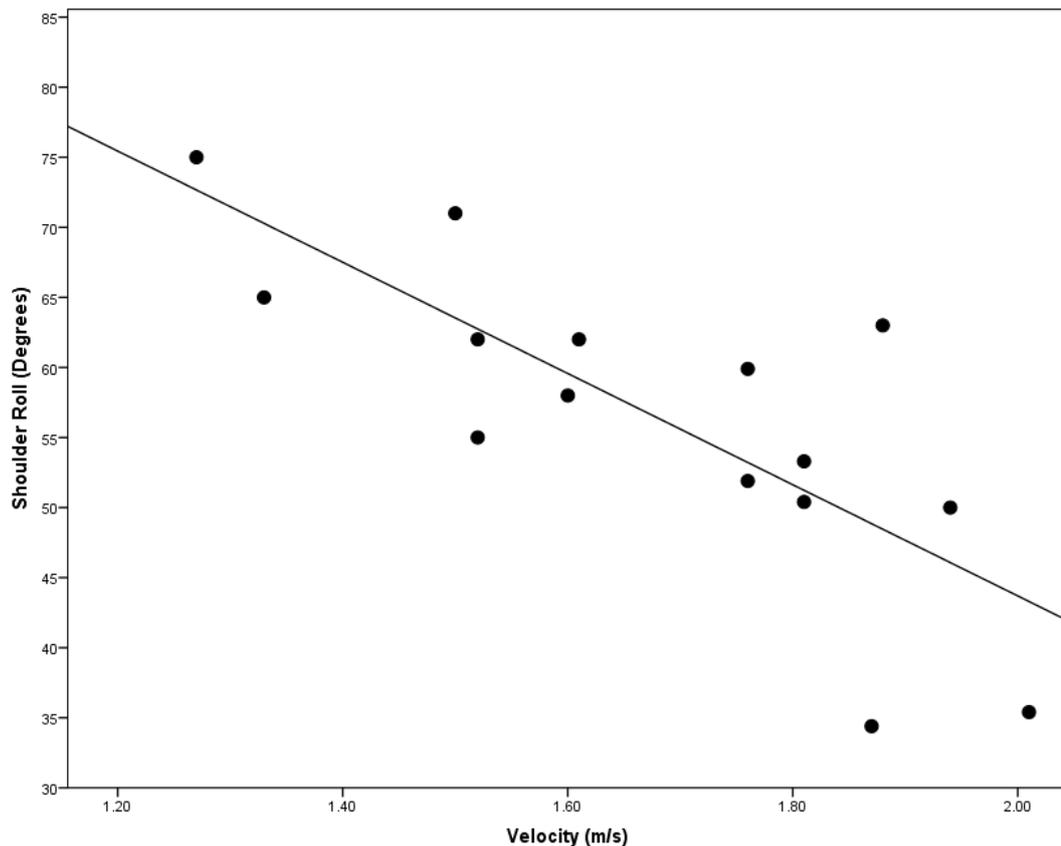


Figure 9: Shoulder roll with respect to Velocity

2.1.1.4 Symmetry, Coordination and Variability

The biomechanical factors that contribute to performance have been identified using research designs focusing on group-based (nomothetic) methods in order to generalise the findings to the swimming population. Previous works (e.g. Craig and Pendergast, 1979; Craig et al., 1985; Arellano et al., 1994) have tended to center on descriptive stroke characteristics because they are more '*readily observable*', such as speed, stroke count and stroke length (Glazier et al. 2006a).

A new trend in research, which could be of use to coaches, is the use of case study work (idiographic) focusing on the analysis of inter-individual movement patterns and the variability of these movements. Human movement will inevitably comprise of elements of variability (Bartlett et al. 2007) which can have an important influence on the success of a given technique (Hiley and Yeadon 2012). However, in previous work, inter-individual variability in biomechanical terms have previously been considered "noise" (Bartlett et al. 2007). Glazier et al. (2006a) discuss that variability can have a functional role as it allows for adaptations to the task under varying constraints. As noted by Hiley and Yeadon (2012, p.11),

"Failing to consider such an important aspect can lead to optimal solutions that are not representative of human technique, resulting in incorrect conclusions"

Movement variability can often be reported as, a *measurement of symmetry* (Formosa et al. 2011; Formosa et al. 2012; Formosa et al. 2013; Sanders et al. 2012; Seifert et al. 2005b; Stamm et al. 2012), *arm coordination* (Chollet et al. 2000b; Fernandes et al. 2010; Figueiredo et al. 2010; Formosa et al. 2012; Seifert et al. 2005a; Seifert et al. 2005b; Seifert et al. 2007a; Seifert et al. 2010), or as *variation in kinematic measures* (Carson et al. 2013; Glazier 2011; Hellard et al. 2008; Petersen et al. 2009; Psycharakis and Sanders 2008; Razman et al. 2011; Trezise et al.; Tucker et al. 2013).

Coordination structures play a significant role in most sports, allowing for the maximum energy transfer between phases of an action. In swimming, elite swimmers show no difference in temporal aspects of coordination between the

shoulder and hip roll during the stroke, whilst in lower level swimmers there is no coordination, showing a time lag between the hip and shoulder roll times (Kippenhan and Hay 1994). There is also variation in body roll angles, which have been attributed to a lacking ability to coordinate between the phases of the arms, limiting air inhalation breathing phase of the stroke (Kippenhan and Hay 1994).

Other coordinative methods have also been used in swimming. Counsilman and Wasilak (1982) suggest that a constant force (a constant propulsion) applied throughout the front crawl stroke would allow for a constant forward velocity. As humans are biped in design, we must rely upon power surges to develop propulsion, for example, walking uses a surge of power from each leg.

In front crawl swimming there are two surges of force produced, one from each arm, from the pull and push phases of the stroke. The principle difference between swimming slowly and swimming fast is the speed at which the hand moves through the water (Counsilman and Wasilak 1982), but it is not just speed; synchronisation of the propulsion from the arms allows a swimmer to maximise forward velocity (Chollet et al. 2008). This notion has been developed into the Index of Coordination (IdC), reported as a percentage, which shows the lag time (or overlap) in propulsive time of each arm (Chollet et al. 2000a; Costill et al. 1992; Maglischo 1993). This is calculated using EQ[8]

$$IDC_{Left} = \frac{\left((TimeEndOfPull_{LeftArm} - TimeBeginningOfPush_{RightArm}) \cdot 100 \right)}{DurationCompleCycle}$$

$$IDC_{Right} = \frac{\left((TimeEndOfPush_{RightArm} - TimeBeginningOfPull_{LeftArm}) \cdot 100 \right)}{DurationCompleCycle}$$

[8]

The three identifications of arm coordination shown in Figure 10 demonstrate how the forward propulsion of the swimmer is affected.

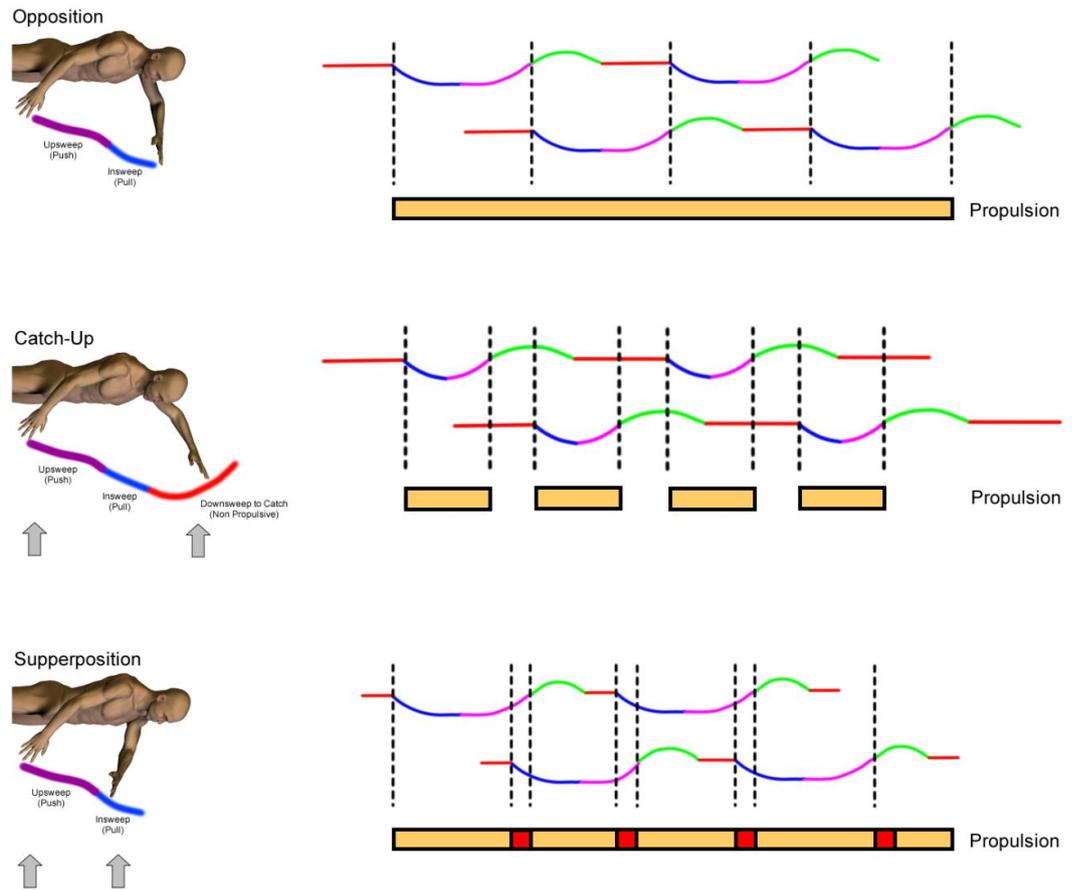


Figure 10: IdC (Index of Coordination)

Opposition is where the propulsive part of the stroke cycle takes the same amount of time as the recovery and Entry/Catch part of the stroke. As the right arm finishes its propulsive phase (end of the push) the left arm has just started the pull, this leads to constant propulsion during the stroke, with an IdC of 0%. Seifert et al. (2010) notes that in practical terms, this should be considered as $-1\% < \text{IdC} < 1\%$.

Catchup identification shows that there is a lag between the end of the propulsive phase for one arm and the start of the other arm, with an IdC $< 0\%$. The lag in

propulsion results in a decrease in inertia of the swimmer, requiring a greater arm speed to maintain forward velocity.

Superposition illustrates both arms simultaneously being in the propulsive phases. The overlap of propulsive phases means that the recovery and entry phases are very short in comparison to the propulsive phases of the stroke (push and pull). The overlap of propulsive phases also results in an increase in forward velocity for a percentage of the stroke with an IdC > 0%.

The entire stroke time, entry to release is considered to be 100%, where IdC was calculated by the lag between the start of the propulsion phase of one arm, and the end of the propulsive phase on the other, over two full strokes (200%). The lag is then represented by the percentage difference. This is averaged by dividing the sum of lag by two. A resultant percentage being less than 0% determines Catchup IdC being used, 0% determines Opposition and greater than 0% shows Superposition.

Chollet et al. (2000a) showed that elite swimmers had a “*greater arm continuity*” and typically used opposition-superposition coordination. The greater arm continuity was shown with the IdC being greater than 0%. Whereas, less skilled swimmers, showed a catch-up coordination where IdC was less than 0%.

The identification of skilled swimmers using opposition and superposition coordination draws a parallel with Counsilman and Wasilak's (1982) suggestion that it would be inefficient to use “*stop-and-go*” propulsion and that it would therefore be logical to apply a constant application of force that would result in a constant forward speed. Table 5 summarises a selection of the research conducted using IdC.

Author(s)	Elite	Novice	Notes
Lerda and Cardelli (2003)	0.36±3.41	-2.80±3.2	Breathing Side
	-1.74±3.7	-2.02±3.2	Non - Breathing Side
Chollet et al. (2000a)	-7.6 ±6.4		800m (1.4ms ⁻¹)
	-3.2 ±5.1		100m (1.67ms ⁻¹)
	-0.9 ±5.6		50m (1.75ms ⁻¹)
Seifert et al. (2004)	-10.5 ±5.3		3000m (1.43ms ⁻¹)
	-9.4 ±5.2		1500m (1.50ms ⁻¹)
	-8.5 ±5.4		800m (1.53ms ⁻¹)
	-7.8 ±4.5		400m (1.61ms ⁻¹)
	-5.9 ±4.6		200m (1.71ms ⁻¹)
	-1.0 ±4.5		100m (1.80ms ⁻¹)
	1.1 ±6.0		50m (1.85ms ⁻¹)
	2.6 ±6.1		Maximal Velocity (1.93ms ⁻¹)
Seifert et al. (2007a)	3.8 ±3.8		Male 100m (1.89ms ⁻¹)
	0.27 ±3.89		Male 100m (1.73ms ⁻¹)
	-0.03 ±3.83		Female 100m (1.55ms ⁻¹)
	4.54 ±4.79		Female 100m (1.58ms ⁻¹)
Schnitzler et al. (2008)	-15.4 ±2.9		50m (1.35ms ⁻¹)
	-15.9 ±2.3		100m (1.25ms ⁻¹)
	-15.9 ±2.3		150m (1.25ms ⁻¹)
	-15.7 ±2.3		200m (1.24ms ⁻¹)
	-15.4 ±1.5		250m (1.25ms ⁻¹)
	-15.5 ±2.4		300m (1.24ms ⁻¹)
	-15.0 ±2.4		350m (1.25ms ⁻¹)
	-15.6 ±2.6		400m (1.25ms ⁻¹)
	-16.8 ±0.3		Average Men 400m (1.29ms ⁻¹)
-14.2 ±0.3		Average Women 400m (1.22ms ⁻¹)	
Figueiredo et al. (2010)	-13.1 ±2.7		50m (1.64ms ⁻¹)
	-13.5 ±3.8		100m (1.48ms ⁻¹)
	-13.9 ±3.2		150m (1.46ms ⁻¹)
	-11.7 ±3.9		200m (1.40ms ⁻¹)
Seifert et al. (2010)	National	Regional	
	-17.5	-18.9	~60-65% effort
	-16.8	-18.2	~70
	-15.3	-16.9	~75
	-11.9	-16	~80
	-7.8	-14	~85
	-6.2	-9.5	~90
	-2.8	-7.4	~95
	-2.3	-5.7	100% - Maximal
	-2.3 ±5		Free Swimming (1.83ms ⁻¹)
Telles et al. (2011)	-0.2 ±3.8		Hand Paddles (1.87ms ⁻¹)
	0.1 ±3.1		Parachute (1.25ms ⁻¹)
	0.0 ±3.2		Paddles + Parachute (1.29ms ⁻¹)

Table 5: Summary of IdC calculations through varying levels and conditions

Seifert et al. (2010) used two 50Hz video cameras to measure the IdC of swimmers through a range of speeds. They found, as with Seifert et al. (2007b) and Chollet et al. (2000a), that as stroke rate increased, the entry phase decreased in duration to maximise the propulsion to non propulsion time. With this, superposition was primarily used with speeds over 1.8ms^{-1} . In an arms only trial, resulting in slower lap times, they found the use of Catchup coordination (IdC $\sim -18\%$). And for speeds of around 1.6ms^{-1} they found the use of opposition coordination (IdC $\sim 0\%$).

Overall, many of the results show a Catchup method utilised by swimmers. The results from Table 5 show a variation in speeds and measured IdC, yet there is a trend as shown in Figure 11, which shows a significant correlation between velocity and IdC, ($r = .875$, $n = 30$, $p = .00$). This shows that faster swimmers do overlap their propulsive phases, however, the fastest swimmers moving at near 2ms^{-1} only overlap their arms by around 5%. The higher IdC values are directly linked, as shown by Chollet et al. (2000a), to a decrease in the entry phase duration and increase in the pull phase duration, where working towards a superposition coordination can also help reduce energy expenditure (Chatard et al. 1990).

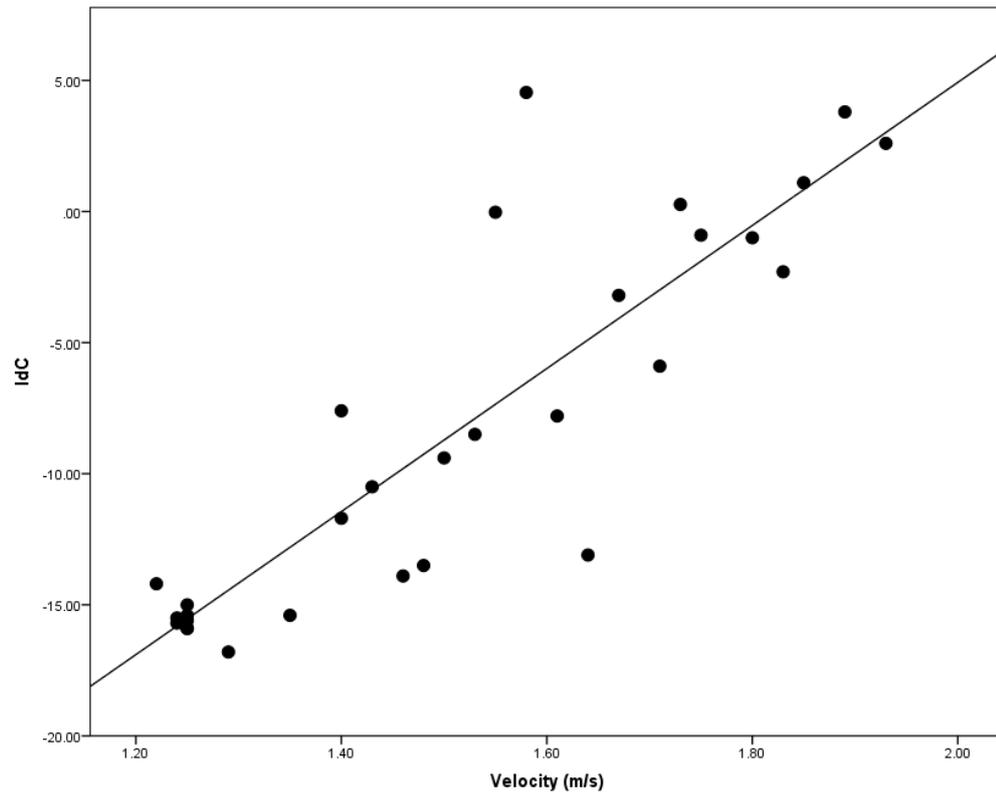


Figure 11: IdC in relation to swimming Velocity

By identifying and monitoring the arm coordination asymmetry, the coach could make recommendations to the swimmer for balancing any excessive asymmetry (Seifert et al. 2005b). Seifert et al. (2005b) suggest that this could be achieved by changing in breathing frequency or side.

Variations in technique over multiple laps using a video based analysis, would be very time consuming for a coach/researcher (Sanders et al. 2012). This is one limitation with video based methods. Measuring various performance identifiers does not provide information on the underlying patterns that generate these factors, such as technique changes over time due to fatigue or injury (Glazier et al. 2006a).

Variability in human movement has been described as having a functional role, and will always be present (Bartlett et al. 2007; Hamill et al. 1999; Latash et al. 2002). It has also been described as having a component of “noise” (Bartlett 2008; Bartlett et al. 2007). Failing to consider such an important aspect can lead to optimal solutions that are not representative of human technique, resulting in incorrect conclusions (Hiley and Yeadon 2012).

Smith and Spinks (1995) and Caplan and Gardner (2009) demonstrated methods of fatigue analysis in rowing by analysing the consistency of the rowing stroke. Stroke to stroke consistency is measured by normalising the data with respect to time, 200 samples were chosen as observations from the dataset showed that some were as low as 150, and some as high as 250. The mean and standard deviation of the values of each 2% of the stroke was calculated using EQ[9] to create a coefficient of variation for each 2% of the stroke. This was then used to create a consistency rating out of 100% EQ[10] .

$$\text{Coefficient of Variation for each 2\%} = \frac{SD}{\text{Mean for each stroke}}$$

[9]

$$\text{Mean Stroke To Stroke Consistency} = 100 \bullet (1 - \text{mean coefficient of variation})$$

[10]

To perform at an optimal level, swimmers are required to maximise propulsion. Yet many swimmers fail to reach their potential due to asymmetries in strength and/or flexibility (Sanders et al. 2011). Asymmetry can occur bilaterally (left-right) or/and antero-posteriorly (front-back).

Psycharakis and Sanders (2008) clearly demonstrated the need to measure hip and shoulder roll separately. They also showed that asymmetries can be identified within swimming, with evidence of a larger roll angle on the preferred breathing side. There is no direct evidence to suggest there is an injury risk with an asymmetry (Psycharakis and Sanders 2010). However, it has been suggested that an asymmetry could impact upon the technique and potentially cause injury (Kippenhan and Yanai 1995; Sanders et al. 2011). An asymmetry could be caused by laterality, genetic or environmental factors, development or disease factors, injury or overtraining/fatigue or a technique of habit (Sanders et al. 2011).

Sanders et al. (2011) question how the symmetry of a swimmer can be identified and measured. Whilst measurement of asymmetries has been identified previously, Sanders et al. (2011) pose the question to identify methods of measurement with little interference to the swimmer. This can then help identify whether they affect performance, and what interventions can be administered by the coach to correct these. An index of symmetry can be calculated using EQ[11] (Sanders et al. 2011).

$$SI = \frac{2(R_L - R_R)}{(R_L + R_R)} \bullet 100$$

[11]

Where R_L is the Left Roll angle and R_R is the Right Roll angle. The results of this show that a value between -10% and 10% for the SI implies symmetry. Left and right-side asymmetries are indicated when $SI < -10\%$ and when $SI > 10\%$, respectively (Psycharakis and Sanders 2008). In context, using this symmetry index can identify a decrease in body roll over a race, or an asymmetry. This could demonstrate a lower level ability of swimmers (Cappaert et al. 1995; Yanai 2004).

2.2 Summary of Front Crawl

There are a variety of kinematic factors that can be recorded from a swimmer, as shown. These confirm and develop the hierarchical model developed by Hay (1993). The relationships between various kinematic factors (body roll, coordination, and arm phases) and velocity have been demonstrated, showing factors which need to be recorded. It needs to be considered that swimmers can have individual combinations of these factors demonstrating the need for coaching the individual, rather than focus groups of swimmers (Cross 1999; Rushall 1985; Toussaint et al. 2006). The factors that are recorded are done so using video based methods (Psycharakis and Sanders 2010) and can be very time consuming for a coach to calculate (Le Sage et al. 2011), and equally for a researcher (Sanders et al. 2012).

Most research has tended to focus on descriptive stroke characteristics because they are more '*readily observable*', such as stroke count (Glazier et al. 2006a), which may not allow a coach to make the best overall decisions for their swimmer.

2.3 Measurement of Factors in swimming

Primarily, kinematic and kinetic factors are determined or calculated from recordings using camera systems, either 2D or 3D (Psycharakis and Sanders 2010). However, there are other methods of data capture, Perales (2001) outlines three classifications of motion capture systems:

System 1: An outside-in system, using external sensors to collect data from sensors placed on the body (i.e. Camera system with reflective markers)

System 2: Inside-out systems have sensors placed on the body that collect from external sources (i.e. Electromagnetic system, where the sensors move in an externally generated field)

System 3: Inside-in systems have their sources and sensors placed on the body (i.e. Electromagnetic suits using a source placed on the body)

Whilst standard video technology, System 1, has typically reduced in price and become more accessible to all with software to aid analysis (such as Kinovea, Quintic and Dartfish), however, to a coach the analysis of a swimmer using this method would require a lot of time to process multiple swimmers, over multiple events (Le Sage et al. 2011). Another alternative could be 3D camera systems. These require considerable setup time and cost, but could offer some automatic tracking. However, due to cost and knowledge of setup and operation, these are not accessible by all (Hay 1993). There is a need for Biomechanists to consider focusing on servicing, as opposed to research, as this will result in quicker improvements to the swimmer (Mason 2005). However, biomechanical systems are not '*something that can be purchased over the counter*' (Mason 2005, p.58). In addition to this, ease of testing is especially the case in swimming, where the demands cannot be easily replicated in a laboratory setting (Anderson et al. 2006). This further emphasizes the need to develop biomechanical systems of use to the majority.

Systems in categories 2 and 3 are difficult to use in a swimming environment due to the typical presences of magnetic forces underneath the pool such as pump and filtering systems, the influence of which are difficult to quantify. A further issue is the physical weight of a magnetic source and power supply attached to the swimmers body. These items could inhibit the swimmer's technique. This issue is also replicated with the use of a sensor suit defined by category 3. An example of this style of suit is that made by Xsens (Xsens Technologies B.V., Netherlands), where a magnetic source is added to the lower back of the suit. However, there is one exception, the use of accelerometers and gyroscopes which can be classed in category 2. These miniature devices with some additional circuitry can be attached to the swimmer to provide kinematic data about the swimmer which can be used to determine certain performance characteristics.

As Troup (1994) recognises, capture of reliable performance data can provide greater insight into the dynamics of swimming and has the potential to enable swimmers to perform to their highest potential.

Traditionally, quantitative measurement of swimming performance has been achieved by analysis of video footage, whereas, more recently miniature sensors in the form of accelerometers and gyroscopes have been fixed to the swimmer to record performance data such as stroke type and stroke rate (Davey et al. 2008). This chapter outlines the processes and results obtained using both video and accelerometer based systems.

2.3.1 Video based analysis of swimming performance

Video based analysis of swimming performance allows calculation of stroke rate, stroke length and assessment of the general characteristics of a swimmer's style, for example, angles of arm joints or degrees of body roll. Video analysis uses either two or three cameras placed at various positions in and/or above the pool.

For quantitative scientific studies reflective markers are located at key positions on the swimmer, such as the wrist (Ohgi 2002). The coordinates are then manually digitised, however various computer software is also available that will track these points. Digitisation can produce errors as shown by Wilson et al. (1999), in three-dimensional kinematic analysis of swimming, acceptable reconstruction tolerance can be ± 1.61 - 2.35 mm on the transverse axis; ± 2.99 - 4.64 mm on the longitudinal; ± 2.59 - 2.83 mm on the vertical axis (Gourgoulis et al. 2008a). The coordinates of these points of interest can then be extracted using the Direct Linear Transform (DLT) method. The DLT is an established algorithm that allows multiple images captured by asynchronous cameras to be extracted on a frame by frame basis (Chen et al. 1994; Marzan and Karara 1975; Pourcelot et al. 2000). This allows a composite 3D graph of position versus time to be constructed with minimum error (Marzan and Karara 1975). DLT results can be displayed as shown in Figure 12.

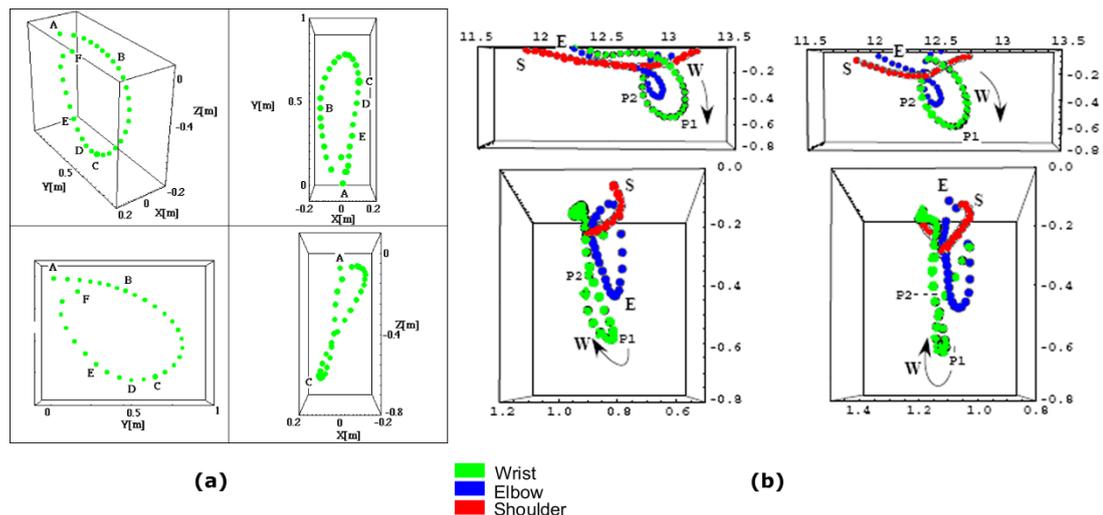


Figure 12: (a) One complete cycle of the hand path constructed from DLT data in 4 perspectives, (A-B Entry Stretch, B-C Downsweep to Catch, C Catch, C-D Insweep, D-E Upsweep, E-F Release and Exit). SOURCE:(Ohgi et al. 2002)

(b) Underwater Stoke paths of swimmer's Shoulder (S), Elbow (E) and Wrist (W) joints SOURCE:(Ohgi 2002). Reproduced with permission © 2002 IEEE

Ideally, cameras used for the DLT method should be synchronised to enable optimum reconstruction of image data (Pourcelot et al. 2000). However, such 'phase-locked' cameras are up to 20 times more expensive than standard camcorders (Pourcelot et al. 2000). Pourcelot et al. (2000) describe a new low cost method based on estimation of the time delay between standard video cameras. A cubic spline interpolation method is then employed to minimise the error in determining the precise position of each moving point being tracked on the subject (Pourcelot et al. 2000). With this approach one camera is used as a reference and the second or additional cameras can be synchronised to the reference camera without the need for expensive phase-locking circuitry (Pourcelot et al. 2000).

Whilst the DLT approach is successfully employed as an analytical tool in many sports disciplines, its application to assessment of swimming performance can be limited by the various difficulties associated with using a camera to obtain images in water. These include the parallax error at the water-air interface and turbulence affecting the view of anatomical points of interest (Ichikawa et al. 1999).

Several investigators have reported problems that result in occlusion of markers leading to a loss of continuity in the data required for successful application of the DLT algorithm (Luinge 2002; Ohgi 2002; Ohgi et al. 2002; Seifert et al. 2005b). Figure 13 illustrates such problems with water turbulence and slow shutter speeds affecting image quality.



Figure 13: Turbulence and blurring effecting anatomical viewing

Kwon (1999) also describes how refraction of light in water can cause errors in reconstruction of trajectory data when using the DLT algorithm. This problem is independent of the imaging approach as there is always a water-(glass)-air interface at some point in the optical path. Some improvement to image clarity might be obtained by employing a wide angle lens, however there is the additional problem of distortion due to short focal length when using this approach (Drenk et al. 1999).

Despite some limitations of video based analysis the technique has formed the basis on which understanding of swimming performance has been built over the last three decades. Whilst 3D camera systems are not available or useable by all (Hay 1993), research and coaching use 2D setups for video analysis and prior to

underwater cameras for swimming purposes, periscope style systems were used. This is also true in coaching, where the increase in accessibility of standard video cameras has allowed for coaches to replay information to athletes (O'Donoghue 2006), but any (biomechanical) analysis performed by the coach will take time to perform (Le Sage et al. 2011).

2.3.2 Accelerometer-based analysis of swimming performance

An increasingly widely adopted alternative to video based analysis employs small, electronic accelerometers located at various sites on the swimmers body. This approach typically supports measurement of linear tri-axial acceleration (Davey 2004; Holmér 1978; Ichikawa et al. 1999; Ichikawa et al. 2002b; Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002) or with an accompanying gyroscope (Ohgi 2002) measurement of tri-axial angular velocity. The use of accelerometers in athletic performance monitoring has been validated by numerous studies covering a range of disciplines including : Ambulatory measurements (Bussmann et al. 2001; Bussmann et al. 1998); Physical activity (Bao and Intille 2004; Lee et al. 2003; Morris 1973; Ravi et al. 2005); Gait analysis (Levine et al. 2001); Orientation and movement (Luinge 2002; Luinge and Veltink 2005; Luinge et al. 2005; Lynch et al. 2005; Roetenberg 2006; Roetenberg et al. 2007); and to improve Athlete performance (Anderson et al. 2002).

The application of accelerometer measurements to water based monitoring requires hermetic sealing of the sensors, instrumentation and power supply and a reliable means of mounting the units on the swimmer. The recent and increasing availability of MEMS (Micro-Electro-Mechanical-Systems) based sensors simplifies the encapsulation of the system and ensures that the measurement system does not significantly affect swimming performance by increasing drag.

As well as overcoming the problems associated with video-based capture the accelerometer approach supports higher sampling rates with more accurate measurements. However, there is potential for noise due to movement artefact which

may require additional signal processing. Furthermore, whereas DLT video analysis requires a minimum of two synchronised cameras, tri-axial accelerometers and tri-axial gyroscopes have been used to capture various performance data using a single combined device (Ohgi 2002) such as stroke rate and stroke type (Davey 2004) and identification of stroke phases (Ichikawa et al. 1999). Using one device placed on the arm however can produce limited results as it will only account for the actions of a single arm but both are used in front crawl swimming. It may be assumed that both arms act identically, however in reality that is unlikely to be the case, for this reason multiple devices should be considered.

The data obtained from accelerometer based measurement systems depends to some extent on the method of operation. The general measurement principle is based upon a mass displacing a linear spring. As a force is applied to the device the spring stretches and the mass is displaced EQ[12]:

$$F = kx$$

[12]

where F is the force measured in Newtons (N), k is the spring constant in Nm^{-1} and x is the spring extension in metres (m). Acceleration is the rate of change of the extension, given by EQ[13]:

$$a = \frac{F}{m}$$

[13]

Where F is the force acting on the body and m is the mass of the body in kilograms (kg), a is the acceleration in ms^{-2} (Roetenberg 2006). To understand the true acceleration of a body, the gravity vector must be removed. This can be done using 3D Pythagoras Theorem, with 1g being taken away from the result leaving actual acceleration, where x , y , z are the values for acceleration at time t EQ[14].

$$a_t = \left(\sqrt{x_t^2 + y_t^2 + z_t^2} \right) - 1g$$

[14]

Using acceleration it is also possible to derive velocity and displacement from the recorded data through integration of the signal. This however can produce incremental errors as demonstrated by an IMU (Inertial Measurement Unit) a device typically used for boat navigation. An IMU comprises of an accelerometer, gyroscope and magnetometer (which typically measures the earth's magnetic field). In an IMU the accelerometer and gyroscope are subject to baseline drift and require continuous compensation to ensure stability of heading and orientation. This can be achieved by using the relatively stable magnetometer signal as a reference. In principle the same technique could be used to improve accelerometer based assessment of swimming performance. However, the magnetic fields produced by water pumps under the pool are likely to introduce significant error in the magnetometer output data.

Gyroscopes are used to measure angular velocity about each axis of the body to which it is attached (rotation about the X axis is Roll (ω_x), Y axis is Yaw (ω_y), Z axis is Pitch (ω_z)). MEMS gyroscopes typically measure angular velocity using the Coriolis effect. The magnitude of the Coriolis effect, in each axis, is proportional to the angular velocity and is realised by EQ[15]:

$$f_c = 2mv\omega$$

[15]

Where f_c is the magnitude of the Coriolis effect, m is the mass in kilograms (kg), v is the velocity of the mass in ms^{-1} , and ω is the angular velocity in ms^{-1} (Luinge 2002). The direction of the accelerometer and gyroscope signals is dependent on the device orientation when placed on the swimmer, previous studies have placed them in different orientations, one such orientation setup is shown in the accelerometer

results section later in this paper, however at this time it seems that there is no standard orientation of such devices within the research community.

Using recent advances in 3D photolithographic techniques mechanical sensors with integrated electronic circuitry have been realised that are capable of performing the preceding measurements over suitable ranges (Figure 14). These devices typically output an analogue signal that can then be processed and stored digitally using embedded microprocessors. This supports realisation of ultra-small sensors, which can be mounted on athletes. Furthermore, such devices can include smart technology e.g. for auto calibration and filtering to remove artifacts.

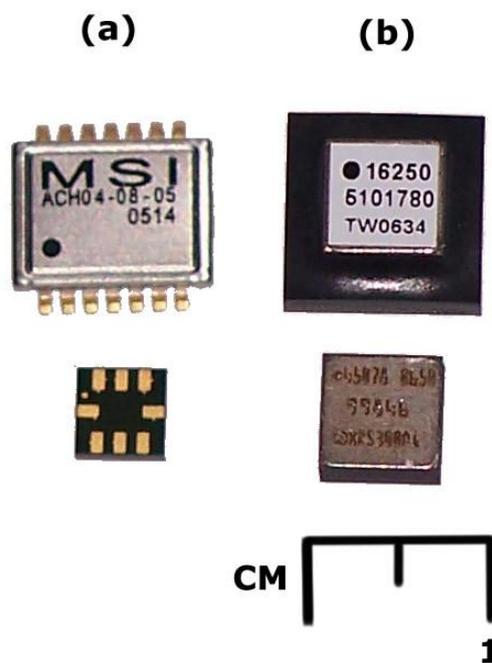


Figure 14: (a) Tri-Axial Accelerometer IC's (b) Single Axis Gyroscopes

2.3.3 Results obtained using accelerometers in front crawl swimming

Holmér (1978) was the first to realise the potential utilisation of accelerometers for use in swimming. Holmér attached three devices to the swimmer, one on the neck, the 5th vertebra and the waist. In a flume with controlled water speeds, the swimmer

swam at 1.2ms^{-1} , 1.4ms^{-1} and 1.6ms^{-1} using both breast stroke and front crawl. Holmér was looking to investigate the horizontal and forward motions of the swimmer. A spectral analysis of the data showed that the swimmer contributed most of his propulsion through his arms, rather than legs. This work was conducted whilst the swimmer was in a flume where the swimmer would be mostly stationary, apart from impulses of forward motion so it is not clear how the accelerometers clearly showed these results. Yet, through verification using video cameras, Holmér showed these were due to arm movements. Although no percentage of contribution was presented, this verified previous works (Counsilman 1955, 1968; Di Prampero et al. 1974) and set the way for future works using accelerometers in Front Crawl swimming.

The use of accelerometers in swimming was not realised in practice until the late 1990s. With developments in technology requiring no analogue based recorders, devices could be made much smaller and be placed on a swimmer with the data downloaded after an event, in a normal pool. Ohgi et al. (1998) used a tri-axial accelerometer connected to a swimmers left wrist which was wired to a Personal Computer (PC) to process the data. The PC was pushed alongside the swimmer. Of the nine swimmers recorded, two results are shown, one for a breaststroke swimmer, the other for a front crawl swimmer. Ohgi et al. (1998) present data at a fast, middle and slow speed, with the images overlaid and describe the start and end of the stroke showing that the hand entry can be seen to be a large negative trough on the X axis of the sensor, and the recovery starts with a large Z axis peak around 0.7s after the hand entry.

Ichikawa et al. (1999) and Ohgi et al. (2000) developed a custom made, stand alone, accelerometer data logger which stored the data on the device for download and processing post event. This allowed no tethering to a PC allowing free uninterrupted swimming. The results highlighted the ability to identify the various phases of the stroke with the manual identification peaks and troughs to represent each phase. The phases of the stroke were visually verified using three cameras using a DLT (Direct Linear Transform) method, where 3D coordinates can be created from

various 2D cameras. There was no mention of the synchronisation method used between the cameras and accelerometers.

Ohgi and Ichikawa (2002) used an accelerometer based data logger recording at 128Hz. Their objective was to compare their acceleration results from the wrist to lactate recorded using a Lactate Pro device. Using two underwater cameras, they manually calculated the phases of the stroke and compared these points of the stroke in relation to their acceleration data visually. There was no measure conducted in comparison to lactate, other than over laying of acceleration graphs demonstrating the fatigue of the five tri-athlete swimmers over 3 x 300m tests.

Ohgi (2002) developed a new data logger utilising an accelerometer and gyroscope. This allowed the measurement of angular rotation of the swimmers wrist. This new device re-confirmed the ability to identify the phases. This addition of the Gyroscope did however assist with the identification of the hand pitch (Figure 15). The hand pitch is an important parameter that allows a swimmer to achieve significant gains in stroke performance. Maglischo (2003) states that the hand should enter the water at an inward facing angle. This can be achieved with medial rotation, as shown in Fig. 8a; this results in the production of a hydrofoil effect. Ohgi et al. (2002), with the use of accelerometers, was able to determine that if the swimmer had small Z-axis positive acceleration and large X negative acceleration (Figure 15) the swimmer had a pitched entry. Conversely, if the swimmer had large Z acceleration then the swimmer had a flat palm entry. This offers a distinct advantage over cinematography where splashes may result in occlusion of the hand, however, this is not currently quantified through the use of sensors but suggested from patterns identified in the data. The findings of their previous work were also shown in subsequent studies (Ichikawa et al. 2002a; Ohgi 2002; Ohgi et al. 2002; Ohgi and Ichikawa 2002; Ohgi and Ichikawa 2003).

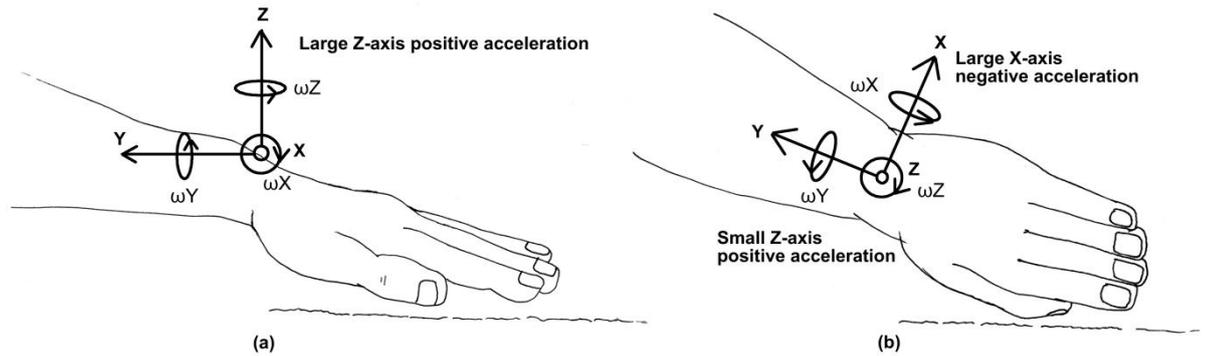


Figure 15: Hand Pitch at entry to the water, (a) Flat palm entry, (b) Pitched hand entry. Notations: ωX , ωY , ωZ are rotational velocity from Gyroscope.

Davey et al. (2008), developing from earlier work (Davey 2004), used a lower back mounted sensor to record lap times, stroke count and stroke rate. These were compared to, and subsequently validated, to video derived counts and real time manual counts and lap timings. No significant differences between the video, manual and accelerometer lap times were found. There was also no significant differences for stroke count and stroke rates using the accelerometer. Using the accelerometer on the lower back, Davey et al. (2008) were able to use the sinusoidal output of the body roll to identify the stroke count, from the Y axis horizontally across the lower back. The X axis, running vertically along the swimmers back, the wall push off and turn were identifiable allowing the calculation of the lap times. With the duration of the lap and the stroke count then known, the stroke rate was calculated.

Daukantas et al. (2008) employed a custom made device using an accelerometer sampling at 200Hz. Placed on the lower back with a belt, they counted the number of strokes per lap for Butterfly and compared these to a manual count. A video camera filming at 25Hz was pulled underwater to film the swimmer, purely for comparative reference. Their synchronisation of accelerometer to camera consisted of using the LEDs on the device to identify the state of the device (recording or not). As the video was used simply as a reference for how many strokes had occurred, their synchronisation methodology did not require significant complexity. Daukantas et al. (2008) note that accelerometers; without additional gyroscopes and

magnetometers; can be used successfully in timing applications such as counting strokes, and identification of phases and measurement of time durations within swimming showing the potential for development in this area. Daukantas et al. (2008, p.1) went further to state that,

“automatic identification of all the intervals, periods and phases using inertial sensor is feasible, but it is a long term goal..”

Fulton et al. (2009b) investigated the lower body of the swimmer, the first study to do so. They placed a single accelerometer and gyroscope device on the thigh and shank, equipment which was commissioned by the Australian Institute of Sport and therefore the devices used are not commercially available to allow independent verification of their findings. This is also the case in other works (Davey et al. 2008; James et al. 2011; Stamm et al. 2012; Stamm et al. 2009; Stamm et al. 2011). They conducted a validity and reliability study, using the gyroscope of the device, to measure kick counts for 12 swimmers with varying disabilities. The data were recorded at 100Hz and processed using bespoke software for their devices. The kick counts recorded from video data were compared to those generated by the gyroscopes. Their findings were that the accelerometer tended to underestimate the kick count by -1.7% when swimming, which in real terms was 2 kicks less per 100m. There were some anomalous results with 2 swimmers of their trial producing errors of up to -7.3%. This was not explainable through closer inspection of the data, but presumably this was due to their disability and or individualisation of their kicking mechanisms.

Bächlin et al. (2009) were the first to offer a multi-device system. Using an accelerometer based data logger on the upper back, lower back and both wrists. From the data recorded, they were able to calculate swimming velocity using the wrist data, this showed the wall-push off at either end of the pool, allowing a time to be calculated. Then, with the length of the pool known, the velocity is calculated. They measured the time per stroke by calculating the time between hand entry from the data, similar to the identification by Ohgi et al. (2000), but automatically using a peak detection algorithm. With the velocity and time per stroke known, distance per

stroke was calculated as the velocity multiplied by the time per stroke. This then allowed the efficiency of the swimmer (measured as distance per stroke vs velocity) to be calculated in line with the findings of Craig et al. (1985) where a swimmer, with improved technique, should swim faster with the same number of strokes per length. Results are shown as an error range. Using the upper and lower back sensors, Bächlin et al. (2009) calculated the body roll and the pitch of the body in the water. They found that pitch angle calculated from a video camera was better correlated to accelerometer on the lower back sensor (Error = $2.4^{\circ} \pm 1.8^{\circ}$) rather than the upper back sensor (Error = $6.3^{\circ} \pm 4.1^{\circ}$), but no statistical calculations were performed to either show a significant difference, or assist with correction of the data. Body roll angle was not assessed against video, stating that the acceleration of the swimmer would not affect the calculations. No details were given on how multiple devices were synchronised to video cameras.

Bächlin et al. (2009) found that lap time calculations showed an error at the start of $\pm 0.3s$ and an error in the wall touch of $\pm 0.2s$, which could result in $0.5s$ error per lap, but considered acceptable. This resulted in an error of $\pm 1.33\%$ for velocity calculations. Error for time per stroke varied depending on swimming speed and the deviation depends on the idiosyncrasies of the swimmer due to the changes in the peaks and troughs in the data, which are used to process the data. Results showed $\pm 13.3\%$. The same results were presented in their later paper (Bächlin and Tröster 2012).

Pansiot et al. (2010) took a novel approach of adding a sensor to the goggles of a swimmer (considered ear worn) to collect the data. This small sensor comprised of a tri-axial accelerometer recording at $50Hz$. It has the capability to transmit data through a $2.4GHz$ wireless transmitter, but this was not used because it would '*not be practical to transmit the measured acceleration data in real-time to a base station*' (Pansiot et al. 2010, p154). No detail as to why this would not be practical was offered.

Data were stored on the device and processed post event. Using the pitch and roll measurements, a similar process to Bächlin et al. (2009), they were able to

distinguish between the stroke types, backstroke, front crawl and breast stroke. They also presented information on the breathing patterns of the swimmers. Based on the time duration of the body roll, they were able to identify the difference between non-breathing and breathing sides, where breathing was a longer time. This was then discussed as a stroke asymmetry. From the work of Chollet et al. (2000a) and subsequent studies (Chollet et al. 2008; Seifert et al. 2005a; Seifert et al. 2005b), that asymmetry is common because of the arm coordination techniques used. The breathing ratio shown by Pansiot et al. (2010) assumes that the durations in the propulsive phases, which are not directly measured, are by the same ratio. There is no use of video cameras for verification or statistical analysis conducted. This work identifies breathing asymmetry and identification of stroke type.

Nakashima et al. (2010), developing from Ohgi and Ichikawa (2002), added wireless communication methods. Their goal was to use sensor fusion to derive positional data from accelerometers and gyroscopes, this could then allow the visualisation of the arm stroke, as offered by 3D camera systems, showing the elliptical paths identified by Counsilman (1969). Nakashima et al. (2010) tested their system on land and produced results which are very close to those offered by 3D camera systems. They concluded that there was a maximum error of 50mm compared to MAC3D (Motion Analysis Corporation). This allowed them to develop software to visually show the stroke in close to real time, with future work to focus on improving the accuracy of the system.

Le Sage et al. (2010) developed a single data logger utilising an accelerometer sampling at 50Hz. This was later upgraded to sample at 25Hz with an additional gyroscope (Le Sage et al. 2011). The system utilised wireless communications where data were processed on the device and the results, such as stroke type and stroke rate, were transmitted to the coach on a PC. The system was synchronised using a pressure pad on the starting blocks and pressure pad under the water at the other end. This allowed lap times to be accurately timed. As the swimmer dived from the pad, a trigger was sent to the PC, this allowed any previous data from the sensor on the swimmer to be ignored, and be stored for each lap.

Stamm and colleagues (Stamm et al. 2012; Stamm et al. 2009; Stamm et al. 2011) and James et al. (2011) have progressively developed from the original presented by Davey et al. (2008), which utilises a lower back sensor similar to Le Sage et al. (2011). Stamm et al. (2011) worked towards determining absolute velocity from a lower back sensor for front crawl swimming. The acceleration gathered from the accelerometer could in theory be integrated to calculate Velocity, but this is often not conducted due to the potential for error in the results. Stamm et al. (2011) compared two methods to calculate the forward velocity of the swimmer. Firstly, using only the forward acceleration of the swimmer, and conducting integration on the signal to derive the velocity (V_{fwd}). Secondly, the total acceleration of the swimmer, that is the addition of each axis of the accelerometer and then integrated for velocity (V_{tot}). Results were compared to an Applied Motion Research Speed Probe 5000 (SP5000). This involves the swimmer being tethered with a small nylon cord, as the swimmer moves down the pool, the cord is drawn out of a reel, the speed of the reels movement is measured as the speed of the swimmer. Wall push off velocity was determined at 1.74ms^{-1} by the SP5000, which was deemed 'close' to 1.45ms^{-1} determined by the V_{fwd} . The mean velocity was shown to be 0.94ms^{-1} by the SP5000, which was considered close to that of 1.33ms^{-1} for the forward velocity from a_y , and also close to 0.84ms^{-1} from V_{tot} . Variation over the duration of the test was also presented as a percentage, results showed $\pm 8.9\%$ variation using the SP5000, $\pm 15.6\%$ using V_{fwd} and $\pm 12.6\%$ using V_{tot} . No additional statistical differences were presented. From the results shown, Stamm et al. (2011) concluded that velocity could be derived for front crawl swimming, but more work was needed. The V_{tot} method shows some promise, however, the percentage difference needs to be significantly reduced.

Stamm et al. (2012) progressed from velocity identification to investigate arm symmetry, similar in principle to that suggested previously by Pansiot et al. (2010), where without directly measuring the arms, an assumption from the body roll (or head roll) is assumed to relate directly to a phase in the stroke. Stamm et al. (2012) used a zero crossing algorithm to identify when the body rolls from left to right, where positive values were a left roll, and negative values showed a right roll.

The zero crossing point identifies when the body is level. With reference to a video camera from the side, the time of the body roll, from zero to zero, for each side. It is assumed that the body is at zero when the arm enters the water, and rolls to the same side as that arm. The duration of this body roll was measured and a regression analysis of accelerometer derived duration to video derived duration, was shown to have an R^2 value of 0.96 and 0.97 for left and right arms respectively. A Bland-Altman plot showed no systematic error. Stamm et al. (2012) did show that for their study of 9 swimmers, as swimming speed increased, the roll duration decreased, with progression from 1.21ms^{-1} to 1.4ms^{-1} and 1.83ms^{-1} the average time decreased from 1.06s, through 0.9s to 0.63s.

Whilst the results are significant for the duration, it seems illogical to infer what the arms are doing, particularly over time where variations in arm fatigue may be shown. This has been demonstrated with work led by Ohgi (Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2003) where the wrist sensors were able to go further than the duration of a stroke, but also observe the phases. This is particularly needed where the phases of the stroke could change over time. A limitation of the work by Ohgi is that using a single sensor on the arm does not allow for a comparison of Left to Right arm phases and durations which could demonstrate asymmetry. There is a need to quantify whether there is a difference in the arm phases and body roll.

Lee et al. (2011) set out to examine the validity of an accelerometer and gyroscope in the assessment of 2D and 3D stroke measurement on a dry swim bench. A tri-axial accelerometer and gyroscope (200Hz) was used on the wrist of six swimmers. This data were processed in comparison to 3D camera system (200Hz) and a 2D camera (25Hz) was used to confirm the phases of the stroke. The sensor data were correlated to the 3D video system. The correlations between sensor data and 3D camera data showed very strong positive results. Temporal factors were recorded, Entry to Entry time ($r = 0.97$), Exit to Exit time ($r = 0.98$), and Propulsive (Entry to Exit) time ($r = 0.85$). It was concluded that the sensors were able to record these two phases of the stroke accurately. However, no statistics were measured for

the other phases of the stroke such as Push and Pull, however, it was mentioned that they were observable. Furthermore, no information was provided to show that the sensor data automatically detected the phases of the stroke.

Daukantas et al. (2008) stated that there was potential to measure the phases of the stroke and the durations therein. Whilst initially identified by Ohgi et al. (2000), there has been no attempt to automatically detect these phases. If phase information was wanted by a coach (or researcher), then this can only presently be calculated using manual digitisation of video. These types of factors can take significant time to calculate (Le Sage et al. 2011). Dadashi et al. (2013) however, have developed a method to identify the phases of the stroke, helping to reduce this time. Dadashi et al. (2013) utilised three commercially available Physilog® (BioAGM, CH) data loggers. These were synchronised with video cameras using a flashing light from the device when turned on. The devices comprise of a tri-axis accelerometer and tri-axis gyroscope recording at 500Hz. They were attached to the swimmers wrists using tape and to the lower back using a Velcro belt. The devices were synchronised with video cameras using the lights flashing on the devices when turned on. This does not provide detail of the time differences between turning on each device. Using peak and slope detection methods from the accelerometer and gyroscope, Dadashi et al. (2013) were able to create an automatic algorithm which could identify the start of the pull, push and recovery. This allowed the identification of IdC using the propulsive phases (pull + push) and non-propulsive phases (recovery to pull). Two independent observers watched the videos of the swimmer, and recorded the stroke phase times. When compared to the timings from their system using Bland-Altman plots, the results showed most of the results for IdC, pull and push and non-propulsive, were within ± 1.96 std deviations. Dadashi et al. (2013) concluded that such a system may help to reduce coaching time from analysis of video, reiterating the same point as Le Sage et al. (2011).

Bächlin and Tröster (2012) processed this information post swim on a PC, yet is still classed as a 'real-time' system, as an output would be generated in a few minutes of the swim. This is similar to the wireless systems of Stamm et al. (2012)

and Le Sage et al. (2011) where some of the parameters are calculated on the device themselves and transmitted to a PC. The benefit of this is that the data is provided 'instantly' to the athlete, coach or researcher.

However, devices calculating real-time data may require updates to their firmware to add new features or refine existing ones. With the exception of Dadashi et al. (2013), all of the systems shown here use custom made data loggers, which do not provide for each of verification of the findings. A commercial off the shelf (COTS) approach would lead to no significant, if any, updates to the firmware of the data logger as it purely collects data. This then also allows a PC based approach; where data is downloaded post swim; to be updated as needed, in a single location rather than over multiple devices and with limited storage space for firmware. This also has an advantage for coaches, supposing a commercial system, where individual software could be written to format output files from different manufacturer's data logger devices. This would help reduce the cost of purchase to coaches.

There is a large gap between science knowledge and its translation into coaching practice (Williams and Kendall, 2007; Bishop, 2008; Reade et al., 2008). This highlights a general issue within sports science, and one that sports technology also appears to be guilty of. Generally within the current swimming technology literature there has been a lack of acknowledgement of the end users' needs for the system. The user has generally been assumed to be the coach, or the swimmer, but none of the work (Table 6) has used a needs analysis to identify the requirements of the system. Le Sage et al. (2011) were the first to really understand the coaching needs of the system by using a questionnaire for coaches, biomechanists and researchers however no details of the number or methods were presented.

The recent adoption of IT based solutions, generally in sport, allow better communication between the coach and athlete (Libermann, 2002). Many organisations view the development of technology in order to measure and enhance performance as a positive (Riot and James, 2013). The development of innovative systems will allow higher-level information to be offered easily and directly to the end user. This in turn allows the end user to solely focus on the decision making

process to act on this information (Baca et al., 2009). Video analysis is very time consuming for the coach to setup, use and analyse (Le Sage et al. 2011).

Furthermore, the results can often be misleading as the video can often be used to only see 3-4 cycles which is misleading when making assumptions about the entire session (Dadashi et al. 2013).

This shows the need for a system which record factors in conjunction with the performance literature, however, this also needs to be supported by coaches opinions to ensure that it is of benefit and fulfills the needs of the coach. This will allow the coach to focus on the decision making process, to make the best choices for their athletes, rather than focusing on the data collection.

Author(s)	Number of Sensors	Location(s)	Sensor Type	Lap Time	Velocity	Stroke Rate	Stroke Count	Distance Per Stroke	Stroke Duration	Kick Count	Fatigue	Hand Pitch at Entry	3D Display of Stroke	Upper Body Roll Angle	Lower Body Angle	Body Roll Timing	Body Pitch	Stroke Phases Velocity	IdC	Symmetry	Body Roll Consistency	Body Roll per Stroke Phase	Output for Coach
Holmér (1978)	1	LB	A		✓																		
Ohgi et al. (1998)	1	LW	A									✓							✓				
Ohgi et al. (2000)	1	LW	A									✓							✓				
Ohgi (2002), Ohgi and Ickikawa (2002)	1	LW	B								✓	✓							✓				
Ichikawa et al. (2002a)	1	LW	B																				
Ichikawa et al. (2002b)	1	LW	B																				
Davey et al. (2008)	1	LB	A	✓ ◇		✓ ◇	✓ ◇																
Daukantas et al. (2008)	1	LB	A			✓	✓ ◇ ✓ *																
Fulton et al. (2009)	1	Thigh	G							✓ ◇													
Bächlin et al. (2009), Bächlin and Tröster (2012), Bächlin and Tröster (2012)	4	LW, RW, UB, LB	A	✓	✓	✓	✓	✓	✓					✓*	✓*	✓*	✓*						
Pansiot et al. (2010)	1	Head																					
Nakashima et al. (2010)	1	LW	B										✓*										
Le Sage et al. (2011)	1	LB	B	✓ ◇		✓ ◇	✓ ◇																✓
Stamm et al. (2011)	1	LB	B															✓ ◇					
Stamm et al. (2012)	1	LB	B																	✓ ◇			
Dadashi et al. (2013)	3	LW, RW, LB	B						✓ ◇									✓ ◇	✓ ◇				

Table 6: Summary of current research into Accelerometer/Gyroscope use in Swimming

2.3.4 Synchronisation and Calibration

The increasing move towards systemic measures of performance necessitates the use of multiple synchronised measurement instruments to enable recordings from several body segments or different pieces of sports equipment. Previous single sensor systems have been synchronised with cameras for validation purposes using the status lights from the device (Daukantas et al. 2008). However, many have offered no details on how this was performed (Bächlin et al. 2009; Bächlin and Tröster 2012; Ichikawa et al. 2002a; Ichikawa et al. 1999; Ichikawa et al. 2002b; Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2002). Bächlin and Tröster (2012) were the first to demonstrate a multiple sensor based system for swimming, but offered no details on how the devices were synchronised, or how this was synchronised to the video. Dadashi et al. (2013) used three devices, and stated that the devices were synchronised using the status lights from the devices, however, there is no indication of how the three devices were synchronised with each other. To achieve accurate results, synchronisation between these instruments is necessary to compensate for the time delay; due to differences in start-up times, variations in instrument response time and instrumentation drift due, for example, to slight variations in temperature between different measurement sites.

Papić et al. (2004) suggest that in human motion analysis and, more specifically for sports events, basic camcorders offer the advantages of lower cost and reduced cabling when compared to specific camera systems such as Vicon (Vicon Motion Systems, Oxford, UK). However, there is a fundamental issue with using multiple camcorders which is the lack of phase locking between each camera – which is also widely known as ‘genlock’ capability. They go on to propose that for 3D kinematic data using camcorders the maximum amplitude of the measured kinematic signal can be used as a reliable synchronisation point.

Temporal realignment of data from unsynchronised accelerometer measurements could be achieved using a suitable signal analysis technique to establish event correlation from different sites. However, in the authors' experience in many

situations the additional effort required to process the data is undesirable, can be difficult to automate and can be prone to error due to subject-to-subject variation. To overcome these potential difficulties other researchers have investigated several approaches to building synchronisation into the measurement system.

Kirovski et al. (2007) developed a wireless synchronisation method to pair mobile phones over Bluetooth™. Their method used a notification to each phone to signify the start of a pairing session. In principle, the same technique could be used to synchronise accelerometer data loggers for monitoring human sports performance. However, at the present time most low cost data loggers either lack wireless functionality or where it is implemented it is often limited in terms of bandwidth requirements, transmission distances or environmental limitations - underwater sports monitoring for example. Consequently, there is often a need for a simple, robust method of synchronising signals from existing low cost data loggers.

If internal real-time clocks (RTC) are available they can be synchronised to the system clock of a personal computer, however RTC time resolution is often limited to one second which is inadequate for sports performance monitoring applications where millisecond resolution is usually required. There is also a penalty with this approach in relation to the physical connection and initialisation of the RTC unit. There is a need here to establish a synchronisation method for non-wireless devices

Calibration is an important factor when considering scientific equipment. Calibration methods for video analysis are well established (Grimshaw et al. 2006; Payton 2008). With accelerometer based approaches calibration typically involves static tests for 0g and (\pm)1g where any systematic offsets are used to compensate the recorded results. However these systematic errors are often far smaller than any acceleration generated by a movement. Most manufacturing companies will also perform their own calibration to ensure inter-instrument reliability but details on these are often undisclosed for proprietary reasons (Moeller et al. 2008).

2.4 Summary of Measurement Methods

Previous studies of swimming performance using sensors have focused on Kinematic rather than Kinetic outputs, with a focus on temporal factors. The primary aim of developing systems such as these are to make basic tasks for the coach, such as lap time and stroke count, easier and less time consuming to record.

This chapter has identified a wide range of variables to consider when determining the performance factors of a swimmer. Sensor based systems have recorded a number of these factors, such as velocity of the swimmer, time per lap, distance per stroke and more recently a method to identify the phases of the stroke. However, previous studies have not collected all the measured data into a single cohesive report for presentation to the coach. Such an approach will be a novel outcomes of the current investigation.

Whilst it is necessary for a coach to have a good understanding of the biomechanics of swimming (Coleman 1998), there are a lot of factors which could be recorded. When designing a system is it important to understand the stakeholders needs (Cheng and Atlee 2007; Kranz et al. 2007; Nuseibeh and Easterbrook 2000; Sharp et al. 1999). The stakeholders for this work are coaches, who can use the primary output, but the system should allow the data to be used by researchers. Le Sage et al. (2011) identified the same stakeholders for their system.

In the following chapter the methodology for the synchronisation and development and characterization of a novel sensor based system that builds on the work reviewed (Table 6 and Table 20) in this chapter is presented.

Chapter 3 - Methodology

Parts of this chapter have been published in the following papers:

Callaway, A., Cobb, J. E., & Jones, I. (2009). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *International Journal of Sports Science and Coaching*, 4, 139-153.

Callaway, A., & Cobb, J. E. (2012). Linear acceleration measurement utilising inter-instrument synchronisation: A comparison between accelerometers and motion based tracking approaches. *Measurement in Physical Education and Exercise Science*, 16, 151-163

3 Experimental Methodology - System Design

This chapter presents the methodology for the study including identification of the performance analysis needs of a swim coach, the development of the measurement system and the experimental design used to characterize the system. The equipment is presented along with its use and setup. The data collection procedures are shown, with full information about the participants studied. The approach used to calculate and validate aspects of the system is also presented.

This research project had three distinct studies.

Phase 1: Firstly, interviews with coaches of varying levels to help evaluate their requirements for swimming coaching (3.1). These factors help to define the elements which are then recorded in the system design (Phase 3). These interviews also identified the coaches understanding and use of performance analysis and associated technologies (Appendix 1).

Phase 2: The second phase (3.2) involved the validation of the instruments used for the study along with developing and validating a method for calibration and synchronising multiple measurement devices. There has been a lack of detail presented by most authors in the methods used to synchronise multiple devices together, and to the camera. There was a need to develop a clear novel method to allow the synchronisation of multiple non-wireless sensors. This process addresses the lack of information surrounding the synchronisation processes used and presented a novel approach which can be used by other COTS devices

Phase 3: The final phase (3.3) was the development of the system. Using the factors identified by the coaches and literature (Phase 1) and using the synchronised devices (Phase 2), the analysis system was created. This phase includes the various stages of development, factors recorded which extend on previous research (Table 6 and Table 20) demonstrating the novelty and contribution to knowledge. Also presented here are the methods used to calculate factors from the accelerometer data. This section also shows a validation method for the system which has been lacking in some previous studies (presented in Table 6).

3.1 Phase 1 - Identification of factors to record

Previous systems for swimming (Bächlin et al. 2009; Bächlin and Tröster 2012; Ichikawa et al. 2002a; Ichikawa et al. 1999; Ichikawa et al. 2002b; Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2002) have not considered the users of the system. However, the system presented by Le Sage et al. (2011) identified the users of their system as both coaches and researchers. They used interviews to gather data from these users and used thematic analysis to analyse the factors and use of the system. Le Sage et al. (2011) did not provide any information on how these were conducted, or more importantly how many people (or types of people) were used in the work. The stakeholders for this current work are coaches, who will use the output. Using the biomechanics literature in the area, there are an array of factors which can be recorded. To better understand the factors needed by the coaches to create a performance monitoring system, interviews were conducted to identify their needs and to confirm the literature in the area.

3.1.1 Subjects

In seeking the coaches they had to be a swimmer themselves (currently or previously), this allowed them to express their previous experiences of being coached through various phases of their career. They also had to be a current active coach at a recognised ASA level to ensure they were up to date with current coaching practice. The selected coaches needed to be of different coaching levels in order to ensure that the requirements of all coaching levels (ASA levels 1 to 3) were met within the data collection of the system. The coaches also had to have completed (or in process of completion) a BSc Sports Science or Sports Coaching based degree to ensure some degree of knowledge of biomechanics (Coleman 1998). Four coaches within the region volunteered to be interviewed, providing an opportunistic sample. Whilst this is a small sample, all coaches had been through the ASA coaching qualification system (ASA Levels 1-3) to ensure that the requirements across all the coaching levels were accounted for. This system is in place to ensures the

consistency and rigor of coaching within British Swimming, so should provide a consistent representative sample of the coaching levels. These were from the same club, however the two lower level coaches had worked at other clubs in other counties so could use their previous experiences to draw upon for the answers.

CS is a Female Level 1 coach (Level 2 swimming teaching) aged 21. She has been swimming since she was 15 and has been a coach for 6 years and is about to start working on her Level 2 Coaching award. CS has also swum to a national level. Has worked at 2 previous clubs in different counties.

SL is a Female Level 2 coach aged 21. She has been coaching for 6 years also and has been a competitive swimmer to a national level. Has worked at another club previously in another county.

ER is a Female Level 3 ASA Club Coach aged 30 and has been coaching for 14 years. She was a former International level swimmer. She has also been awarded a place on the Advance Coaches Offer and is a member of the ASA young coaches network. ER is a full time Head Coach.

SW is a 30 year old Male level 3 coach. He has been coaching for around 14 years and swam at a national level. He has been a Talent ID coach, and Inter-County coach as part of England Talent coaching staff. SW is an Assistant Head Coach.

3.1.2 Procedure

Interviews were scheduled at a time to suit the coach and were audio recorded with their permission. They were conducted during December 2012 to April 2013. No pilot data was collected. Semi-structured interviews were used to allow conversations to develop and to allow flexibility in the questioning (Gratton and Jones, 2010; Purdy, 2014). The key information gathered focused on:

- What factors are of use to a coach?
- Which biomechanical factors do they currently engage with what level of swimming ability and how is this determined?
- What is their understanding of performance analysis?

- Would they use an enhanced performance analysis system?

The results were coded using thematic analysis to identify the key themes arising from the interviews (*Qualitative Data*), following methods proposed by Gratton and Jones (2010). Factors of importance to the coach are presented in 3.1.2.1 to allow the development of the system, which at large supported the literature. The other themes identified are shown and discussed in Appendix 1.

3.1.2.1 Factors of importance

The coaches were each asked for which factors of a stroke, in their opinion, were of importance to record.

ER: [On factors at level 2] ... distance per stroke, how many strokes they took per length for efficiency, making them aware of pacing and turns and recording what they can achieve over 5, 10, 100.

SW: holding distance per stroke [Stroke Length] that every length should be a similar stroke count, and how they pick up pace by maintaining a low stroke count

CS: ...as they're getting more tired their technique will change, so it would be quite interesting if an analyst could see which parts are the bits that are changing the most from being tired and then they can try and work on that throughout training and trying to keep their technique the same

SL: ... how much the hip rotates, some people's hips rotate, you know, all the way around, and their shoulders, other people's it stays still.

The factors identified by the coaches generally supported the literature, which included Stroke Count, Stroke Rate, Stroke Length (interchangeable with distance per stroke) which relate to the features shown by Hay (1993) in his hierarchical model. It was also identified by SW that lap times are recorded by stop watch, which also has a stroke count function available on the device. The factors identified here are very similar results to previous works using accelerometers (Bächlin and Tröster 2012; Davey et al. 2008; Le Sage et al. 2011; Ohgi 2002). Glazier et al. (2006a) discuss that these performance parameters do not provide information on the

underlying patterns that generate these factors. Despite this need, identified by Glazier et al. (2006a), most research tends to focus on descriptive stroke characteristics because they are more '*readily observable*', such as stroke count. Yet, variations in technique over multiple laps using a video based analysis, would be even more time consuming for a coach. CS did note that as the swimmer gets tired, their technique will change, and this should be considered. These changes over time have been previously presented (Ohgi 2002; Ohgi et al. 2002; Ohgi and Ichikawa 2003), but there was no real presentation of depth here and no statistical backing to clearly identify any significant changes in factors over time.

SL described a notational based technique analysis called BALBT, standing for Body, Arms, Legs, Balance and Timing. Using a printed sheet of paper,

... you go down this sheet and you comment, just what you see, not what you don't see. So, say I was looking at body position, and the head was, you know, out of the water so many centimeters, I would write that. I wouldn't write 'needs to put head down further'; you just write what you see. And then from that you know what to work on. They also give you .. this tick sheet, so it's got all of the movement of the arm, like the insweep, outswEEP, all of that. Every single bit of the stroke broken down, and you just literally tick what you see, and that's all you do.

The use of BALBT identifies the need to measure some additional factors not identified by the other coaches. The balance refers to the body roll, already identified by CS. The inclusion of timing and phases of the stroke show that these are important to the coach. These factors have been identified using accelerometers on the body, yet these were displayed as raw accelerometer data (Ohgi 2002), with no statistical processes underpinning the phases or timing of the stroke.

In summary it was determined from this investigation that at minimum the system should provide measure of:

- Lap Time
- Average Velocity
- Stroke Count

- Stroke Rate
- Distance Per Stroke
- Body Roll Angle
- Phases of the Stroke

To achieve the measurement of these factors, multiple devices will be required on the swimmer. Previous systems have used an accelerometer sensor on a single wrist (Ichikawa et al. 2002a; Ichikawa et al. 1999; Ichikawa et al. 2002b; Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2002; Ohgi and Ichikawa 2003; Ohgi et al. 2000) with recent developments to multiple device systems (Bächlin et al. 2009; Bächlin and Tröster 2009, 2012). A single device system could identify the lap time and velocity. However, stroke count and stroke rate and phases of the stroke would only then be identified on a single arm, which does not highlight the differences between the sides of the body. A multiple device system is needed to measure the differences in the sides of the body, as well as the differences in upper and lower body angles. These multiple device systems have used four data loggers. These are placed on the wrist (x2), upper back and lower back (Bächlin et al. 2009; Bächlin and Tröster 2009, 2012). It is not clear why previous works using multiple sensors have not calculated the additional factors identified here. Daukantas et al. (2008, p.1) has stated that,

“automatic identification of all the intervals, periods and phases using inertial sensor is feasible, but it is a long term goal..”

One reason may be that the algorithms developed do not allow for a consistent detection which is why Daukantas et al. (2008) thought it was a long term goal. During the design process of the system, it seems logical to attach sensors to other upper body segments to ensure a range of data is collected to design a reliable system. Sensors have yet to be placed on the upper arm of the swimmer. Placing sensors here may aid in the reliability of the phase detection. Therefore, six devices will be used for this system, with the new device placed on the upper arm.

The methods of identifying and calculating the factors using accelerometer data is presented in section 3.3.8. Through the process of calculation there are some additional factors which can be calculated as a matter of process, for example, when identifying the stroke count per lap, the duration of each stroke can also be calculated. These additional factors have not previously been measured and contribute, in part, towards identifying the underlying patterns, which Glazier et al. (2006a) shows has not previously been considered.

3.2 Phase 2 - Synchronisation of Multiple Independent Devices

This section outlines a method for synchronising multiple devices. The equipment is described and the method used to synchronise them is also described. The synchronisation technique also includes a method to calibrate the accelerometers by removing offsets in the device. The results are correlated to a video camera, acting as a criterion (reference) measure. The individual devices are also correlated to one another to ensure their validity.

3.2.1 Equipment

The Waterproof X6-2mini (Gulf Coast Data Concepts, USA) is a hermetically sealed, compact tri-axial accelerometer data logger weighing 38g and measuring 2.95 X 1.6 X 5.9 cm (Figure 16a).

This device was chosen over others on the market primarily due to cost. At the time of purchase these were £150 per device. Other similar waterproof devices such as those by MSR (Modular Signal Recorder, Switzerland), at the time of purchase, cost £600-800 per device. This would not be a feasible solution as it would be out of price range for most coaches and lower level clubs. Since a multiple device system was required, a wireless option would have added additional cost to the system as would a gyroscope. Cost was the driving factor behind the decision. The only other equipment a coach would need to use this system in the future would be a magnet and a USB cable to download the data to their laptop. Wireless devices using

Bluetooth® would not work with multiple devices as the protocol does not allow for multiple channels (multiple devices) per port (per Bluetooth® dongle) and would require multiple laptops and would complicate the data collection process. Using the X6-2 devices allows a straightforward data synchronisation process to be created (presented in this chapter) which will allow for easier future use by researchers and coaches.

Each X2-mini has the ability to be set up for a data range $\pm 2g$ to $\pm 6g$. Data is output into CSV file format in either 12-bit or 16bit format with user selectable data rates of 20, 40, 80, 160, and 320 Hz. It uses an internal 250 mAh Li-Poly battery which charges via USB (Figure 16b). Data are stored to a 1GB microSD card internally, which is read via USB. These devices have no external switches and instead rely on a reed switch, operated by magnets, in order to switch on and off.

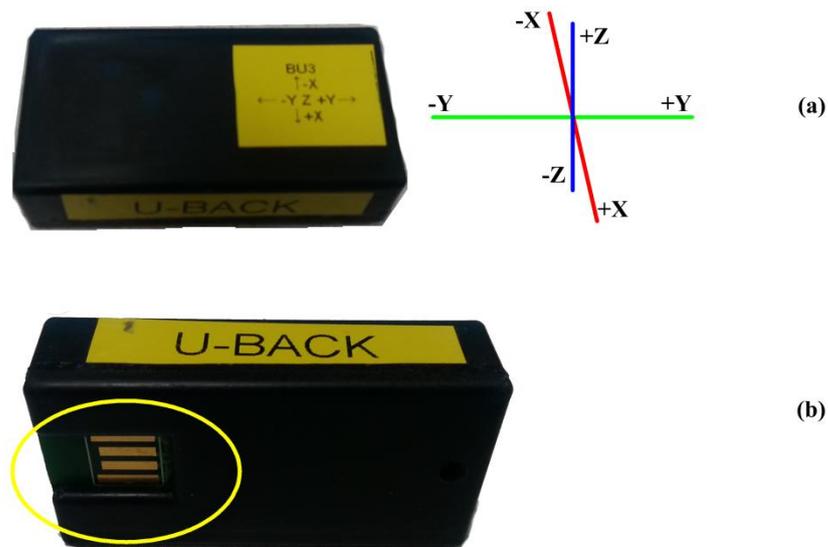


Figure 16: X6-2 Mini (a) Axis Orientation. (b) USB Connection

The device requires a setup file where the operator can establish the devices internal workings. The setup file for the devices was set as follows:

```
; PRODUCT_ID = X6-2mini  
microres  
16bitres = on  
gain = low  
deadband = 0  
DeadBandTimeout = 0  
samplesperfile = 50000  
statusindicators = High  
SampleRate = 320
```

The devices were set with micro resolution on, meaning time stamps were recorded in milliseconds. Samples were taken at 320Hz at 16 bit resolution, which was the maximum rate on the device. This allowed potential down-sampling later in the system should it be needed, however, this is towards the upper end of the range of sample rates used in existing systems: 25Hz (Le Sage et al. 2011), 128Hz (Ohgi 2002), 256Hz (Bächlin et al. 2009; Bächlin and Tröster 2012) and 500Hz (Dadashi et al. 2013). Deadband settings on this device allow for the sensor not to record unless the new reading is larger than the previous, this was deactivated so as to record all data. The number of samples to be stored in a file (CSV) before creating a new file on the device was initially set to 25000. Preliminary testing of the devices showed that by setting this to 50000 samples, there was no need to write additional code to combine these files automatically later in the process.

Previous works (Bächlin and Tröster 2012; Davey et al. 2008; Davey 2004; Ichikawa et al. 2002a; Ichikawa et al. 1999; Ichikawa et al. 2002b; Le Sage et al. 2011; Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2003; Slawson et al. 2008; Stamm et al. 2012; Stamm et al. 2011) have all used custom made data loggers. This has several limitations, in that the system is bespoke to them and their clients (such as Stamm and Davey working with AIS) and then not useable

by the coaches or other analysts. This also offers limitations in testing the equipment for validation purposes. The process taken with this work is to treat the sensor as a pure data logger, recording the movements of the swimmer for post processing. As the devices used are non-wireless, the data will need to be post processed, involving removing from the swimmer, connecting to the PC and downloading the data, then process the data and deliver to the coach. The delay was envisaged to be minimal. An issue with use of multiple non-wireless devices is that there is no clear way to synchronise them. The next section addresses how this was overcome.

3.2.2 Synchronisation and Calibration technique

The synchronisation method developed in this study requires the creation of a set of peaks (maxima) at the start of the data set. Subsequently, through identification of these maxima each data from multiple instruments can be automatically aligned. An example of this can be seen in Figure 17. Here, an accelerometer was placed on the seat of a rowing ergometer. The placement of the accelerometer in this specific situation allowed the software to automatically calibrate the devices by detecting any 0g systematic offset for the axis under investigation and applying this offset to all of the data for that axis (Figure 17a). Only 0g offsets have been used as the final system will look for temporal features of the signal, rather than the magnitude of the signal. By moving the seat, a set number of times (3 in this instance), local maxima can clearly be seen from the surrounding static data (Figure 17b). These were then used to post-synchronise the data of all the instruments by temporally aligning the data. This same principle was used to synchronise the video data and the instruments. Digitizing the video data of the seat movement using Quintic (v17, Quintic Consultancy Ltd., Coventry, United Kingdom) produced a kinematic output of the horizontal movement of the seat. This data also produced the same 3 peaks of within the data allowing these to be synchronised to the instruments using the same algorithm.

Dependent upon the application, the generation of the maxima in positions A and B could be performed on a bench, where other applications may lend themselves

to an in situ approach. Consider for example measuring the kinematics on a footballer with a data logger attached to each leg, the footballer would then stand still for a few seconds, then perform a set number of vertical jumps. The resultant impact of the landing would show clear peaks in the data above the static data of standing still. The footballer could then complete the task and the data be post-processed to align these initial peaks.

Once the synchronisation peaks have been generated (Figure 17b), the devices remained stationary generating a 0g output (a straight line) which helps to isolate the peaks from the surrounding data for ease of detection (Figure 17c). During this time, the instruments could then be attached, if necessary, to a person or object (Figure 17e). If the instruments are moved then the signal generated over this time would then require cleaning from the dataset after synchronisation (McMinn et al. 2010).

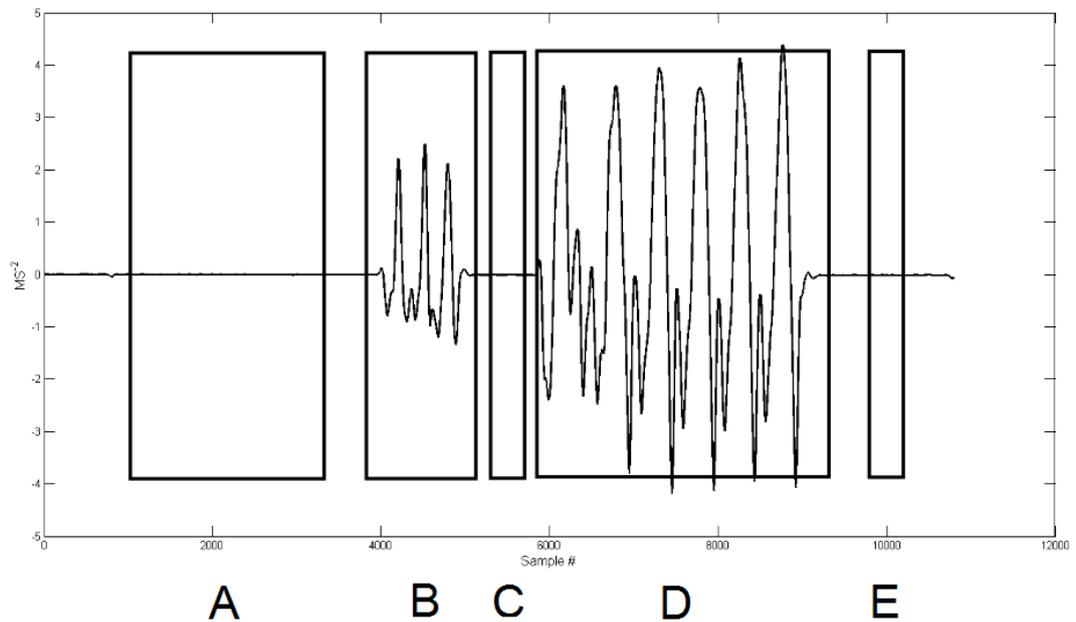


Figure 17: Five phases of the accelerometer recording: (a) the accelerometer on the seat, which also allows a 0 offset for all axes to be recorded, (b) 3 movements to sync to, (c) time to place the accelerometers on to the body/equipment, (d) the recording, and (e) time to switch off.

Using this approach it was possible to investigate the hypothesis of Sato et al. (2009) suggesting a strong positive correlation between video derived kinematic data and that obtained from accelerometers under the same measurement conditions. The study was designed to collect kinematic data on a linear axis from the data loggers and compare it to video derived kinematic data of the same movement, which was used as the reference method.

3.2.2.1 Instruments

Six X6-2mini data loggers were used, set to record at 320 samples per second with 16 bit resolution with a full-scale range of $\pm 6g$. The output files from these instruments provided time-stamps with a resolution of 0.1ms, and the digital signals produced by the accelerometers were stored as 'counts', these were converted to ms^{-2} in MATLAB® (R2007b, The Mathworks Inc, MA, USA) during the post processing.

FujiFilm Finepix HS-10.

Video data were recorded using a single camera set to record at 240fps set at 35mm focal length. Two 400W site lamps were used to provide additional lighting.

Concept 2 Model D.

A Concept 2 (Model D) rowing ergometer was used to create the linear data for the study. The rowing ergometer was leveled by raising the front on blocks to ensure a linear axis, it was verified with a spirit level on the horizontal beam.

3.2.2.2 Equipment Setup

The video cameras were setup in accordance with guidelines published by Grimshaw et al. (2006). The camera was positioned in the centre of the range of movement and 2m away from the ergometer perpendicular to the motion which was ensured using a 3-4-5 triangle method using 1m rulers, to the centre of the tripod. The centre of the lens was set to 37.5cm above the ground, with a custom reflective marker (2cm diameter) on the ergometer seat set to the same height (Figure 18a).

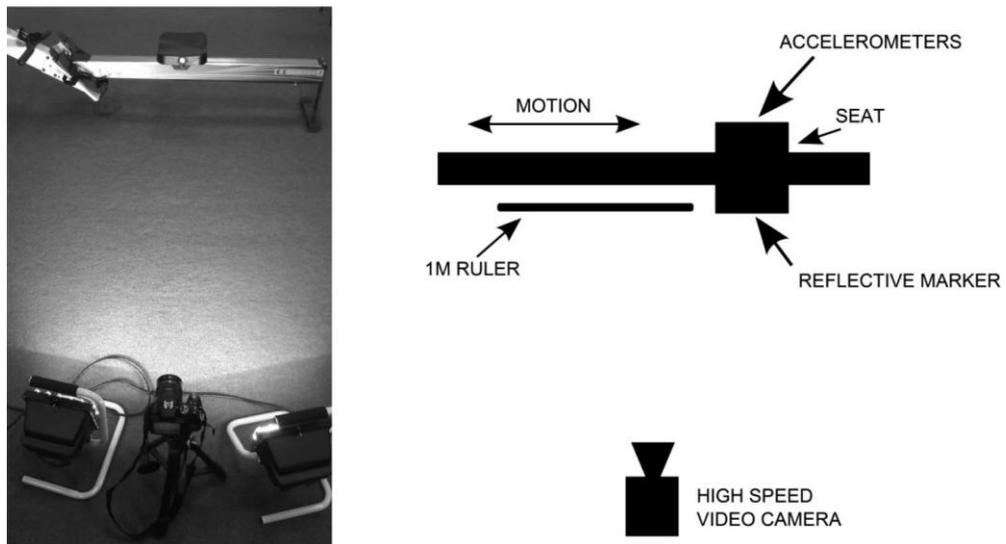


Figure 18: (a) Experiment setup. (b) Overhead view of experimental setup.

A 1 metre ruler with reflective tips used for the horizontal calibration of the video, was placed directly under the seat. A rectangular plate was secured to the ergometer seat, on the opposite side to the reflective marker, to allow the accelerometers to be placed along the same axis (Figure 18b). They were aligned so the positive direction (kinematic direction) of the tested axis was directed towards the fan cage of the ergometer and considered as the X direction. The tests were repeated with a rotation of accelerometers to allow for $0g$ and $\pm 1g$ on each axis to be tested. The MATLAB® (R2007b, The Mathworks Inc, MA, USA) script used for the processing, also took the offsets for the axis into account at the start of the sampling process. This was appropriate for this particular setup as the axis tested was at $0g$ when stationary.

3.2.2.3 Procedure

A male athlete aged 27 and with no prior rowing experience was used as the participant in this test. He was used to generate movement in the seat of the rowing ergometer rather than assessing rowing performance. With institutional ethical approval and the individuals informed consent and a general health and fitness questionnaire was completed prior to commencing data collection. Following basic acclimatisation, the participant was instructed to sit in the seat with his legs at full extension. Six data loggers were then turned on and then the video camera. The athlete was instructed to complete three small movements, a slight flexion of the knees to allow around 20cm of movement in the seat then back to full extension. This method allowed three local maxima to be created in the data set. The athlete then returned to the start position with legs at full extension and remained stationary for five seconds, then completed six full rowing strokes. The video camera was stopped and the accelerometers turned off. This process was repeated three times once each for the three axes, X Y and Z.

3.2.2.4 Data treatment - Implementation of Synchronisation Technique

The data were downloaded from each accelerometer instrument as a comma separated values file (.csv). These were then read into a custom MATLAB® (R2007b, The Mathworks Inc, MA, USA) script which processed the data as shown in Figure 19.

Data were read into the MATLAB® (R2007b, The Mathworks Inc, MA, USA) script. In each experiment only the axis being investigated was read. The first 1600 data samples, where the instrument was stationary on a bench after turning on, were used to calculate the offset of the axis. This offset was then applied to all the data. The data were then converted to ms^{-2} from data counts. Any variance in instrument power up time was removed by subtracting the first time stamp from all subsequent stamps to ensure all instruments started from a common zero reference position. In the event that the instrument mis-recorded any information, this was stored as a NaN (Not a Number) in the csv file. In the event of a detection of such

an event an average of the previous and subsequent readings was taken to fill the gap in data. The accelerometer data were then interpolated to 240Hz in order to match the sampling frequency of the kinematic video data. Generally, filtering has been ignored from previous studies (Davey et al. 2008; Lee et al. 2011; Ohgi 2002; Ohgi and Ichikawa 2002; Ohgi et al. 2000), but to maintain best practice all data were then low pass filtered using a 2nd Order Butterworth filter with a cut-off frequency set at 3Hz. This was found to be visually the best filtering from initial tests, and is similar to that of Le Sage et al. (2011) and Pansiot et al. (2010) at 5Hz. The first three maxima were identified in each set of six recordings for each trial. The data were shifted left or right dependent on the mean distance these maxima were from the first instrument's maxima.

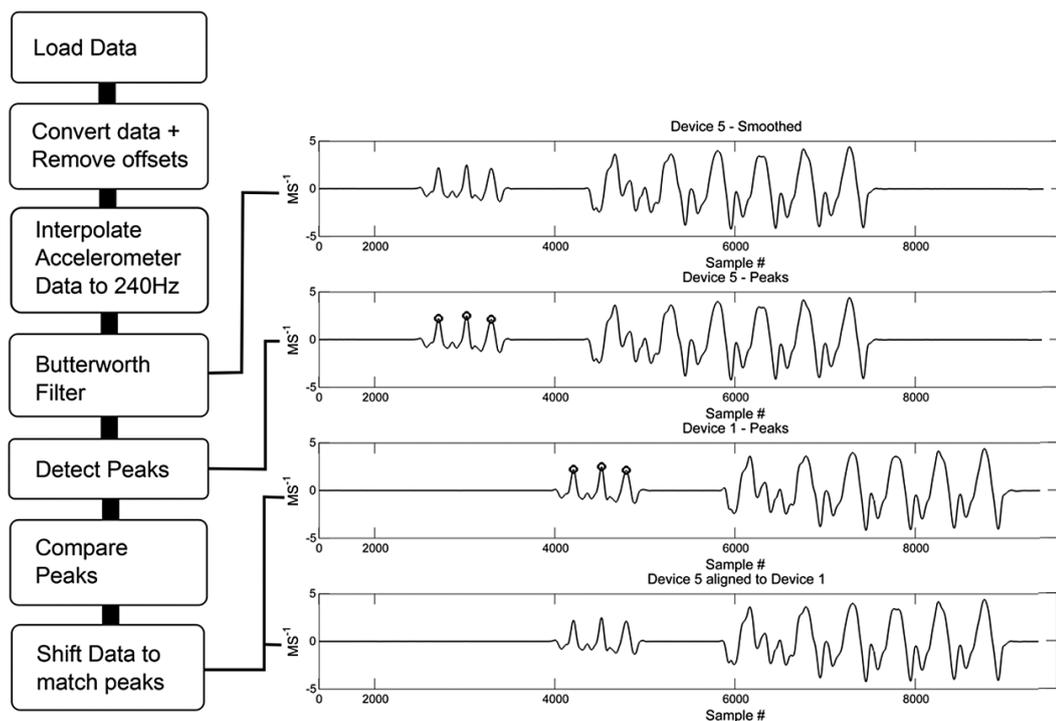


Figure 19: Outline of the processes in the MATLAB® script.

In addition to this method, there are some considerations that should be acknowledged that can affect data collection when using data loggers. There can be a variance in sample rates, for example one instrument may have a sample rate of

120Hz whereas another may have a slight variance and sample at 126Hz. This could create an issue depending on the end use for the data. For example, physical activity investigations may not be greatly affected by this variance because of the equations used, but involving multiple instruments could be problematic.

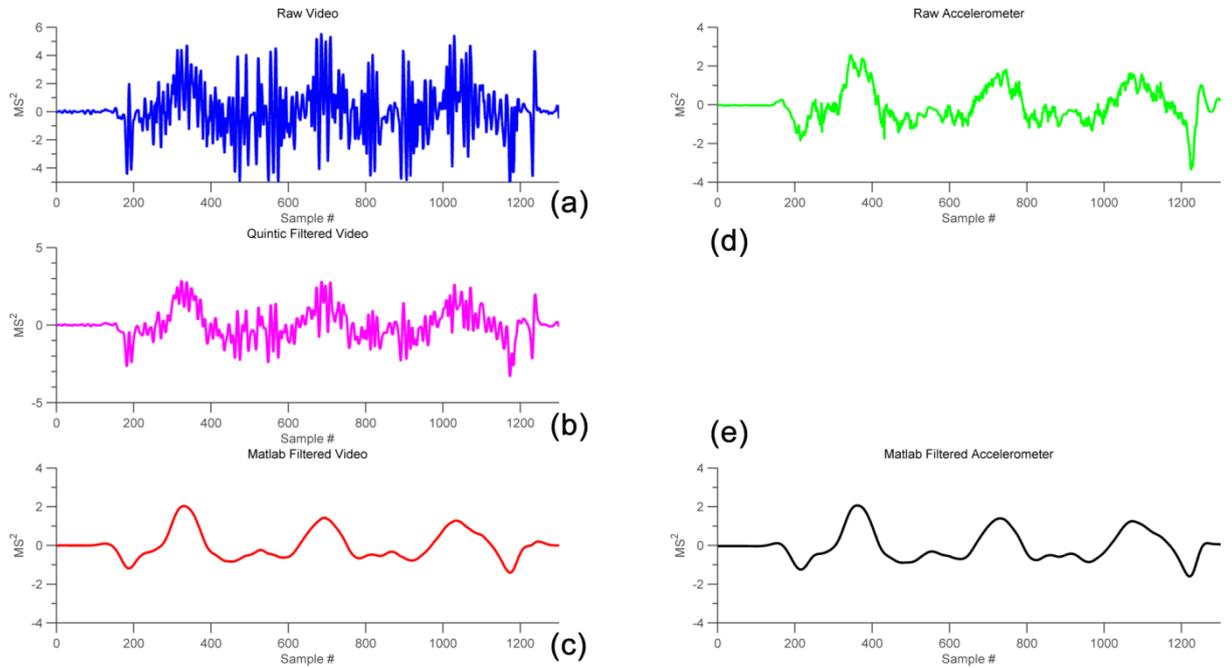


Figure 20: a) Raw video data b) Quintic filtered data c) Raw video data filtered by Matlab d) Raw video data e) Matlab filtered accelerometer data

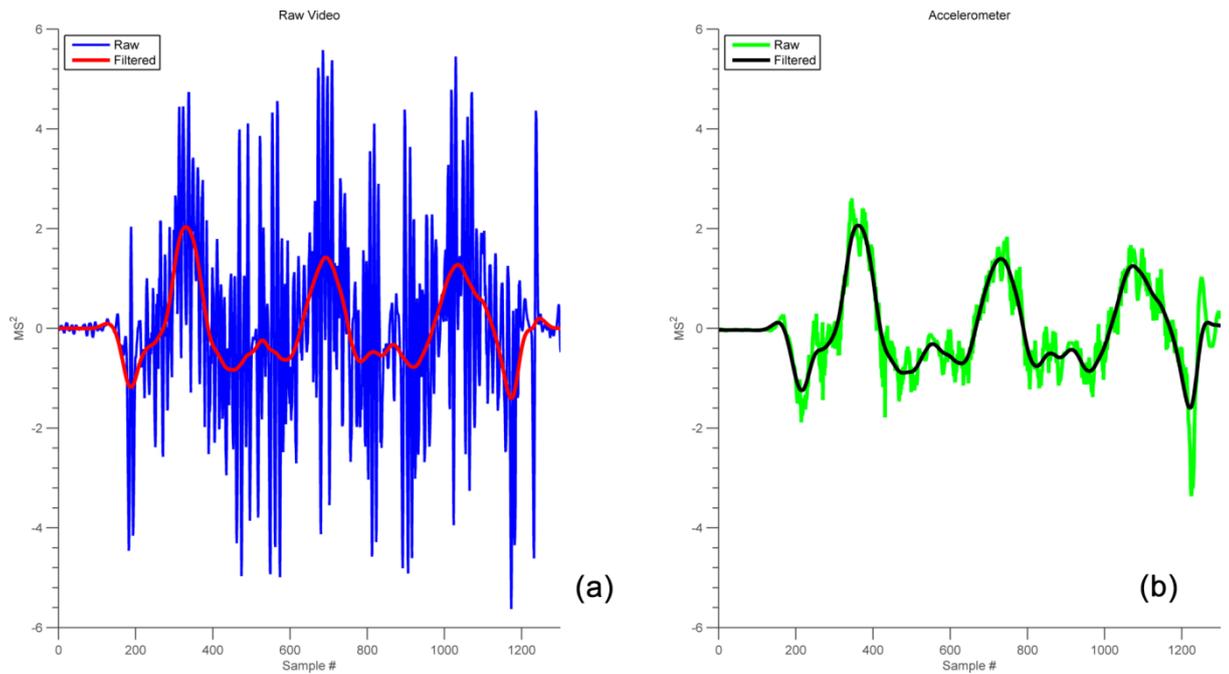


Figure 21: Overlay of Raw and Filtered data through Matlab a) Video Data b) Accelerometer

Quintic Biomechanics (v17, Quintic Consultancy Ltd., Coventry, United Kingdom) sports analysis software was used to generate the kinematic data from the motion of the reflective marker using the automated tracking feature (Figure 18a) with the direction of movement always in the kinematic X direction.

	Peak 1	Peak 2	Peak 3
Raw Video	4.7	5.5	5.4
Raw Accelerometer	2.5	1.6	1.6
Quintic Filtered	2.8	2.6	2.6
Video Matlab Filtering	2	1.4	1.27
Accelerometer Matlab Filtering	2	1.3	1.25

Table 7: Magnitude of the peaks in the data presented as ms^{-2}

Table 7 demonstrates the magnitude of each of the 3 peaks. There is a large variation in the peak values between the video and accelerometer, e.g. 5.5ms^{-2} video and 1.6ms^{-2} accelerometer. This is likely due to the Quintic algorithm which

calculates the acceleration as a second order derivative from the position on the video screen, which will induce error into the calculation. This is also shown with the accelerometer raw data (Figure 18d) showed far less noise than the video derived data (a).

Using Quintic optimal filters, there is a large reduction in the peak values from the raw video data (Figure 18b, Table 7), e.g. 5.5ms^{-2} to 2.6ms^{-2} . This also brings the magnitude of the peaks closer in line with the raw accelerometer data. However, the Quintic filtering did not offer sufficient filtering to allow for accurate peak detection due to the excess noise still present in the signal (Figure 20b).

The accelerometer was filtered using a 2nd Order Butterworth filter with 3Hz cut-off frequency which produced a noise free signal. This was chosen through several iterations and was chosen as it allowed a clear identification of the peaks using the peak detection algorithm. This filter removes the noise of the signal without overtly damaging the magnitude of the signal (Figure 21b). Using this same filter in Matlab, the video data filtering produced better visual results than the Quintic filter (Figure 20b and c). This is also demonstrated with similar values presented for the peaks between the video and accelerometers when filtered using this method (Table 7).

3.2.2.5 Calculations and Statistical Analysis

All data files were aligned using the MATLAB Script. Validation of the alignment process was conducted using the cross covariance check in MATLAB. If the data were synchronised then the maximum peak would appear where the time lag equals zero.

Validity of the instruments was assessed by comparing each device to the video (Quintic) derived kinematic data. This was achieved using Pearson's R correlation. Inter-instrument reliability was assessed by comparing each device using Intraclass Correlation Coefficients (ICC) due data being heteroscedastic in nature. This was determined using the Breusch-Pagan test for heteroscedasticity (Table 8) which was conducted using MATLAB (Breusch and Pagan, 1979; Greene, 2003). Caution needs to be applied when interpreting this data as it will be affected by sample heterogeneity. Limits of Agreement was demonstrated using Bland-Altman plots and by determining the percentage of data within the 95% limits. The precision of the reliability was also assessed using Root Mean Square Error (RMSE) with Standard Deviation to show the error associated with each of the relationships.

Test	Instrumen t 1	Instrumen t 2	Instrumen t 3	Instrumen t 4	Instrumen t 5	Instrumen t 6	
X	1	0.000	0.000	0.000	0.000	0.000	0.002
	2	0.000	0.000	0.000	0.000	0.000	0.000
	3	0.000	0.000	0.000	0.000	0.000	0.000
Y	1	0.000	0.000	0.000	0.000	0.000	0.000
	2	0.000	0.000	0.000	0.000	0.000	0.000
	3	0.000	0.000	0.000	0.000	0.000	0.000
Z	1	0.001	0.008	0.000	0.000	0.010	0.009
	2	0.001	0.000	0.000	0.000	0.000	0.000
	3	0.000	0.000	0.000	0.000	0.000	0.000

Table 8: Breusch-Pagan results of residual data showing heteroscedasticity, *p* values presented.

All analyses were conducted over the entire data set for each test, over 7000 data samples per file (post-interpolation) and conducted using SPSS v.19.

3.3 Phase 3 - Design of System

This section outlines the design and validation of the system using the calibrated and synchronised accelerometer dataloggers. This includes the placement of the sensors and attachment methods, the experimental setup for data collection and the factors recorded and the methods used to interrogate the data to retrieve these with the flow of system also identified.

3.3.1 Placement

Sensors in previous works were placed on "the wrist" (Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2003) and "between the shoulders" (Bächlin and Tröster, 2012) and on the "lower back" (Slawson et al. 2008; Stamm et al. 2012; Stamm et al. 2011). These do not offer precise, repeatable, anatomical locations for the placement of the sensors. The visual locations shown in these previous works (Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2003; Slawson et al. 2008; Stamm et al. 2012; Stamm et al. 2011; Bächlin and Tröster, 2012) were used as a reference to identify the locations of the sensors in line with ISAK guidelines and using terminology supported by the Australian Sports Commission (Norton and Olds 2002). The upper arm sensor was placed at the distal end to mirror the placement at the distal end of the forearm for the wrist sensor.

Wrist sensors (LW and RW) are placed at the distal end of the Ulna and Radius, with the -Y axis end of the device proximal to the Styloid Process. Arm accelerometers (LA and RA) were placed close to the Olecranon Fossa (elbow). Lower back (LB) sensor was placed at vertebrae L4, in line with the Iliac process. Upper back (UB) was placed on the vertebra T5. These are shown in Figure 22.

The Z axis along the Sagittal Plane, +Z frontal facing. The Y axis along the Coronal Plane, +Z frontal facing and the X axis along the transverse plane, +X frontal facing.

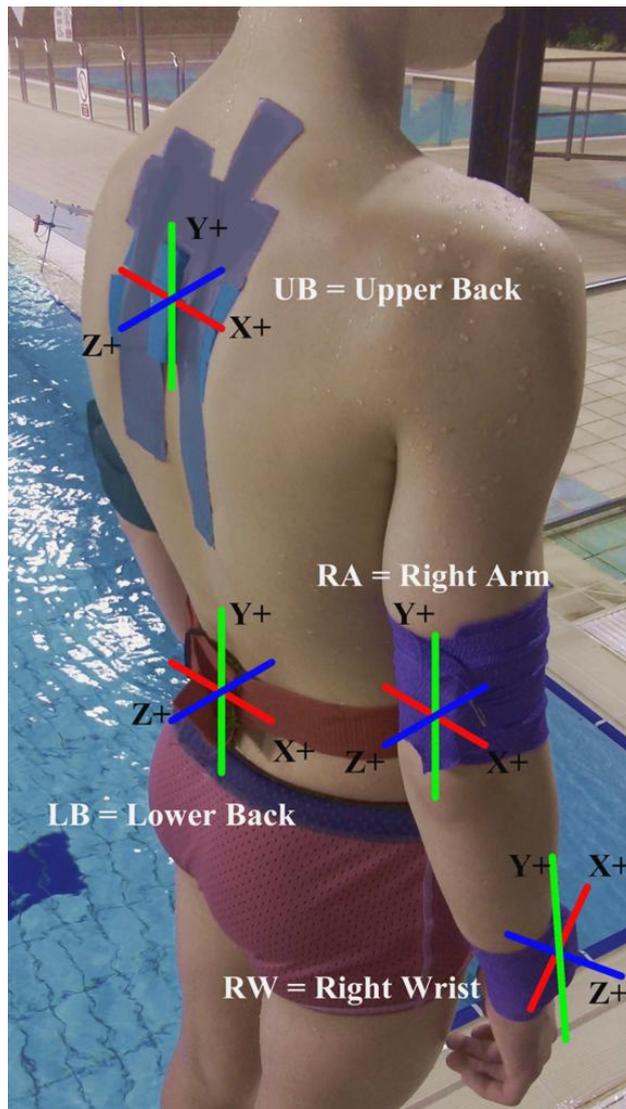


Figure 22: Device placement and attachment method and orientation

3.3.2 Sensor attachment methods

Previous studies have used tape for the wrists (Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2003) and lower back (Slawson et al. 2008; Stamm et al. 2012; Stamm et al. 2011), however, the use of Vet Wrap on the arms particularly allowed for a more comfortable removal. Bächlin and Tröster (2012) used a lycra based method for the upper back and plastic strapping for the wrists.

For this system, neoprene rubber straps were used to secure the devices to the swimmer. Velcro was added to the straps to create a watch like strapping, with a small pocket to slide the device into.

The upper arm strapping seemed to work well and not appear to create any additional drag. However, the wrist sensor appeared to create significant drag as shown in Figure 23. After this session, the swimmer was asked about how they felt and it was reported that the wrist sensor did create a lot of drag.



Figure 23: Movement in wrist strapping and additional drag (bubbles) visible

The upper back sensor was attached using a lycra harness attached to buckles and straps to allow it to be customised to suit any individual, similar to that of Bächlin and Tröster (2012). This was found to be far too loose when wet, not allowing the sensor to be securely fastened to the upper back (Figure 24). This was replaced with taping the sensor to the swimmer, a method which has also been used in previous studies (Dadashi et al. 2013; Fulton et al. 2009b; Ohgi and Ichikawa 2002; Stamm et al. 2012). The lower back was attached using a webbing waist band with a small pocket for the device and seemed to work well.

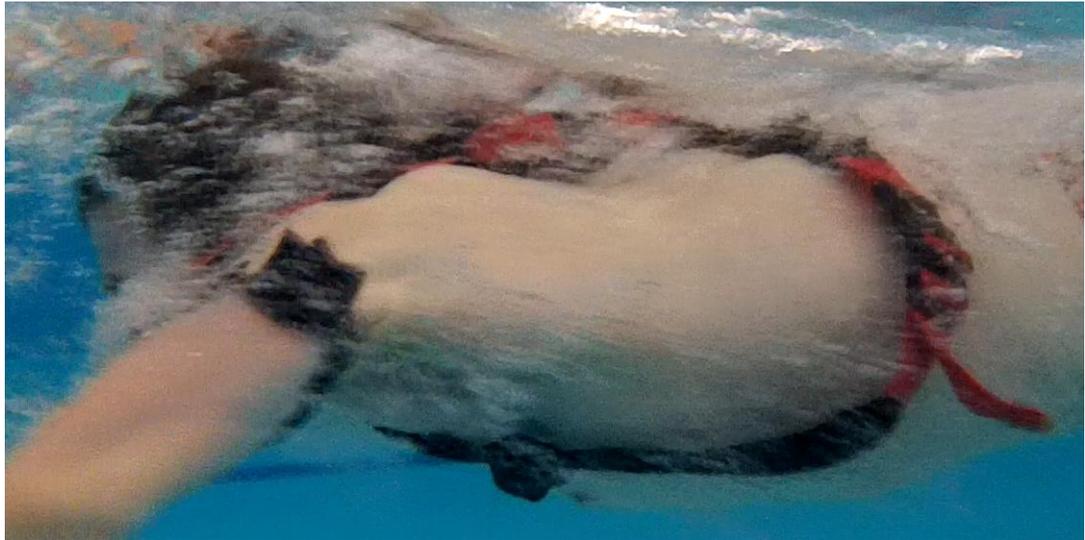


Figure 24: Upper back strapping - not working

As noted by Muller et al. (2000), systems like this need to minimise the degree to which they affect the performance of the athlete. The fixation methods were then modified for the wrists and arms, the neoprene was replaced with 3M Vet Wrap which is a self-cohesive bandage typically used for sports injuries and veterinary practices. This allowed the devices to be placed directly onto a single layer of the wrap on the skin in the correct anatomical position, and the bandage wrapped over the device to secure it and secured with a safety pin. This also reduced the need to clean strapping to avoid any skin contamination between participants as they were discarded after each swimmers use. The neoprene would have required cleaning post swim before use by another swimmer, adding to time constraints per session.

The neoprene strapping meant the device was sitting above the anatomical landmark by 4 mm (2 layers of 2mm Neoprene, one for the strap, one for the pocket) which meant the device was prone to movement by the water. The Vet Wrap allows the device to be much closer to the anatomical land marks and secured down onto that land mark, thus reducing any additional movement. A major concern with the Neoprene was the excessive drag created (Figure 23),but with the change in strapping there is little to no visible drag (Figure 25).



Figure 25: No visual signs of drag created by the Vet Wrap bandages

The swimmers used in this work were all asked how the strapped devices felt. No swimmer noted that the upper back created any issues. The arm sensors were of no issue to the males, but the lower back sensor was found to create some drag. The opposite was true for the females, the lower back sensor created no issues, but they stated that the arm sensors felt heavy. However, they all stated that none of this noticeable affected their technique.

3.3.3 Experimental setup and procedure

An overview of the experimental setup is shown in Figure 26. Sample numbers from similar previous studies, not race based analysis, vary from 4 to 18 swimmers (Alberty et al. 2005; Berger et al. 1999; Cappaert and Heest 1999; Fulton et al. 2009a; Haffner and Cappaert 1999; Liu et al. 1993; Marinho et al. 2011; Monteil et al. 1996; Ohgi et al. 1998; Ohgi et al. 2002; Osborough et al. 2010; Sanders 1996; Satkunskiene et al. 2005; Seifert et al. 2010; Stamm et al. 2012; Stamm et al. 2011; Toussaint et al. 2002) averaging seven swimmers for a study. In biomechanical research, sample sizes are often smaller due to the recording of an array of biomechanical factors (Mullineaux, 2007). Whilst this may introduce bias into the results of a comparative study, i.e. subject 1 vs subject 2. The purpose of this study

was not to compare data between swimmers but to validate the system being used for coaches. With 12 swimmers volunteering for the study, and with a number of laps (8 per swimmer) being produced for each swimmer, there was a large amount of data generated over a variety of biomechanical factors for validation purposes. However, this process of using previous n-of-other studies method to determine the number of swimmer required, may produce insufficiently powered results.

Video analysis is often used as either a validation method, or as a method for digitalization where frame rates range from 25Hz to 72Hz (Berger et al. 1999; Burkett et al. 2010; Cappaert and Heest 1999; Deschodt et al. 1996a; Deschodt et al. 1996b; Haffner and Cappaert 1999; Holmér 1978; Liu et al. 1993; Osborough et al. 2010; Sanders 1996; Satkunskiene et al. 2005; Seifert et al. 2010; Toussaint et al. 2002). An underwater camera, Kodak PlaySport Zx5 filming at 60fps filmed from the side from a trolley; using a procedure very close to that described by Osborough et al. (2010) and Seifert et al. (2010). The camera was attached to a trolley to allow it to be pushed alongside the swimmer as they move down the pool. Due to flag poles at 5m from each end, the trolley could only move between them. This camera was 4m from the swimmer, who swam in the second lane of the pool with the lane divider removed for clarity.

A global camera was setup to view the whole experiment and was used as a global time stamp. This was filmed using a Panasonic camcorder filming at 30fps. This was turned on first and then the instruments were turned on in view of this camera. The instruments were then "bumped" three times, using the instrument synchronisation protocol from Phase 2 (3.2.2). These three bumps then allowed a consistent time point in the global camera and within the accelerometer for post data collection synchronisation. The instruments were then attached to the swimmer in the positions identified in Figure 22.

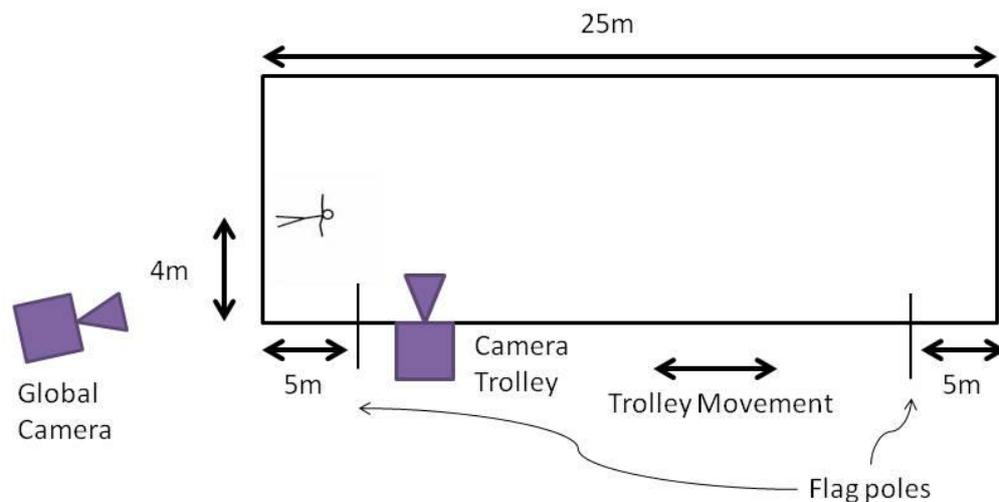


Figure 26: Experimental camera setup

Thompson and Taylor (2007) advise a warm up for aerobic and anaerobic swimming tests, up to 1000m. The swimmers used here all underwent their normal 600m warm up, under the coaches advice.

Previous studies which have investigated technique based analysis have all used various distances including 50m (Osborough et al. 2010), 50m under different speeds (Ichikawa et al. 2002b; Ohgi et al. 1998), 2 x 50m (Satkunskiene et al. 2005), 100m (Deschodt et al. 1996a; Deschodt et al. 1996b) and 2 x100m under varying conditions (Fulton et al. 2009a).

The purpose of this study was to demonstrate the validity and reliability of the system. To achieve this the system needs to be able to cope with changes in technique and still accurately determine the factors being measured. Fatigue has been previously used to identify alterations in technique, Alberty et al. (2005) used 2 x 25m to measure technique, followed by a 200m all out maximal effort to induce fatigue, followed by additional 2 x 25m, measuring the technique change from the first measurement. This shows that fatigue could be used to replicate a change in technique. After a discussion with the coaches considering the ability of their

swimmers and the work of Alberty et al. (2005), an agreement was reached as to an appropriate protocol to use. The swimmers swam 4 x 25m (100m) being recorded, the sensors were then removed and the swimmer swam 8 x 25m (200m) to induce fatigue, then with the sensors were reattached and they swam 4 x 25m (100m) being recorded. . The distances were increased to compensate for the attachment of the sensors. This method also inherently tests the repeatability of the sensor placement of the system through the removal and reattachment of the instruments to the swimmers. Data was collected over 4 sessions with 3 different swimmers measured in each session.

3.3.4 Subjects

Testing was conducted over multiple sessions following consent from the Bournemouth University Ethics Committee with consent forms for the individuals and supervised by the swimmers coach. The sessions were conducted in a temperature controlled indoor 25m swimming pool.

Twelve swimmers, comprising of six males (19 ± 2 yrs, 179.8 ± 13.23 cm, 70.75 ± 15.5 kg) and six female swimmers (17 ± 0.8 yrs, 165.5 ± 7.04 cm, 54.4 ± 7.9 kg), all injury free, completed the testing protocol after completing informed consent and counter signed by the coach as their guardian.

3.3.5 Development of Camera Trolley

The underwater cameras were mounted to a camera trolley (rig) and pushed to follow the swimmer up and down the pool. The camera rig was developed over several sessions with swimmers. It was made using beading for the axels with 1" box frame to create a chassis. A wooden handle was used (Figure 27b) connected to one axel so it could be pushed and pulled. There was a lack of control with this method, so weight was added to the middle of the rig to stabilise it. The control using a handle at the rear/front of the rig did not allow for the control necessary to keep in line with the swimmer. A new handle was created to allow weight to be added to the

centre of the rig, through downward pressure. This also gave control to the rig as it moved along the pool (Figure 27c and Figure 28).

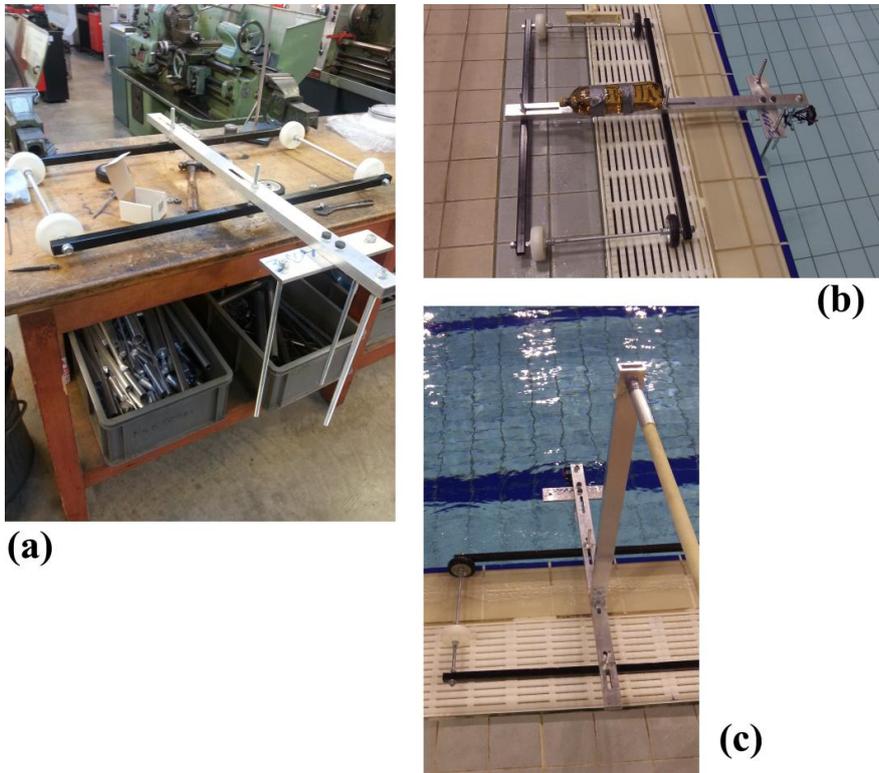


Figure 27: (a) Initial Development, (b) Rig with wooden handle and weight added for control. (c) Remodeled rig with new handle.



Figure 28: Example of the camera rig in use

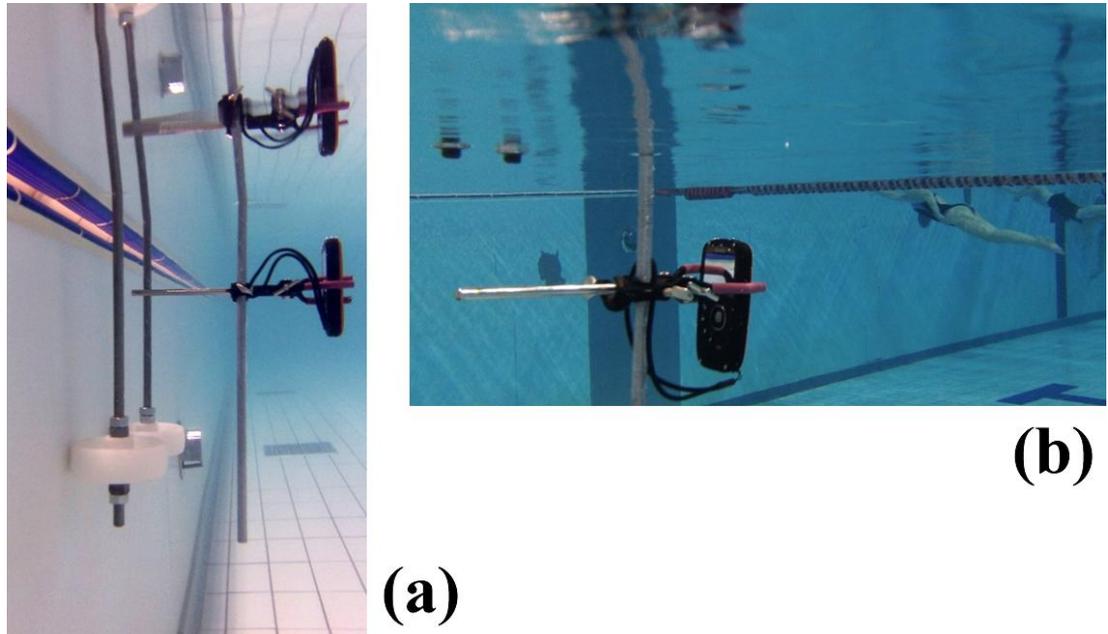


Figure 29: Underwater section of camera rig

The underwater section of the camera rig consisted of six downward facing poles. Two of these poles were used to attach wheels to (Figure 29a) so that the rig would stay true to the side of the pool and limit movement towards the swimmer. The camera was attached to the rig using a retort stand clamp to hold the camera (Figure 29b).

3.3.5.1 Limitations

When the sensors were removed and reapplied to the swimmer, there was a small delay of around two minutes for removal and five minutes for attaching the sensors. During this period, there was a chance for recovery, however this was consistent between swimmers.

There were two swimming pools used which varied in design. In one swimming pool the rubber wheels used fitted well into a groove (Figure 30). However, this meant that the wheels to push against the wall (Figure 29a) did not actually touch the wall and just created drag.

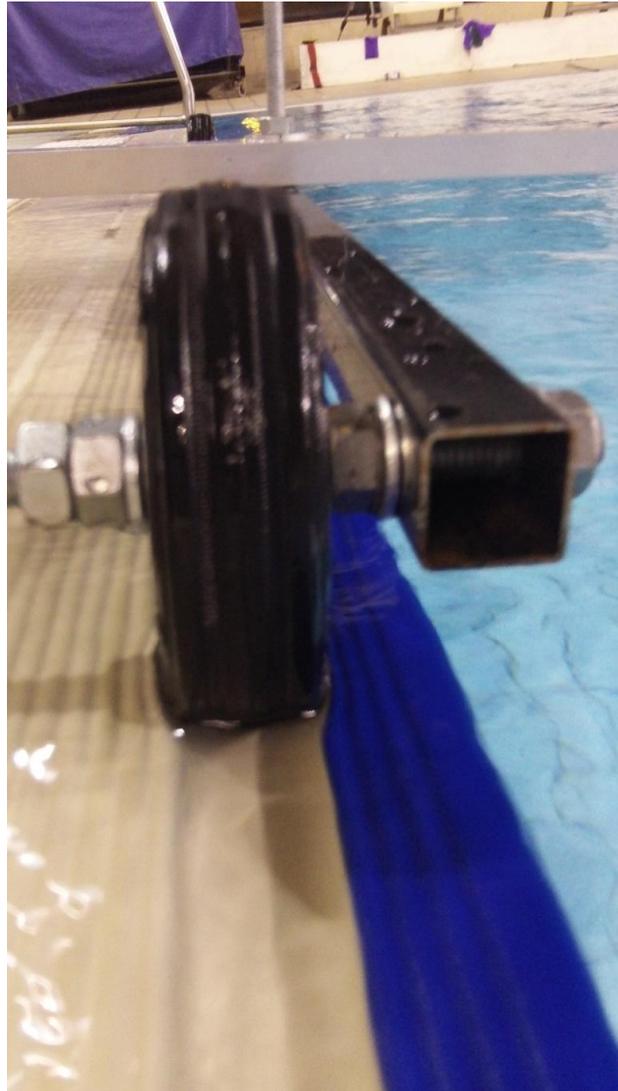


Figure 30: Rubber wheels on the camera rig

The two pools used also had different slope angles at the side of the pool, resulting in different water levels. Figure 30 shows the water over the edge of the pool, meaning that the wheels sometimes aquaplaned, but also with the high water level, it was not always possible to put a second camera just above the water level (Figure 31).

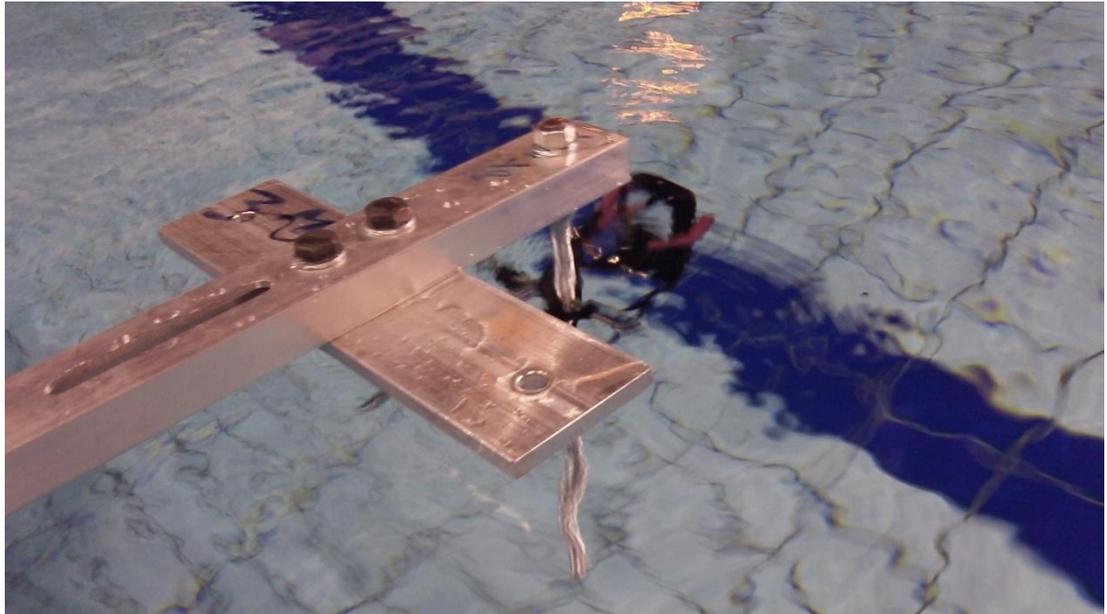


Figure 31: Top view of the rig

On three of the swimmers the upper body sensors became detached from the swimmer, whilst on another the lower back device battery ran out of charge. On one swimmer the Right Wrist sensor slipped from under the Vet Wrap bandage. For the swimmers with upper/lower back issues the opposite sensor was duplicated to replace the missing data. This means the profile data is not a true representation of the swimmers but does show the system in use.

3.3.6 Data Treatment

Le Sage et al. (2011) state that the use of video cameras are not only time consuming in their digitisation, but also can produce inaccurate measurements due to the difficulty in determining reference positions on the swimmers due to lighting conditions, splashes and the water–air interface. For this reason, temporal based measures are used to validate the new system.

3.3.6.1 Data Preparation, Calibration and Synchronisation

The software was developed in two stages. Firstly, a data setup file (Supplement Appendix) combines the data from multiple sensors (Figure 32). This read all the data into MATLAB® and then synchronised using the 3 peaks at the start of the data

(Figure 19). The instruments were synchronised using the method developed in Phase 2 (3.2.2). This was conducted by the pool side by placing all 6 devices on a flat surface (e.g. the step to a starting block or the floor) and turned on using the magnet. The devices were then all lifted together to generate three bumps for the data to be post synchronised. Once all data were synchronised, the zero offset of the data before the three peaks shows the error in the device, and could be removed from all devices.

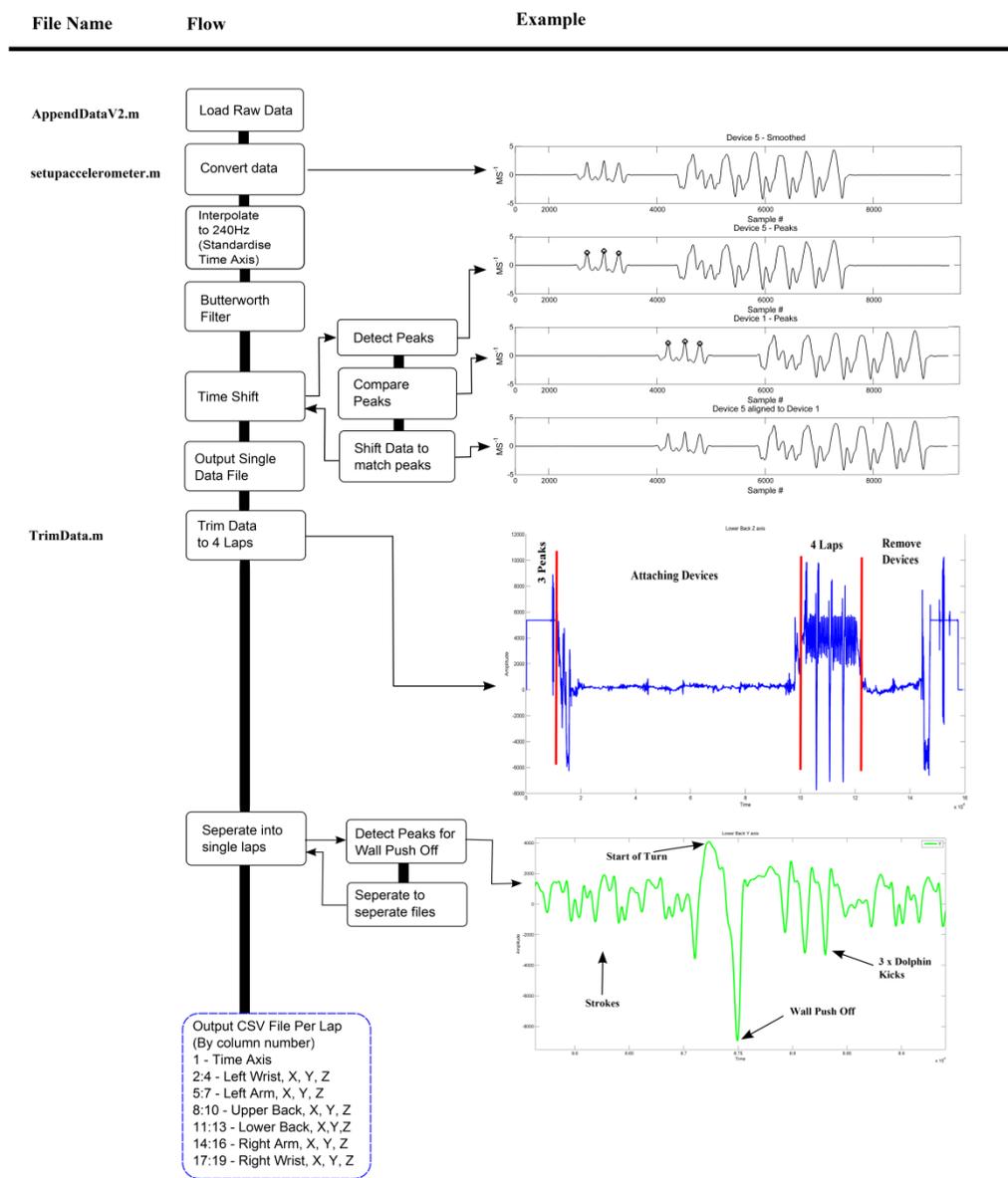


Figure 32: System Flowchart - Data setup

Once the data has been synchronised it is presented to the user allowing any excess data outside of the four laps to be removed prior to future processing. This involved plotting the data to find the start and end of the 4 laps (Figure 33) and then manually entering these sample times into the script to then allow it to save a CSV file of the 4 laps externally. Care needed to be taken when trimming the data to 4 laps to clearly identify the first wall push off and last wall touch to avoid inducing errors. MATLAB's zoom function allowed the signal to be magnified allowing more precise control over the sample number selected for start and end.

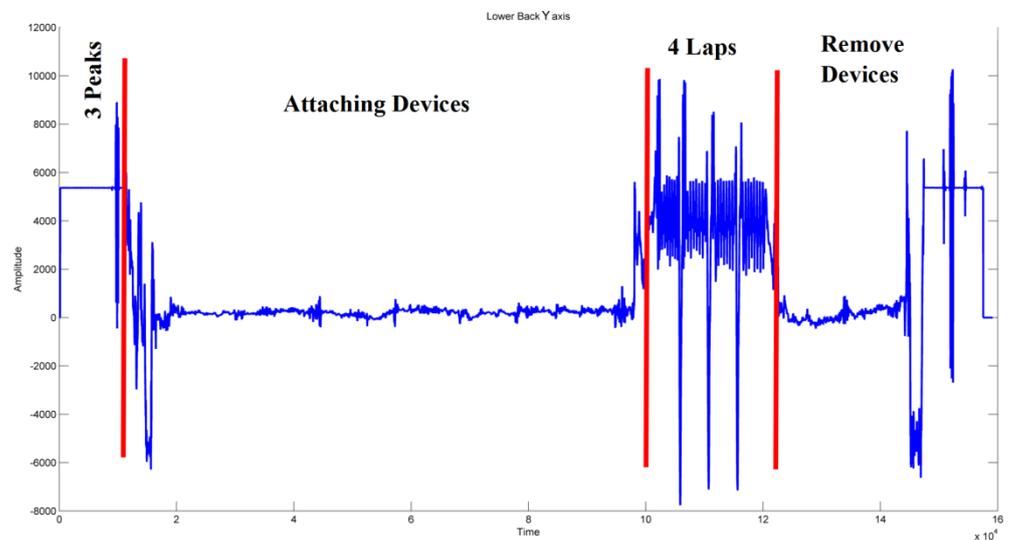


Figure 33: Lower back Y axis data showing the various phases recorded by the device

After this process, the individual laps could be identified on the Lower Back Y axis by finding the trough associated with the wall push off (Figure 34). This was then able to be found for all the 4 laps used (Figure 35), and then trimmed as individual laps and saved externally (Figure 36) with data converted to time (S) and accelerometer count converted to Acceleration (ms^{-2}), with some axis data flipped to the correct orientation and 'easier' to work with. The synchronised data were stored as a matrix combining each devices sensor axis data into a separate column. This allowed the data to be easily trimmed to the start and stop points for each device,

Left and Right Wrist, Upper and Lower Back, Left and Right Arms. This was process was done so that each lap was then a single CSV file.

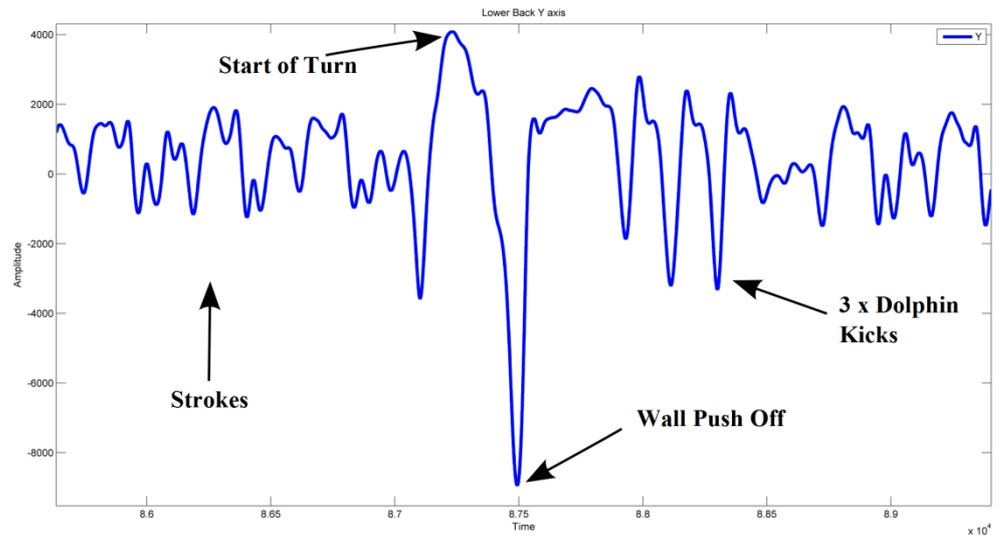


Figure 34: Lower back accelerometer Y Axis with highlighting of various features

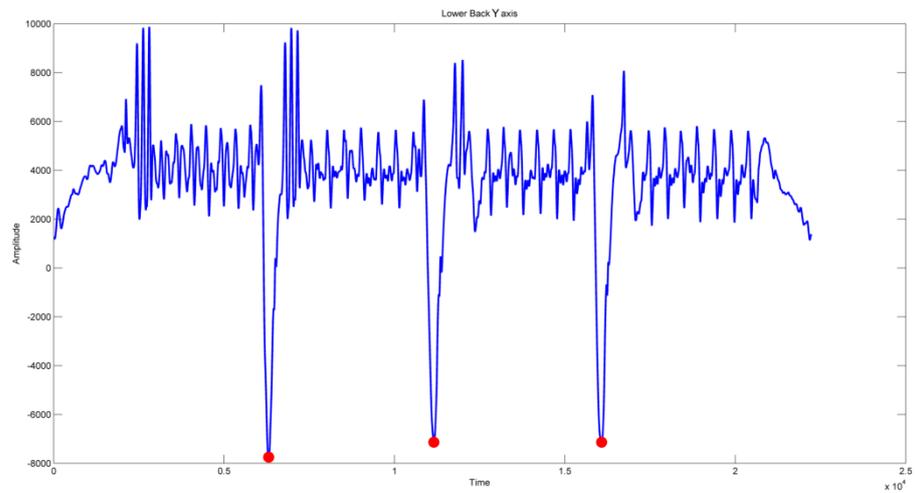


Figure 35: Peak detection to find the troughs (turn at end of the lap) used on Lower Back Z Axis to identify laps. Troughs identified using red circles.

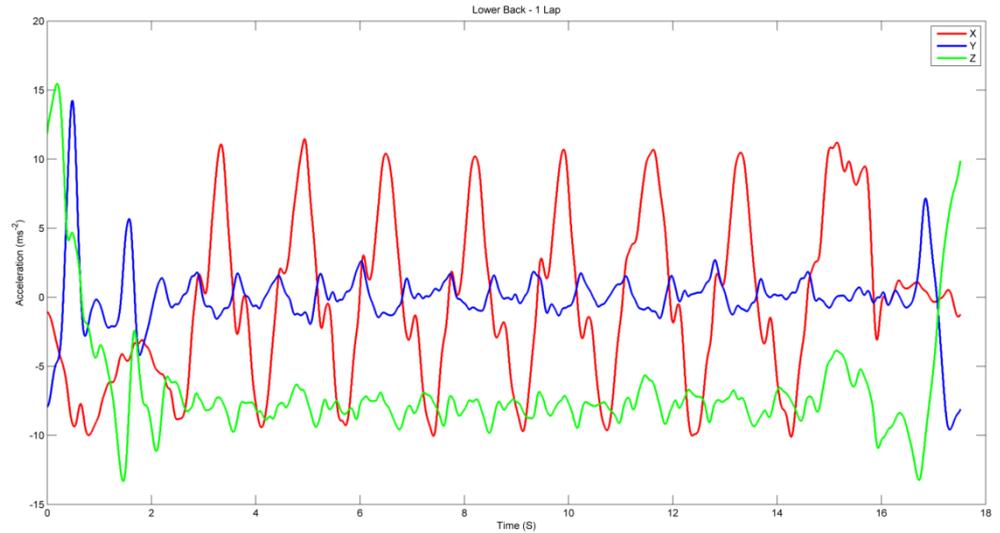


Figure 36: Lower back sensor trimmed for a single lap

To save on processing time, each lap of raw accelerometer data was then converted into standard SI units before any of the following calculations were completed, EQ[16].

$$\text{Converted Data} = \left(\frac{\text{Count}}{5440} \right) \bullet 9.8\text{ms}^{-1}$$

[16]

Where the count is the number of units counted by the accelerometers, which is divided by how many counts is equal to 1g (Gulf Coast Data Concepts, USA). This is then multiplied by 9.8ms^{-1} to convert the output into acceleration units in Acceleration (ms^{-2}).

3.3.7 Performance Swimming (System)

The second phase of the system involved taking this data and extracting key information from each lap of data, an overview of the process is shown in

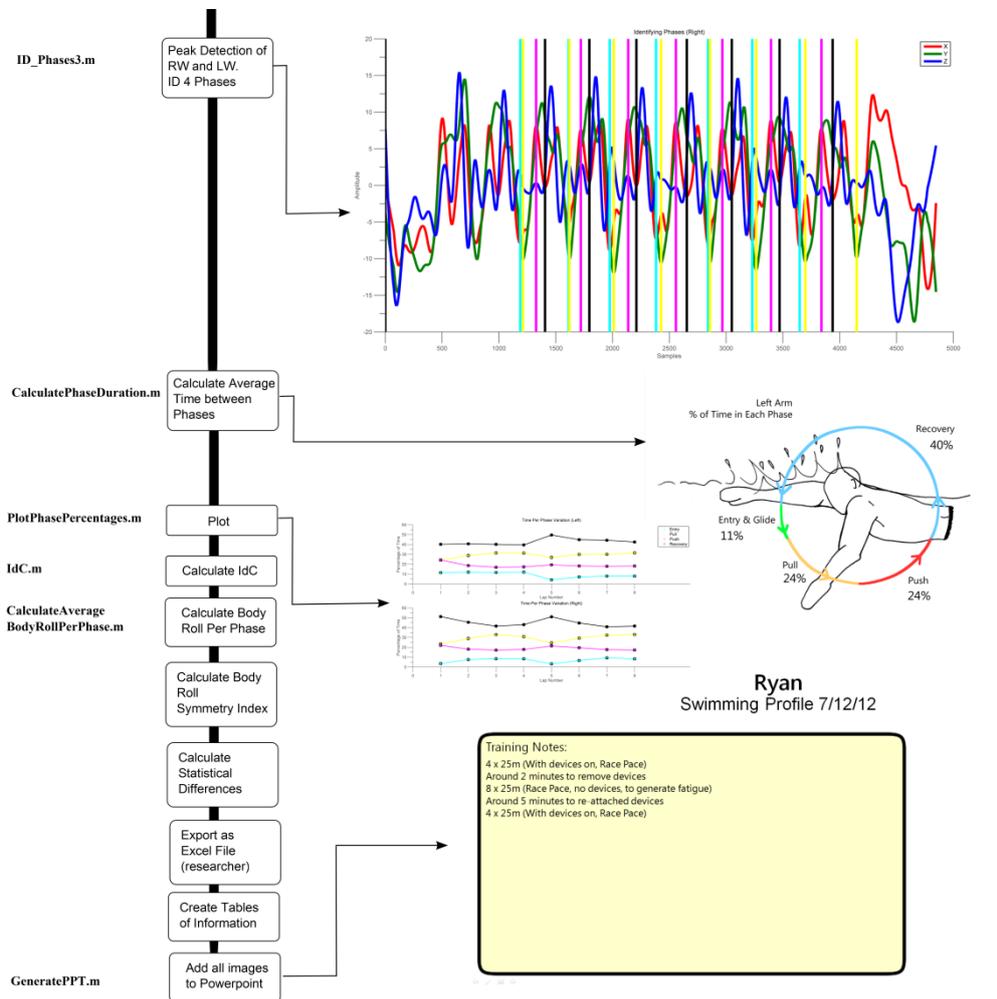
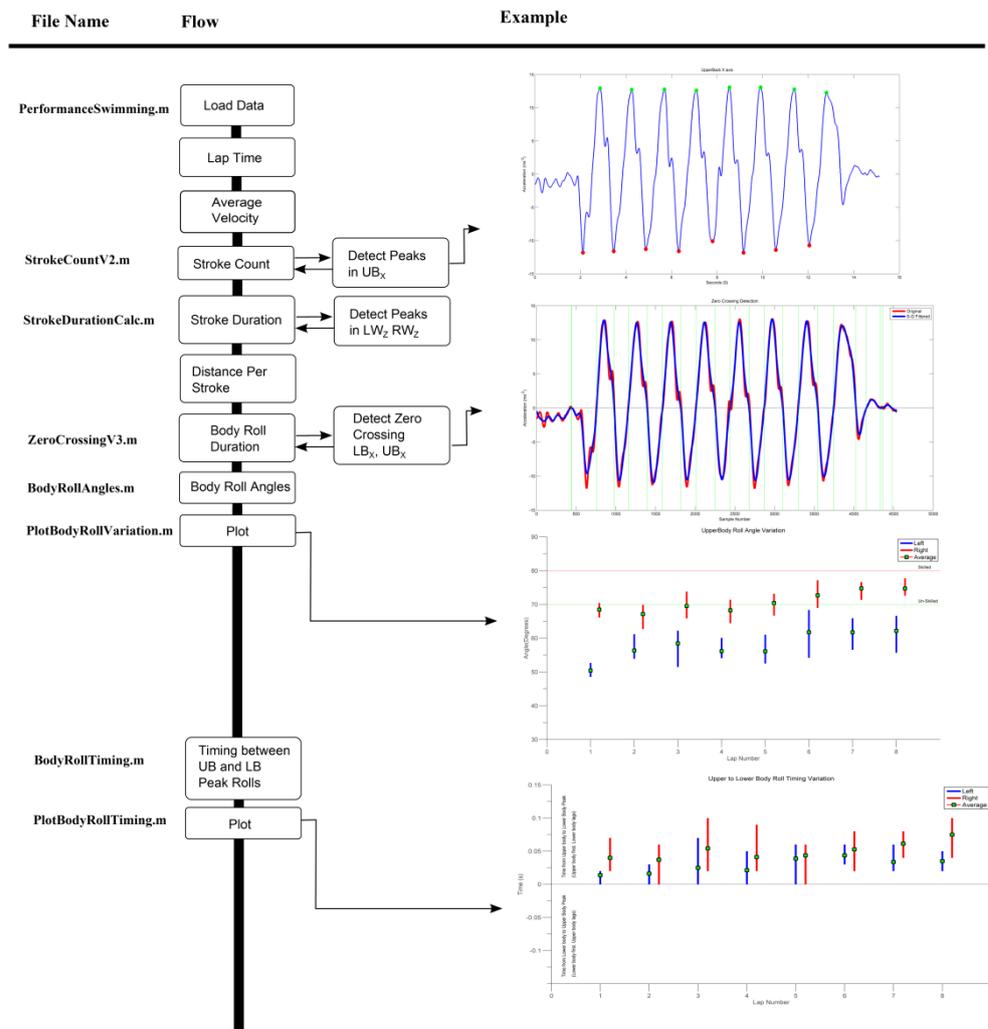


Figure 37. The remainder of this chapter details the factors recorded and is split into two sections. First the kinematic factors in line with the hierarchical model by Hay (1993) and key information as detailed by the coaches. These are, lap time, stroke rate, average stroke distance, distance per stroke and average velocity, termed Core Information. As noted earlier, Glazier et al. (2006a) state that these are some of the basic factors to record and that movement variation is more time consuming using camera systems, so has tended to be ignored or missed by some researchers. The second set of factors look at this variation in body roll and stroke phase duration, adapting work from rowing by Smith and Spinks (1995) and Caplan and Gardner

(2009) and with the request from some of the coaches as indicated. Validation of these factors is also identified.

The code for each of these calculations is shown in a Supplement Appendix (Volume 2).



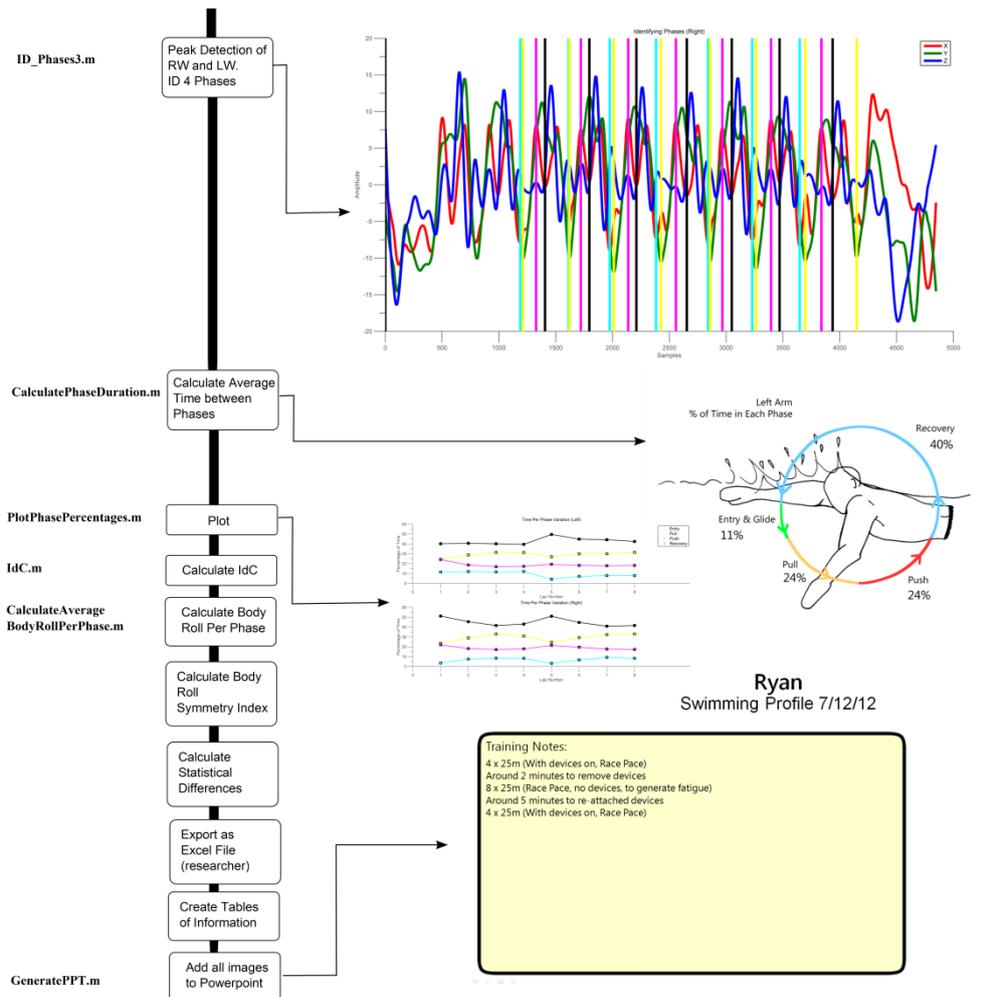


Figure 37: System Overview

3.3.8 Core Information

3.3.8.1 Lap time and Average Velocity

Due to the way the laps were identified (Figure 36) each file was of the length (time) of the lap by default, so lap times were the last time stamp in the data file in seconds (S).

Average velocity can be calculated by dividing the lap distance ($d = 25\text{m}$) by the lap time (t), EQ[17].

$$\bar{v} = \frac{d}{t}$$

[17]

Verification of the lap times was achieved by taking the lap times viewed from the global positioned camera (Figure 26) for 95 laps. Lap times were taken from the videos on two occasions, one by the researcher, one by a coach, to ensure inter-rater reliability, which was analysed using Pearsons r correlation (O'Donoghue, 2012). Results showed a very strong positive correlation between the two video derived lap times ($r = 0.977$, $n = 95$, $p = 0.00$), confirming their relative reliability of large effect (Cohen, 1988). Absolute reliability was assessed using the method of Mean %error presented by O'Donoghue (2012). This method is more stringent than the one presented by Hughes et al. (2004) as it takes into account a theoretical maximum and minimum value to divide the modulus of the times by. The maximum and minimum values could be set to any value above and below the data set. To ensure a critical and repeatable approach to the analysis of the data, they were set to the maximum and minimum values from within the data set. The results showed a Mean %Error of 2.15% (± 1.93).

The mean of the two inter-rater video derived lap times was then used as a comparison to the lap times from the sensors. All statistics were conducted using SPSS v.19. The lap times were analysed to find normality using Kolmogorov-Smirnov test. The lap time data were found to be normally distributed (Mean Video = 0.540, Sensor = 0.611) leading to the use a Paired-Samples t-Test between the mean of the video times and the sensor. All significances were set to $p < 0.05$. Average velocity was not assessed using statistics as it is a byproduct of a constant divided by the lap time.

3.3.8.2 Stroke Count

Stroke count was identified by using the upper body sensor. The Upper Back X Axis (UB_X) axis provided clear data to allow the use of peak detection to identify the upper and lower (Left and Right) body rolls which are associated with each stroke (Figure 38). These were then counted in the software per lap.

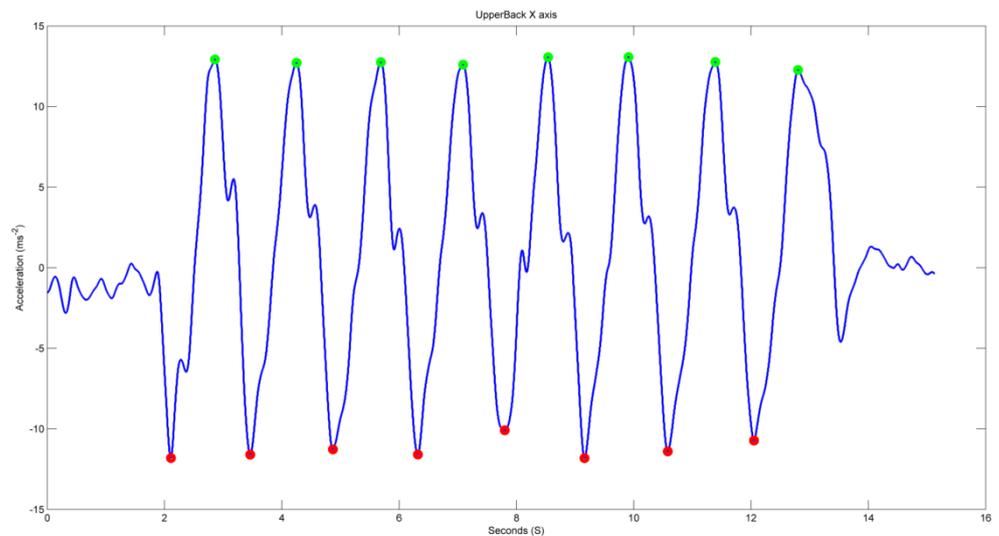


Figure 38: Using local peak and trough identification on UB_X , the number of strokes can be calculated. Green circles show Left Body Roll, Red show Right Body Roll. The last stroke does not count as it is not a full stroke

The number of strokes per lap (each hand entry) for each swimmer were observed from the video and compared to the accelerometer output from the system to check the count. Stroke count was assessed using Pearson's R Correlation according to the recommendations of O'Donoghue (2013).

3.3.8.3 Stroke Rate and Duration

Stroke rate has previously been found as 60 seconds divided by the duration of two body rolls using lower body mounted sensors (Davey et al. 2008). However, Craig et al. (1985) state that stroke rate should be calculated as the duration from Right [or

left] arm/hand entry to the Right [or left] arm/hand entry over five strokes to ensure consistent measurements.

Bächlin and Tröster (2012) used the Y axis of the wrist sensor (LW_Y and RW_Y) to determine the duration of the stroke (SD) where the Y axis can determine the entry and exit of the hand through local minima detection. This progresses from work done by Davey et al. (2008) and the development of that system by Stamm et al. (2012) using a lower back device relying on using the body roll, where each roll is considered a stroke. A limitation of this method is that the lower back roll may not always relate to the stroke duration, the body could from time to time, finish slightly before and after the hand entries. Using a direct measurement of the wrist should allow for a greater level of accuracy in the output.

The method implemented here involved using peak detection to identify the troughs in the wrist sensors Y axis, after the first body roll. This allows the swimmer to be closer to swimming pace rather than adding any additional acceleration from the wall push off, as can be seen in Figure 39. The difference between each sequential trough identifies (LW_{YMin}) the stroke durations (Figure 39, EQ[18])

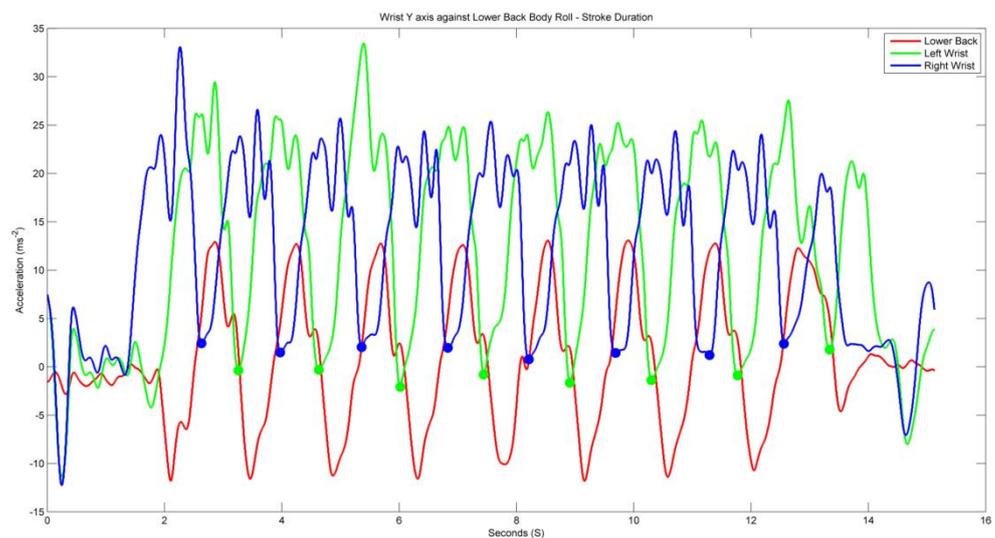


Figure 39: Calculating stroke duration using Left Wrist Y Axis (LW_{YMin}) (Green) and Right Wrist Y Axis (RW_{YMin}) (Blue) troughs highlighted with circles. Lower back X Axis (LB_X) (Red).

$$SD = \left(\frac{\sum_{n=1}^6 (LW_{YMin\ n+1} - LW_{YMin\ n})}{5} \right)$$

[18]

Using the work of Craig et al. (1985), the duration of 5 strokes were then used to calculate the Stroke Rate using EQ[19].

$$SR = 60 / \left(\frac{\sum_{n=1}^6 (LW_{YMin\ n+1} - LW_{YMin\ n})}{5} \right)$$

[19]

Where the Stroke Rate (SR) is calculated by summing the time between 6 peaks, giving 5 complete stroke times. This is divided by the 5 strokes to calculate an average. 60 seconds is then divided by this to calculate a rate per minute. Stroke duration can be taken by finding the local minima in each LW_Y and RW_Y .

The stroke rate and duration were verified from the video data and compared to the accelerometer output from the system. Using SPSS v.19, the data were tested using a Student's t-Test to check for significant differences.

3.3.8.4 Average Distance Per Stroke

Bächlin and Tröster (2012) developed from the SD (stroke duration) by incorporating \bar{v} to calculate the Distance per Stroke (DPS) using EQ[20].

$$DPS = \bar{v} \bullet SD$$

[20]

Typically (Craig et al. 1985; Hawley et al. 1992; Schnitzler et al. 2008), Stroke Length (DPS) is calculated as EQ[21]:

$$DPS = \frac{\bar{v}}{SR}$$

[21]

Whilst this method has been shown to overestimate distance per stroke by 4-5% (Thayer and Hay 1984), it has been accepted as a systematic overestimation which does not generally effect subsequent comparisons (Hawley et al. 1992).

Outputs from both methods were compared (EQ[20] and EQ[21]) and results showed that the method used by Bächlin and Tröster (2012) produced stroke distances, on average, an additional 1.5% greater than that of the method used by Craig et al. (1985). Perhaps Bächlin and Tröster (2012) did not use this method as their system did not calculate stroke rate. Because of this additional overestimation, the method utilised by Craig et al. (1985) was implemented in this system. As with Hawley et al. (1992), no attempt was made to derive a correction factor for Stroke Distance.

3.3.9 Body Roll - Upper and Lower body

3.3.9.1 Duration

Duration of the body roll was determined by using a zero crossing algorithm (EQ[22]) on the Lower Back (LB_X) sensor and Upper Back sensor X axis (UB_X). It reads through each sample in the data until it finds a change in sign, showing where it crosses zero.

$$(LB_X(n - 1) < 0) \ \&\& \ (LB_X(n) > 0)$$

[22]

Results from using this algorithm were not very successful due to multiple zero crossings being found as shown in Figure 40. These extra crossings are identified as the swimmers style as they stabilise after each roll.

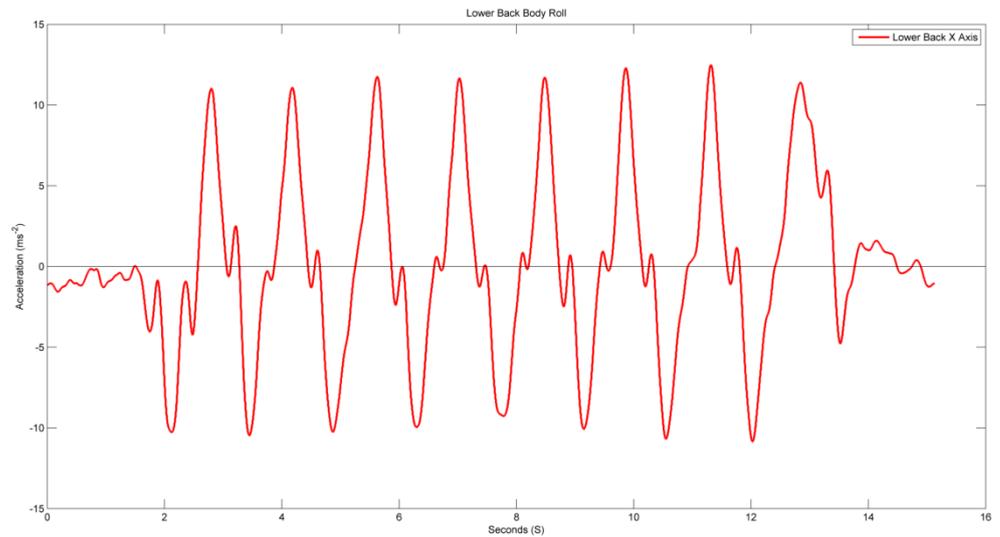


Figure 40: Lower Back (LB_X) body roll showing multiple Zero Crossings on each body roll

A 2nd degree Savitzky-Golay FIR smoothing filter with a span of 150 samples was used to smooth the data (Figure 41) to help make the zero crossing clearer to EQ[22].

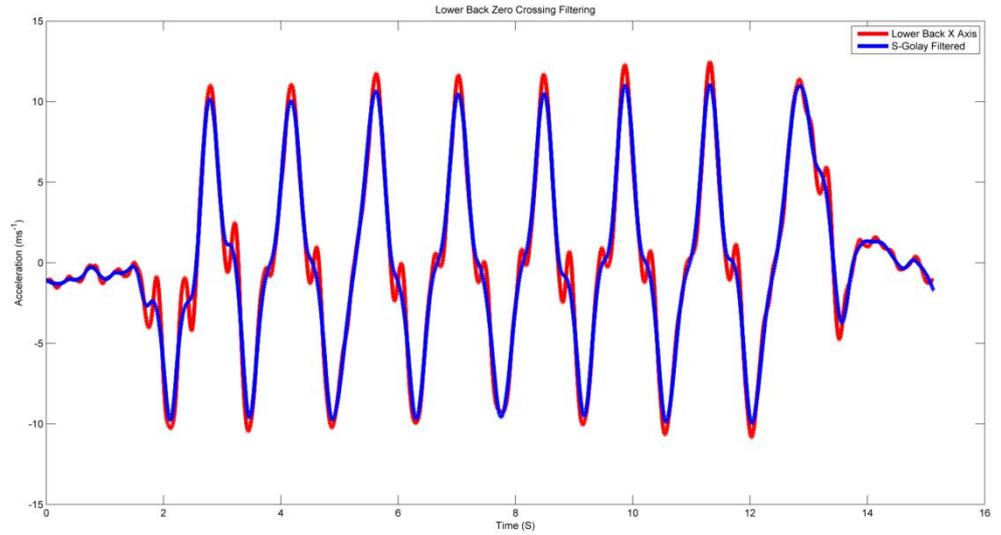


Figure 41: Savitzky-Golay FIR smoothing filter (Blue) used on the Lower Back X Axis to aid Zero Crossing Detection (Red, Original)

This helped with the detection process (Figure 42), but also identified additional zero crossings at the start and end of the lap and were further filtered to the first hand and last hand entry ($LW_{YMin(n)}$).

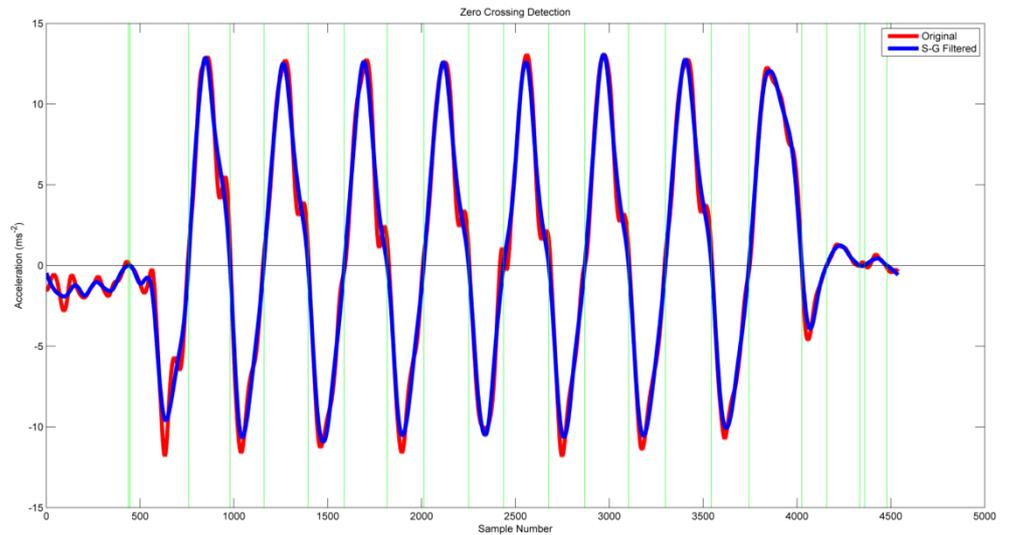


Figure 42: Zero crossings identified (Green)

3.3.9.2 Timing

The maximal and minimal peaks of LB_X and UB_X allowed the identification of timing differences of the peak body roll for each stroke (Figure 43).

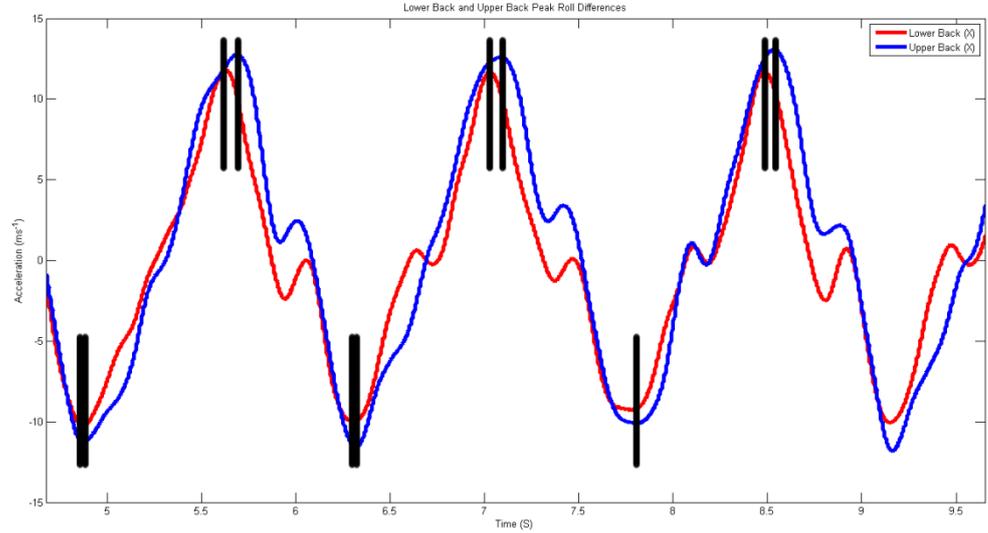


Figure 43: Example of the variation between the Upper and Lower body peak roll (Times between black lines shows the time difference between the peaks in the Upper and Lower body roll)

3.3.9.3 Body Roll Angle

Upper and lower body roll angles (UB_A , LB_A) were calculated using EQ[23]

$$LB_A = \tan^{-1} \left(\frac{LB_X}{LB_Z} \right)$$

[23]

Where LB_X and LB_Z are the X and Z axis or the Lower Body (where UB_X and UB_Z are substituted for Upper Body). Bächlin and Tröster (2012) noted that the gravity component on these axes is much larger than compared to the other components and that the body's pitch in the water has no effect on this measurement.

Bächlin and Tröster (2012) noted that the gravity component on these axes is much larger than compared to the other components and that the body's pitch in the water has no effect on this measurement. However, Bächlin and Tröster (2012) did not validate this method. To ensure the validity of this approach a test was devised using an accelerometer attached to the centre of a 1m ruler. Two reflective markers were added, 25cm either side of the accelerometer (Figure 44). The ruler was then freely rotated left and right, along the X axis (representing LB_X and UB_X). The ruler was also moved forwards and backwards (towards and away from the camera) during the rotations, representing the swimmers movement in the LB_Y and UB_Y axis. This was conducted to identify whether or not this approach would produce a true angle which could then be used to determine the swimmers body roll.

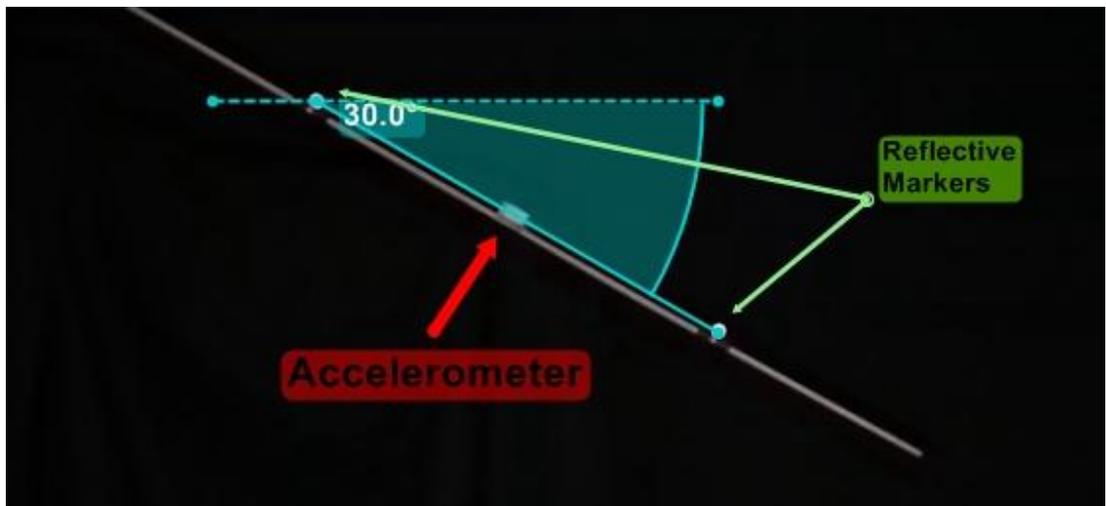


Figure 44: Rotation of the accelerometer

The video camera was positioned at 90 degrees to the ruler following the guidance of Grimshaw et al. (2006) and Payton (2008). Because the measure recorded was angles, calibration in terms of measurements of centimeters to pixels, was not necessary. The videos were analysed using Kinovea v0.8.19 to find the peak angles of each rotation and compared to the output from the accelerometers using EQ[23]. Using SPSS v.19, the data was compared to find a normal distribution using the Kolmogorov-Smirnov test. The data, video angles and accelerometer angles,

were found to be normal (Video = .298, Accelerometer = .319) leading to the use of a paired samples t-test to test for any significant differences. Hopkins (2004) notes that in addition to a Person correlation, to show the strength of the relationship, the results can be extended to include Regression analysis with supporting Bland-Altman plot. This will then provide an equation which can allow for a correction to the accelerometer data.

3.3.10 Stroke Phases

Phases of the stroke have been previously identified (Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2003), but no attempt of an algorithm to calculate them automatically has been attempted until recently (Dadashi et al. 2013). There has been no attempt to extend this measurement of IdC towards measuring fatigue and variation of the phases therein.

To develop an algorithm capable of detecting all the phases of the stroke automatically development started with identifying the Hand Entry. This was previously defined as a LW_X / RW_X minima by Ohgi (Ohgi 2002; Ohgi and Ichikawa 2003) which was reconfirmed in the present system. This was calculated using the global video to measure the time from the initial 3 bumps (synchronisation) to the first hand entry by the swimmer. This time was then used on the accelerometer (LW_X / RW_X) to determine the correct minima (Figure 49).

The algorithm was then developed to find subsequent local minima and maxima using peak detection. These locations were initially identified by taking the time from hand entry, on the underwater camera, and using frame by frame analysis method to determine the start point of each phase. The time from hand entry of each point could then be plotted against the sensor data to identify the correct minima and maxima of each axis. It was observed that the phases of the stroke coincided with body roll movements allowing further verification of the phases (Figure 45, Figure 46, Figure 47 and Figure 48). With the correct maxima and minima detected manually, the algorithm was then designed to find these on the LW and RW sensors in relation to either a body roll zero crossing or peak body roll (Figure 49).

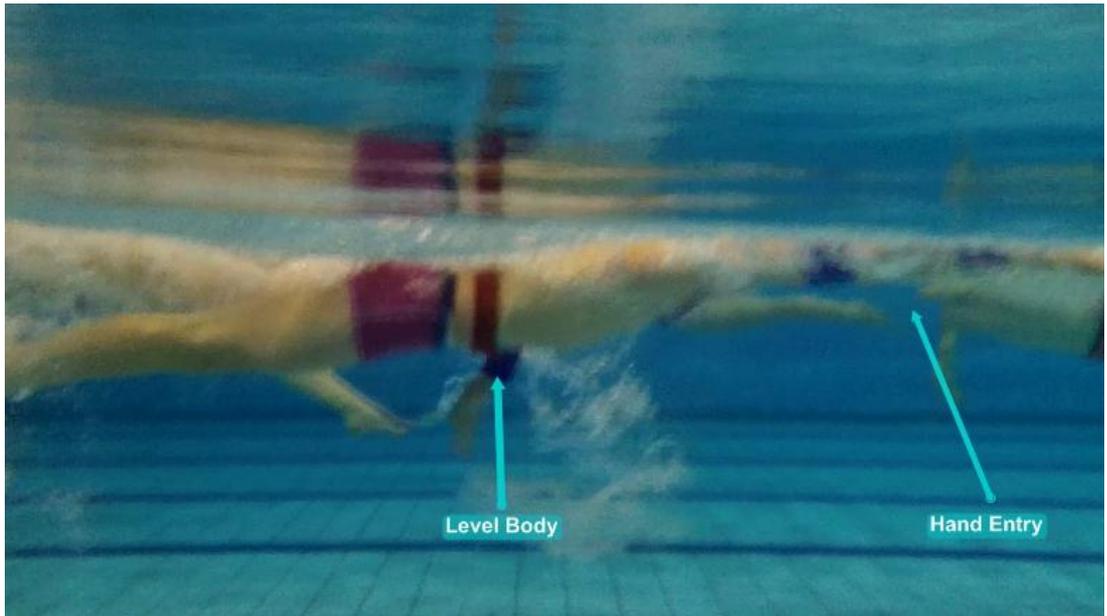


Figure 45: Hand Entry

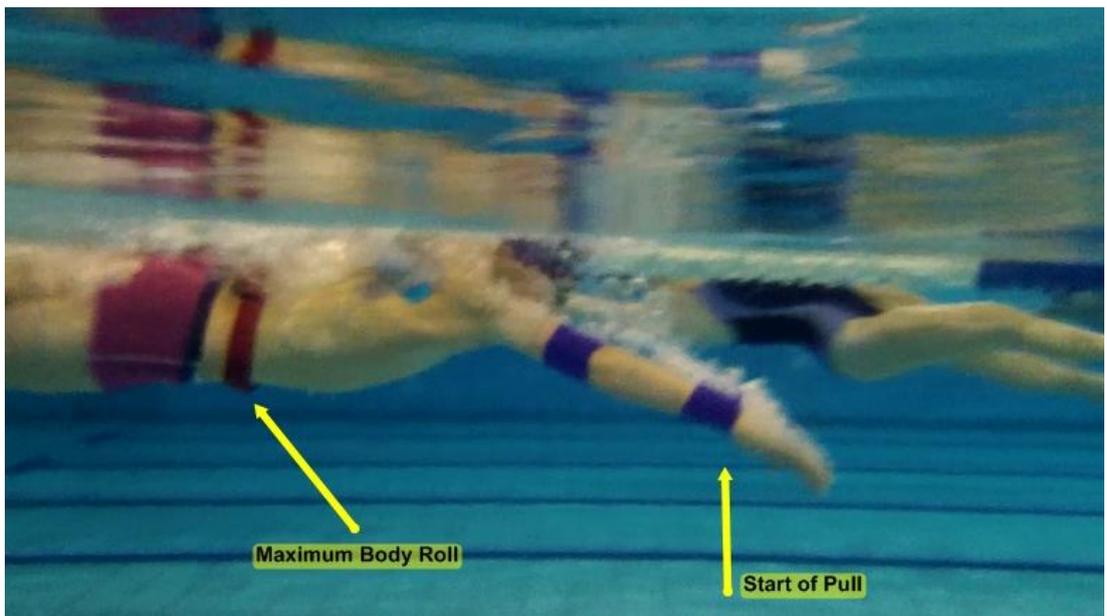


Figure 46: Start of pull phase

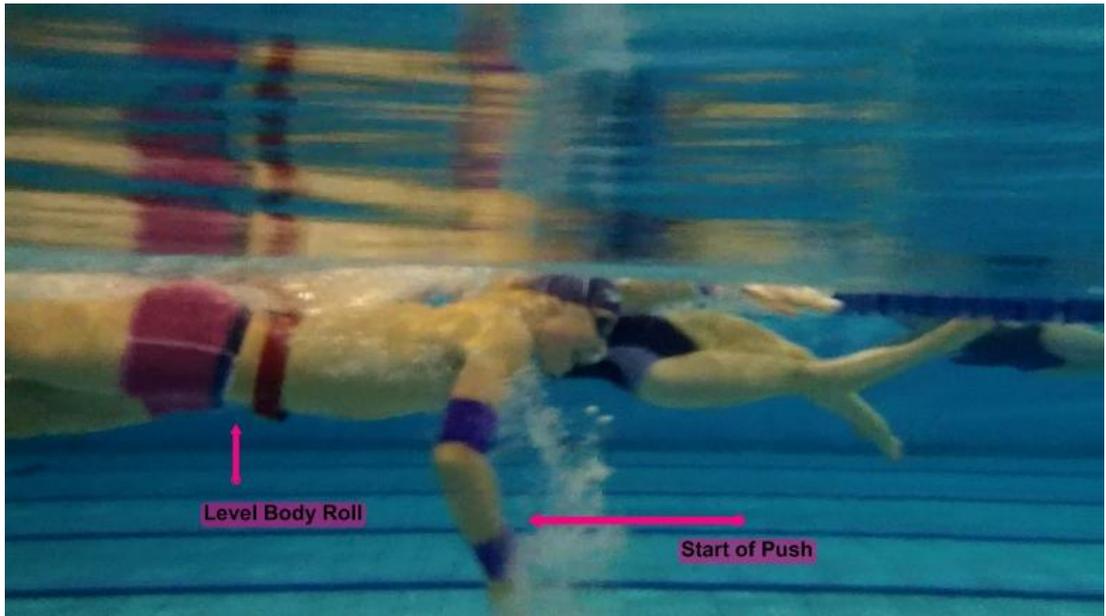


Figure 47: Start of push phase

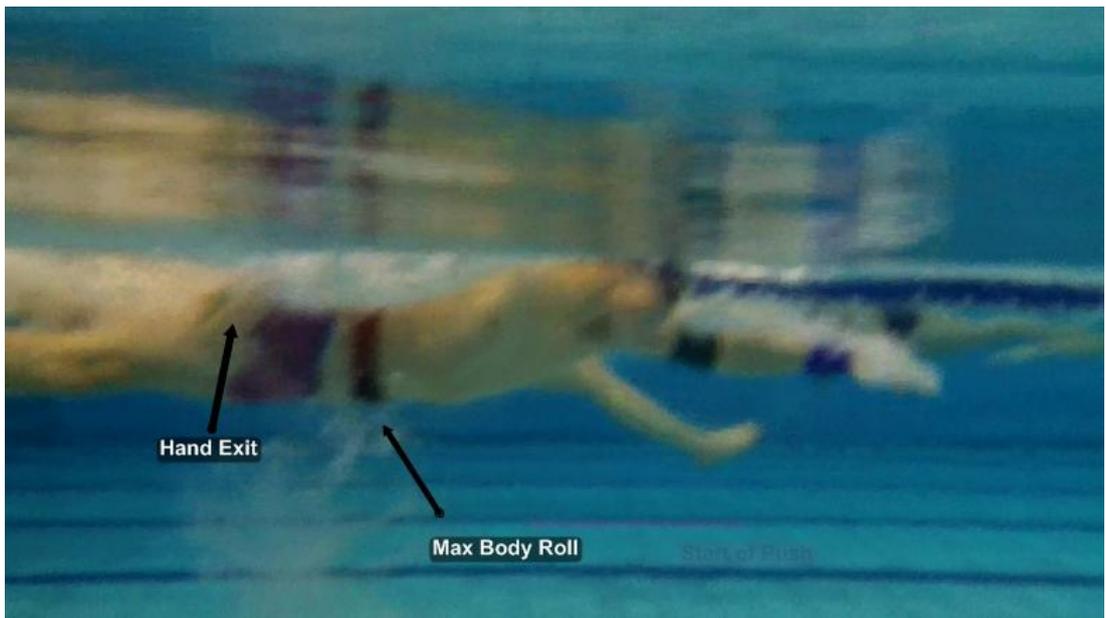


Figure 48: Start of Exit

This use of body roll allowed for the timings of each phase to be extracted allowing durations of each phase over multiple laps, for both left and right arms, to be identified (Figure 50). This coordination pattern was found with all swimmers, although there are some variations swimmer to swimmer. This is also in line with the

literature which states that body roll has a relationship to hand path and thus the phases of the stroke (Psycharakis and Sanders, 2010).

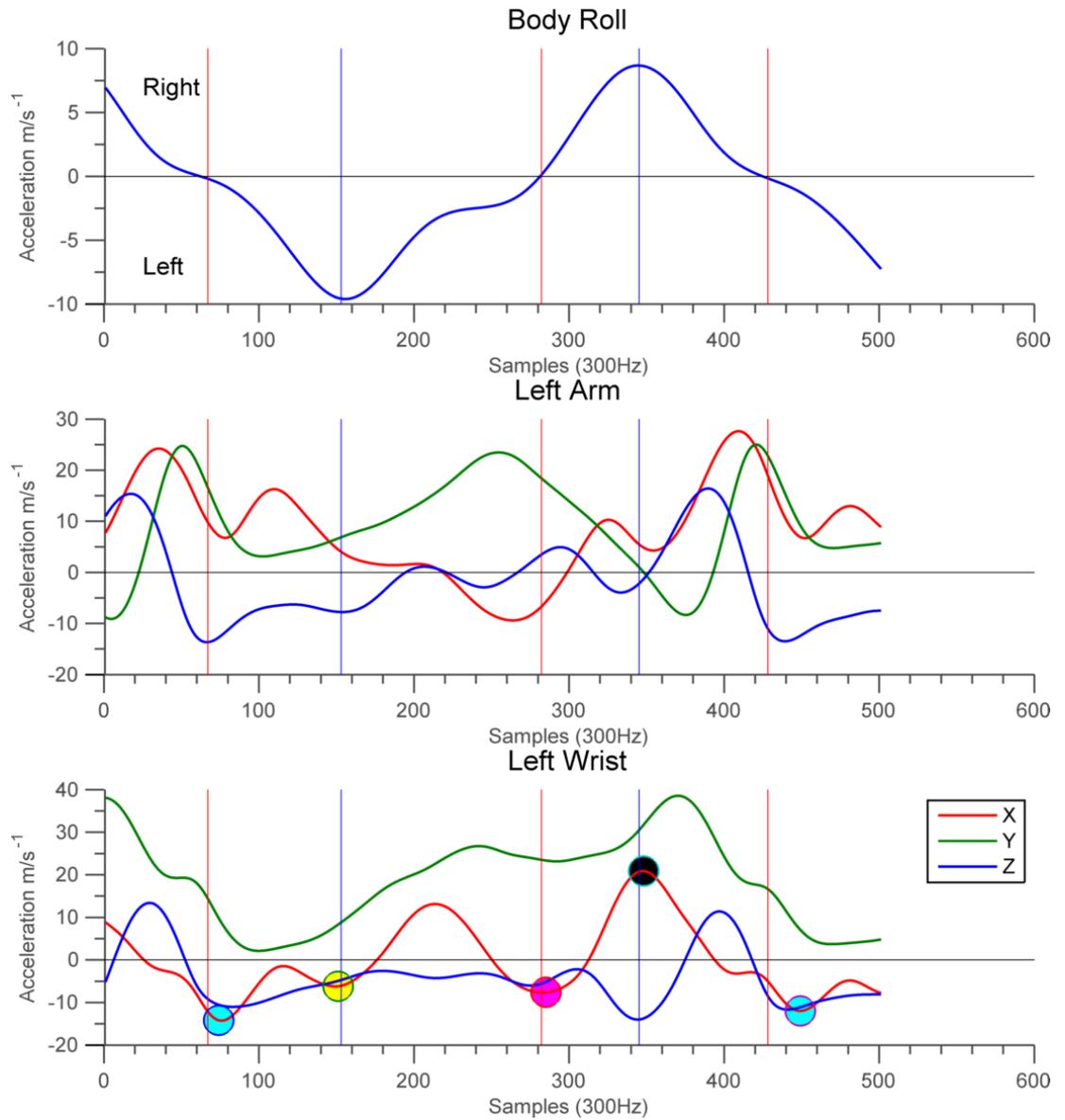


Figure 49: Identification process of the phases in the stroke (Swimmer R). Entry (Cyan), Start of Pull (Yellow), Start of Push (Magenta), Start of Recovery (Black). Zero Crossing Body Roll (Red), Peak Body Roll (Blue).

The hand entry was identified as a local X minima in the region of the body being at a zero crossing (level body). The algorithm first identifies the local minima for the whole X axis, and then looks for ones which are close, typically within 100 samples, of the zero crossing time (when the body is level). This identifies all the hand entries for the length. The start of the pull is identified by the next X minima, near a peak body roll on the same side as the arm, e.g. for a left arm stroke, a left body roll. The push was the local minima between two LW_X/RW_X maxima and near the next zero crossing and the start of the opposite body roll. The recovery was found to be the peak of the opposite body roll, which also coincides with a LW_X/RW_X maxima.

The arm sensor was added to the swimmer to aid the development of the algorithm. However, initial attempts to add in detection methods for maxima, minima or where signals overlap, did not add to the consistency of the algorithms output.

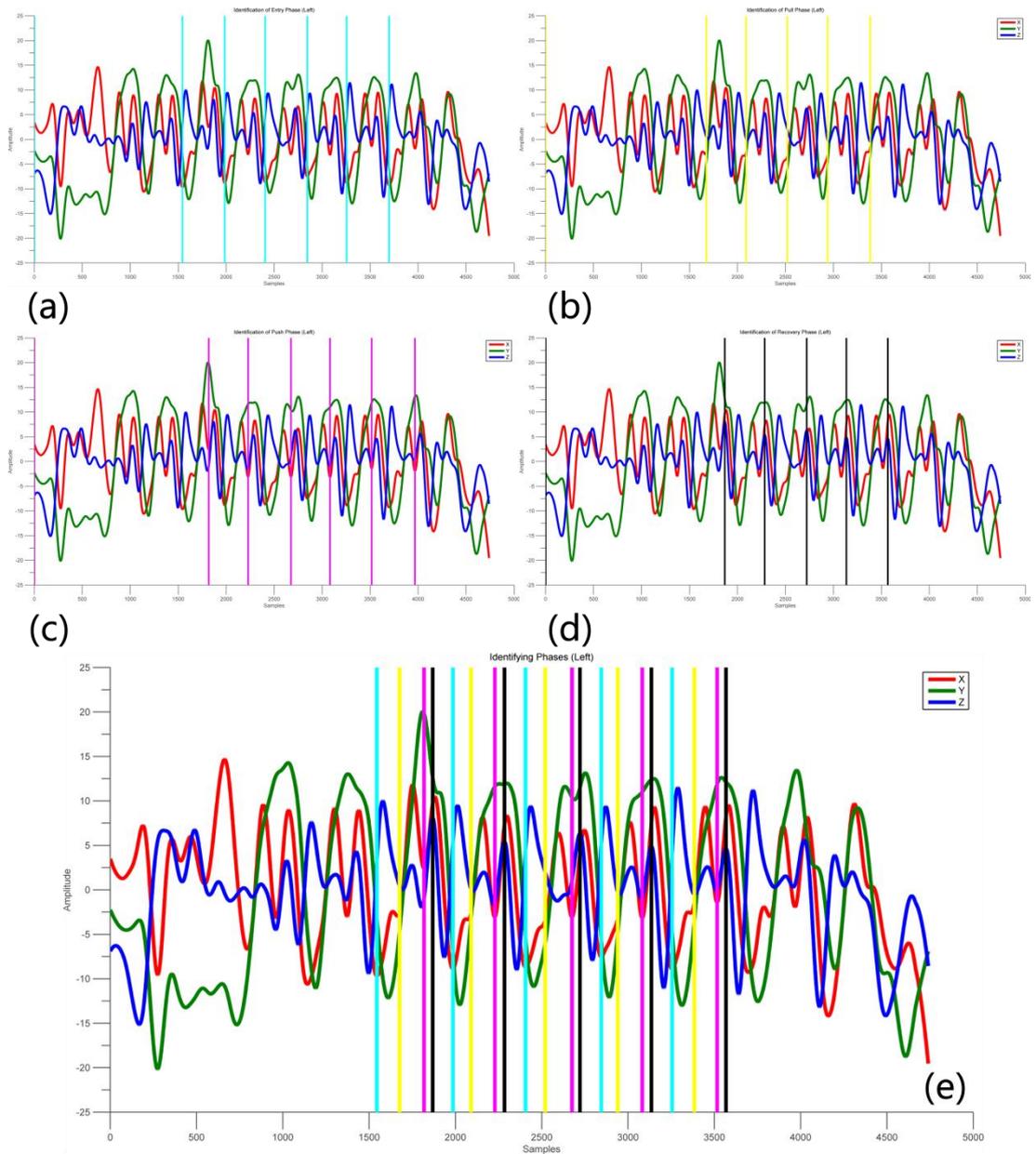


Figure 50: Stroke Phases automatically detected for a stroke. (a) Entry (Cyan), (b) Start of Pull (Yellow), (c) Start of Push (Magenta), (d) Start of Recovery (Black) (e) All phases

The algorithm was restricted to start only after the first full stroke, as the first stroke tended to start underwater after the wall push off, this meant that there was no clear hand entry on which to base the following stroke phases. The last stroke was sometimes "soft" where they stretched for the wall to finish, rather than fully completing a stroke. This was also removed automatically by the algorithm by

defining the last hand entry as the end of the recovery phase for the previous stroke but defining no further phases after that.

Reliability of the algorithm was analysed for 78 full strokes of 5 swimmers. The recovery phase used 71 samples as on occasion there was no following hand entry to finish that phase for 7 of the strokes viewable on the video camera. The number of swimmers and strokes was selected based on quality of video footage. The trolley videoing reliability was questionable, as discussed earlier, and the best videos of the swimmers was chosen offering clear viewing of the swimmer without the camera breaching the surface of the water.

Reliability was analysed using Mean Error (\pm SD), Mean Absolute Error (MAE), 95th Percentile for MAE, Root Mean Square Error (RMSE), and Standard Error from Mean (SEM) for each phase against the durations of the phase from the video (Hughes et al. 2002; O'Donoghue 2013; O'Donoghue 2010). Systematic and random bias are also reported for each axis and presented in Bland-Altman plots.

3.3.10.1 Index of Coordination (IdC)

IdC has been extensively used in swimming (Chollet et al. 2000b; Formosa et al. 2012; Osborough et al. 2010; Schnitzler et al. 2008; Seifert et al. 2005b; Seifert et al. 2004; Seifert et al. 2007a; Seifert et al. 2007b; Seifert et al. 2010). Described by Chollet et al. (2000b), the arm coordination can be quantified as defining the stroke into four clear phases, as shown previously. The coordination is then the time lag between the beginning of the propulsive phase (Start of Pull) of the first right arm stroke and the end of the propulsion (end of Push, i.e. start of recovery) of the left arm (LT1), then the beginning of the propulsion of the second left arm stroke and end of the propulsion on the right arm (LT2) which can be calculated by EQ[24]:

$$LT = \left(\frac{LT_1 + LT_2}{2} \right)$$

[24]

Where LT is the overall lag time created by taking the time from the end of the Left Arm propulsion (start of recovery) (LT_1) to the start of the Right Arm pull (LT_2). This is then represented as a percentage of the entire stroke.

Three models of stroke coordination are displayed by (Chollet et al. 2000b), an IdC of 0% shows *Opposition*, where both arms are in phase with each other, so as one phase ends, the other begins. In practical terms this is normally $-1\% < IdC < 1\%$ (Seifert et al. 2007a). A negative IdC shows *Catch Up*, where there is a lag between each arm's propulsion. The third type is termed Superposition, where both arms generate propulsion, in part, at the same time represented by a positive percentage.

Whilst Bächlin and Tröster (2012) used the Y axis of the wrist sensor (LW_Y and RW_Y) to determine the duration of the stroke (SD), they did not extend to look at the phases of the stroke. The work of Davey et al. (2008) and the development of that system by Stamm et al. (2012) using a lower back device attempt to look at the arm symmetry. However, as previously noted the issue with this is that it does not rely on a direct measurement of the arms and their variability over time. By identifying the precise timings of the phases of the stroke, IdC can then be calculated using the methods implemented by Chollet et al. (2000b).

3.3.10.2 Symmetry Index

The symmetry index was calculated using EQ[25] (Repeated from EQ[9[11]]),

$$SI = \frac{2(R_L - R_R)}{(R_L + R_R)} \bullet 100$$

[25]

Where R_L is the Left Roll angle and R_R is the Right Roll angle. The results of this show that a value between -10% and 10% for the SI implies symmetry. Left and right-side asymmetries are indicated when $SI < -10\%$ and when $SI > 10\%$, respectively (Psycharakis and Sanders 2008).

This method has been previously used to identify the symmetry difference of body roll angle (Psycharakis and Sanders 2008), and is being extended in this work to include:

- IdC
- Upper Body Roll Angle
- Lower Body Roll Angle
- Stroke Duration
- Phases of the Stroke

This ability to identify not only the individual measures of each factor, but also whether there is a asymmetry associated with this, should be of use to the coach.

3.3.11 Stroke to Stroke Body Roll Consistency

Ohgi et al. (2002) demonstrated that these sensors could be used to measure fatigue, but did not offer any method to assess this other than overlaying data. In addition to the Symmetry Index, Smith and Spinks (1995) and Caplan and Gardner (2009) demonstrated methods of fatigue analysis in rowing by analysing the consistency of the rowing stroke. Stroke to stroke body-roll consistency is measured by normalising the data with respect to time, 200 samples was chosen as observations from the data set showed that some were as low as 150, and some as high as 250. The mean and standard deviation of the values of each 2% of the stroke was calculated (EQ[26] Repeated from EQ[9]) to create a coefficient of variation for each 2% of the stroke. This was then used to create a consistency rating out of 100% (EQ[27] Repeated from EQ[10])

$$\textit{Coefficient of Variation for each 2\%} = \frac{SD}{\textit{Mean for each stroke}}$$

[26]

$$\textit{Mean Stroke To Stroke Consistency} = 100*(1-\textit{mean coefficient of variation})$$

[27]

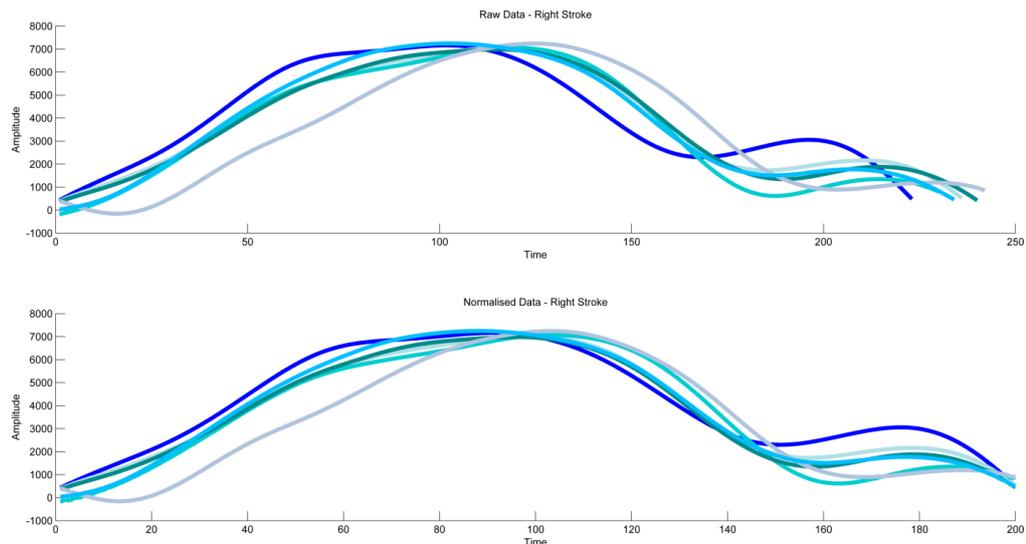


Figure 51: Graphical representation of body roll consistency. Top graph shows variation in body roll to the Right with different times per stroke. This is then normalised for time in the lower graph to 200 samples. Each line is a new stroke in the same lap

Due to the nature of the swimmers, and noted earlier (3.3.9), the body roll has a stabilizing movement after the zero crossing of the roll. This created some false consistency measures in the data resulting in consistency over 100%. During the normalisation of time, the data was also shifted vertically by the smallest values in the data set which removed this error.

3.4 System Output

The system generates a PowerPoint output automatically and saves it with the name and date of the swimmer. It comprises of 22 pages of information, gradually increasing in the level of detail.

Page 1 offers a notes section on the procedure for testing. The procedure used here, as noted above, was 4 x 25m (recording), 8 x 25m (to induce Fatigue), 4 x 25m (recording).

The second page offers overview of the factors recorded and which have been affected by fatigue. This information is generated by using paired samples t-tests to

show if there is a significant ($p < 0.05$) difference between Pre and Post fatigue over all the factors recorded. This is reported to the coach as a simple, Yes or No, where Yes shows there is a change, No shows there is no change due to fatigue (Figure 52).

Summary - Core Info				
Time	Avg.Vel	Count	Rate	DistPerS(m)
Yes	Yes	No	Yes	No

Summary - Body Roll					
Lower Angle (L)	Lower Angle (R)	Upper Angle (L)	Upper Angle (R)	Timing (L)	Timing (R)
Yes	Yes	Yes	Yes	No	Yes

Summary - Stroke Duration		
Left	Right	Coordination (IdC)
Yes	Yes	Yes

Summary - Left Stroke Phase Duration			
Entry	Push	Pull	Recovery
Yes	Yes	Yes	Yes

Summary - Right Stroke Phase Duration			
Entry	Push	Pull	Recovery
No	Yes	Yes	Yes

Overview

These tables show if there is a difference before and after fatigue.

If there is a difference in the core info, the tables below show where these changes occurred. If there is no difference in the core info, the tables show potential compensation strategies to ensure consistent lap times/rate etc.

Figure 52: Example Overview output

The Core Information, identified as necessary by the coach, is shown on Page 3. This shows the Time, Stroke Count, Stroke Rate, Average Velocity and Distance Per Stroke for each of the 8 laps performed. This information is also presented on Pages 4-5 graphically for quicker interpretation by the coach.

Core Info					
Length	Time (S)	Stroke Count	Stroke Rate	Avg.Vel(m/s)	DistPerS(m)
L 1	15.53	20	90.15	1.61	2.21
L 2	15.95	18	82.35	1.57	2.20
L 3	16.94	18	86.55	1.48	2.19
L 4	16.25	18	87.90	1.54	2.28
L 5	15.63	19	93.15	1.60	2.50
L 6	16.16	18	82.35	1.55	2.32
L 7	16.85	18	86.25	1.48	2.21
L 8	16.26	18	89.70	1.54	2.32

Figure 53: Core Information output

Body roll variation is then shown (Pg 6-7) for upper and lower body, graphically showing the angle with their maximum and minimum (Figure 54). Right side and Left side rolls are shown separately in Red and Blue. Horizontal lines are added based on Kippenhan and Yanai (1995) recommendations for skilled and unskilled swimmers, to quickly identify to the coach the need for change.

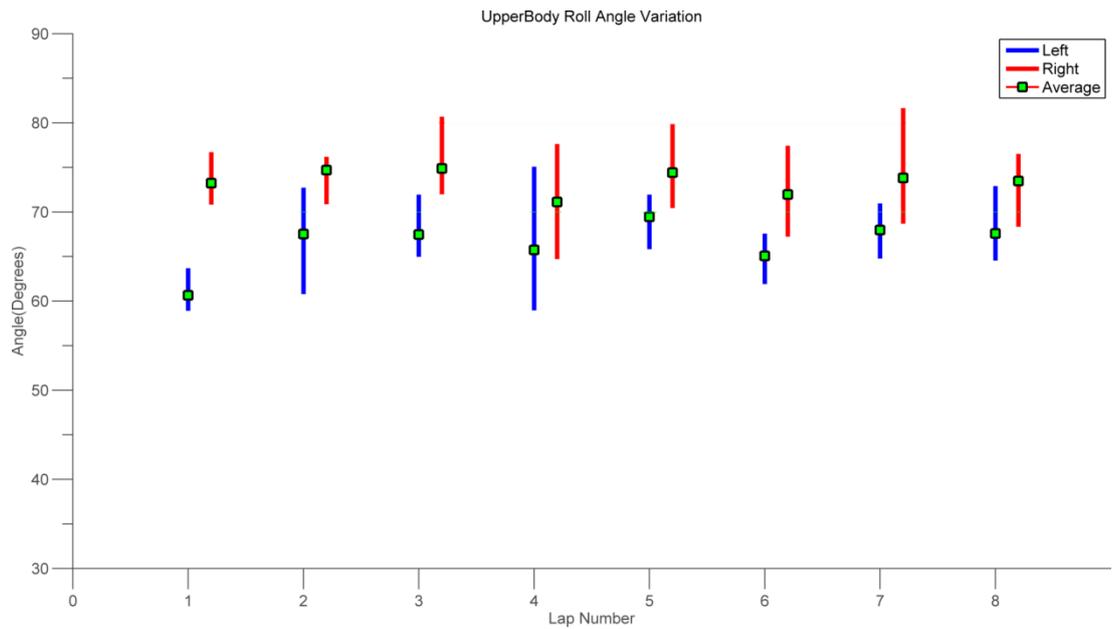


Figure 54: Body Roll Variation

Page 8 shows the coach the difference between upper and lower body roll times (Figure 55). There is a note added here for interpretation, the marks above the zero show that the upper body was first (the lower body lags) by the average time. Marks below the zero show the lower body was first (the upper body lags). The error bars show the standard deviation of the times.

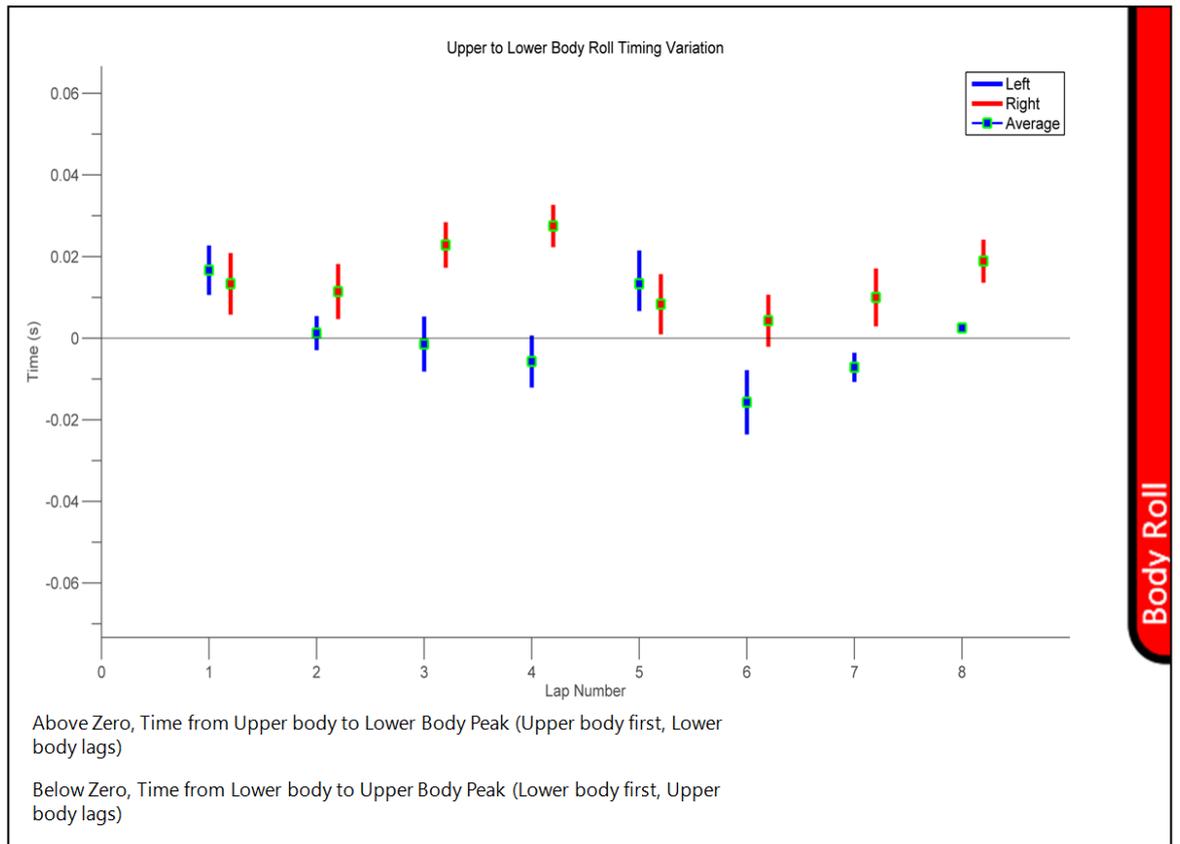


Figure 55: Timing Variation between upper and lower peak roll

The symmetry information for various factors is then shown to the coach in an easy to read manner. When the symmetry index is calculated, numbers between -10 and 10 show no dominant side, numbers higher and lower than this show a dominant side. The software automatically replaces this with the appropriate word to save the coach processing time, Figure 56.

This table tells you which side is dominant showing potential asymmetry

Symmetry: Dominant Side

Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Left	Right	Right	Equal	Left	Equal	Right	Equal
L 2	Equal	Right	Right	Equal	Equal	Equal	Left	Right
L 3	Equal	Right	Right	Equal	Left	Equal	Right	Right
L 4	Equal	Equal	Equal	Equal	Equal	Left	Equal	Right
L 5	Equal	Equal	Equal	Equal	Left	Equal	Right	Right
L 6	Equal	Right	Right	Equal	Left	Equal	Right	Right
L 7	Equal	Equal	Left	Equal	Equal	Left	Right	Equal
L 8	Equal	Equal	Equal	Equal	Equal	Left	Equal	Equal

Figure 56: Symmetry presentation to the coach

3.4.1 Percentage of time per phase

Figueiredo et al. (2012) displayed camera gathered data as a percentage of time of the stroke, which is a useful way to interoperate information for use by a coach. This is shown in two forms. Firstly as a line based graph (Figure 57) and secondly as a graphical representation using an image of a swimmer (Figure 58). On discussion with the head coach (ER), this was appreciated as it gave an overview for her and she would probably use the graphical overview to help explain to the swimmer with this as an example. Figure 58 shows an overview of all the stroke durations from all the laps, Pages 11-16 show each lap in this form so the coach can identify, from the overview, something of interest to show graphically to the swimmer.

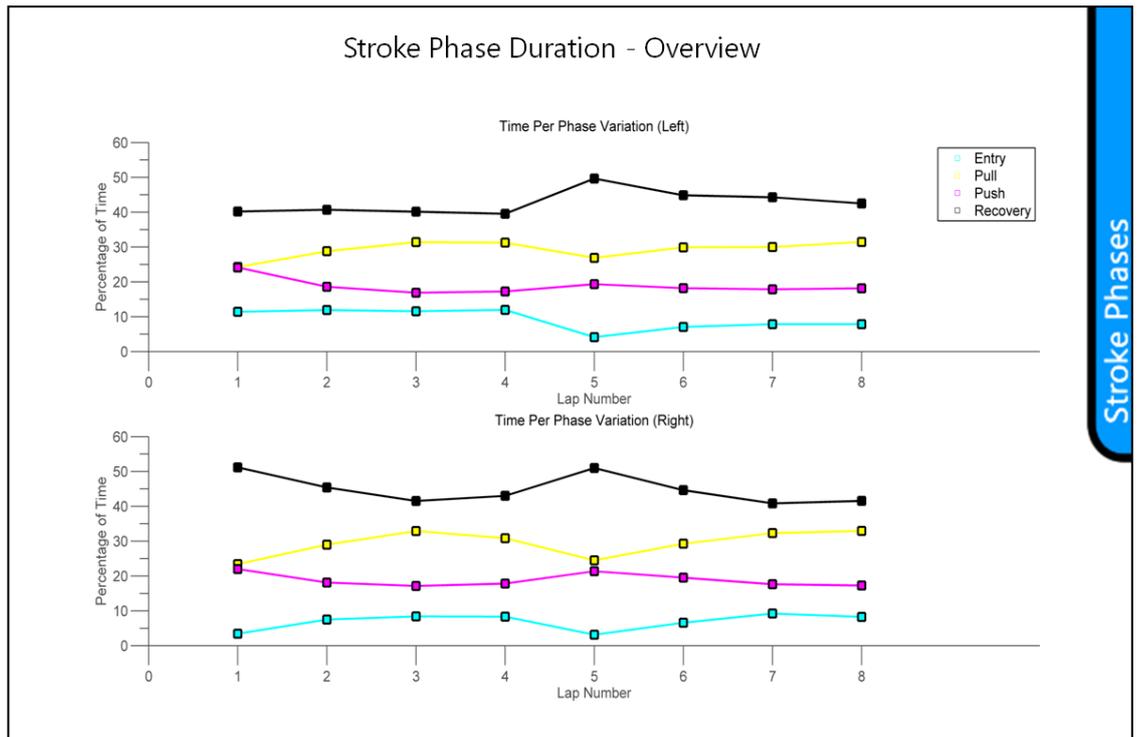


Figure 57: Stroke Duration (Percentage) Overview

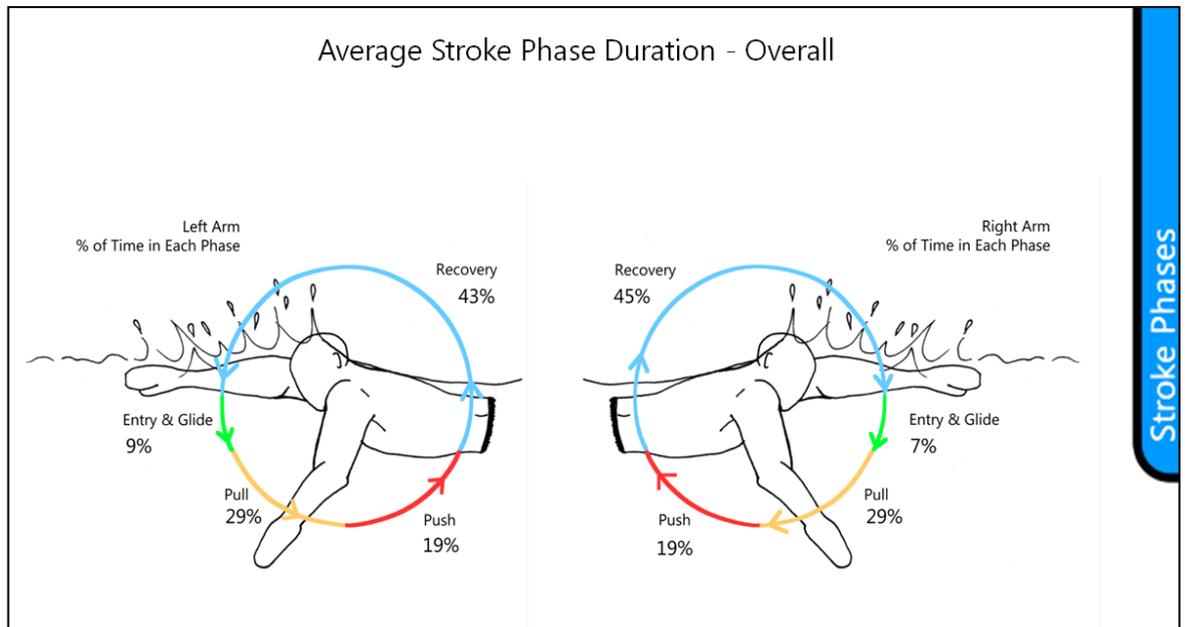


Figure 58: Stroke Duration (Percentage) - Graphical

The lap by lap break down is primarily to be used by the coach after the identification of any immediate concerns. The following pages, 11-22, offer detailed views of each factor, which should be read in detail by the coach. Average stroke durations are presented in tabular form (Figure 59).

RIGHT: Average Duration for Each Phase (Seconds)					
Length	Stroke Duration	Entry-Catch	Push	Pull	Recovery
L 1	1.21	0.04	0.28	0.27	0.62
L 2	1.38	0.10	0.40	0.25	0.63
L 3	1.47	0.12	0.48	0.25	0.61
L 4	1.47	0.12	0.45	0.26	0.64
L 5	1.22	0.04	0.30	0.26	0.62
L 6	1.37	0.09	0.40	0.27	0.61
L 7	1.46	0.13	0.47	0.26	0.60
L 8	1.51	0.12	0.50	0.26	0.63

Figure 59: Average duration for each phase

IdC is presented to the coach in tabular form, with the length times (Figure 60). Also added is a description for the coach.

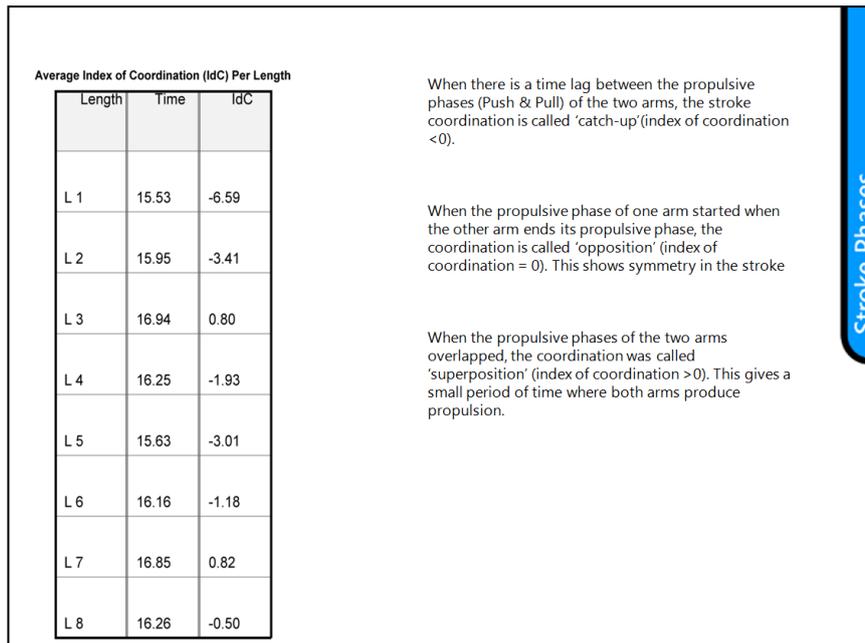


Figure 60: Average Index of Coordination

Average body roll angles are presented in tabular form with a percentage of consistency for the coach (Figure 61), and also the average body roll angle per phase is presented (Figure 62).

Body Roll Angles and Consistency (%) (Upper, Lower)								
Length	Left Angle	Right Angle	Right Con(%)	Left Con(%)	Left Angle	Right Angle	Right Con(%)	Left Con(%)
L 1	50.40	67.82	97.35	96.93	47.97	50.68	94.81	95.69
L 2	56.34	67.15	93.68	96.36	46.97	50.74	96.37	94.12
L 3	58.13	69.54	93.78	96.19	49.44	53.23	94.58	95.01
L 4	56.43	69.09	96.11	94.83	51.26	52.66	95.23	94.56
L 5	56.96	70.39	93.56	97.40	44.98	49.95	94.52	96.24
L 6	61.28	72.69	91.31	95.66	46.86	53.25	93.27	93.66
L 7	62.12	74.75	95.08	97.71	49.45	55.84	94.96	93.98
L 8	62.31	75.29	94.19	96.74	51.40	57.11	94.32	95.85

Figure 61: Body roll angles and consistency

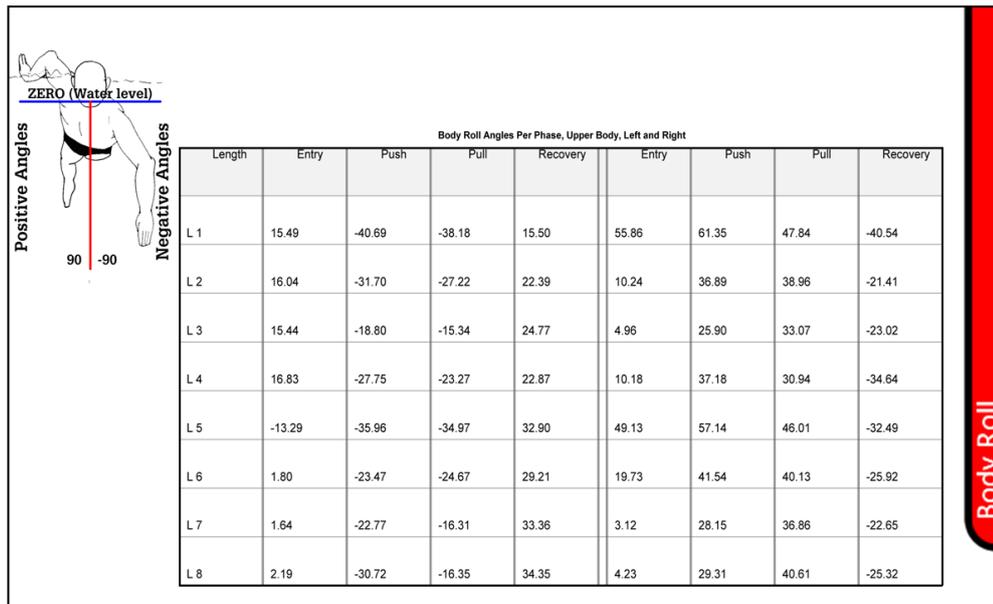


Figure 62: Body roll angles per phase. Upper body left, Lower body right.

3.5 Summary of Method

The chapter has presented the factors which are important to the coach:

- Lap Time
- Average Velocity
- Stroke Count
- Stroke Rate
- Distance Per Stroke
- Body Roll Angle
- Phases of the Stroke

These factors were similar to those used in previous works using accelerometers (Bächlin et al. 2009; Bächlin and Tröster 2009; Davey et al. 2008; Le Sage et al. 2011; Ohgi and Ichikawa 2002; Ohgi et al. 2000), except for phases of the stroke, which has only recently been attempted (Dadashi et al. 2013). This chapter also outlined the methods used to extend these factors to include the timing variation between upper and lower body peak rolls, phases of the strokes, percentage of time

per phase, Index of Coordination (IdC), stroke to stroke consistency of the body roll was also presented, as well as the body roll angle per phase of the stroke. The symmetry between left and right sides for:

- IdC
- Upper Body Roll Angle
- Lower Body Roll Angle
- Stroke Duration
- Phases of the Stroke

was also calculated.

To achieve the recording of these factors, several independent waterproof devices required a synchronisation method. This involved using "bumps" which can be seen in each device and temporally aligned prior to the extraction of the aforementioned factors. The following chapter outlines the results of the validation and reliability methods for these factors.

Chapter 4 - Results

Parts of this chapter have been published in the following papers:

Callaway, A., Cobb, J. E., & Jones, I. (2009). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *International Journal of Sports Science and Coaching*, 4, 139-153.

Callaway, A., & Cobb, J. E. (2012). Linear acceleration measurement utilising inter-instrument synchronisation: A comparison between accelerometers and motion based tracking approaches. *Measurement in Physical Education and Exercise Science*, 16, 151-163

4 Results

This chapter outlines the results of the design. Firstly the validation of the synchronisation method. The validity and reliability of the swimming system design in comparison to video derived data. A selection of individual results are then presented.

4.1 Validity of the Synchronisation Method

Using the cross covariance method (Signal Processing Toolbox) in MATLAB (Figure 63), demonstrated the validity of the synchronisation procedure. The maximum time lag found, after the sampled data from the instruments were shifted, was one sample. This is equivalent to 0.0416 seconds. Investigation showed that this error was due to a misidentification of a maximum in the software. However, this error was minimised by taking the mean distances between the first three peaks. This error occurred in only 2 of the 54 recordings made.

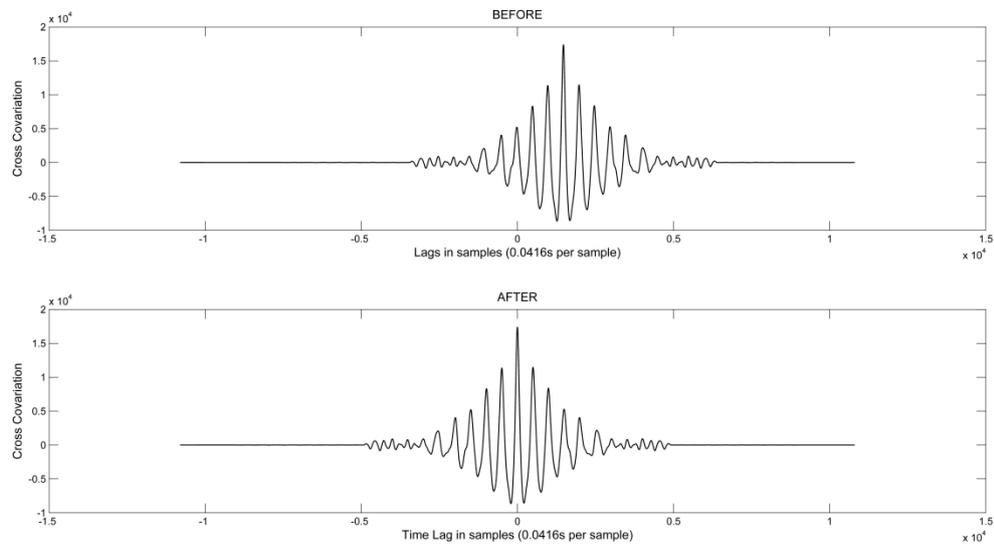


Figure 63: Showing the difference in time lag before and after the time shifting process.

4.1.1 Instrument Validity

The relationships between each instrument and the video derived kinematic data are presented in Table 9. Pearson's r were calculated using the mean value from the three tests on each axis, and were performed for all of the data recorded.

All tests produced significant results ($p = 0.00$). All instruments showed strong positive correlations to the kinematic data from Quintic. Results were greater than .975 (X axis) , .967 (Y axis) and .987 (Z axis), respectively demonstrating large effect sizes on all devices (Cohen, 1988).

	<i>Instrument 1</i>	<i>Instrument 2</i>	<i>Instrument 3</i>	<i>Instrument 4</i>	<i>Instrument 5</i>	<i>Instrument 6</i>
X Axis	0.975	0.978	0.978	0.975	0.977	0.976
Y Axis	0.976	0.974	0.972	0.975	0.967	0.976
Z Axis	0.993	0.991	0.994	0.993	0.975	0.987

Table 9: Correlation Coefficients of each instrument on each axis. All results are of significance ($p = 0.00$)

4.1.2 Inter-Instrument Reliability

Inter-instrument reliability was tested using ICC for each axis (Table 10, Table 11, Table 12). All results showed significant ($p = 0.00$), strong positive correlations for each axis, over each independent test. This demonstrates the reliability of the devices. These were all of a large effect size ($r > 0.9$) (Cohen, 1988).

<i>X Axis</i>	<i>Instrument 1</i>	<i>Instrument 2</i>	<i>Instrument 3</i>	<i>Instrument 4</i>	<i>Instrument 5</i>	<i>Instrument 6</i>
Test 1	0.991	0.991	0.992	0.991	0.991	0.989
Test 2	0.950	0.956	0.956	0.954	0.958	0.954
Test 3	0.976	0.979	0.980	0.975	0.974	0.977

Table 10: Intraclass Correlation Coefficient X Axis ($p = 0.00$)

<i>Y Axis</i>	<i>Instrument 1</i>	<i>Instrument 2</i>	<i>Instrument 3</i>	<i>Instrument 4</i>	<i>Instrument 5</i>	<i>Instrument 6</i>
Test 1	0.962	0.961	0.960	0.965	0.936	0.964
Test 2	0.900	0.990	0.980	0.989	0.992	0.989
Test 3	0.970	0.968	0.972	0.965	0.969	0.969

Table 11: Intraclass Correlation Coefficient Y Axis ($p = 0.00$)

<i>Z Axis</i>	<i>Instrument 1</i>	<i>Instrument 2</i>	<i>Instrument 3</i>	<i>Instrument 4</i>	<i>Instrument 5</i>	<i>Instrument 6</i>
Test 1	0.900	0.990	0.994	0.989	0.989	0.987
Test 2	0.940	0.993	0.995	0.994	0.993	0.993
Test 3	0.990	0.987	0.992	0.990	0.940	0.975

Table 12: Intraclass Correlation Coefficient Z Axis ($p = 0.00$)

Bland-Altman plots for each axis (Figure 64, Figure 65, Figure 66) showed that all error for all devices was under 5%. Table 13 presents the amount of data within the 95% Limits of Agreement (LoA) within the Bland-Altman plots. All devices show very high and consistent levels of data within the LoA.

		<i>Instrument</i>					
		<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>6</i>
<i>Axis</i>	<i>X</i>	94%	93%	94%	93%	93%	93%
	<i>Y</i>	94%	93%	94%	94%	93%	94%
	<i>Z</i>	93%	94%	93%	93%	94%	94%

Table 13: Percentage of data within 95% Limits of Agreement

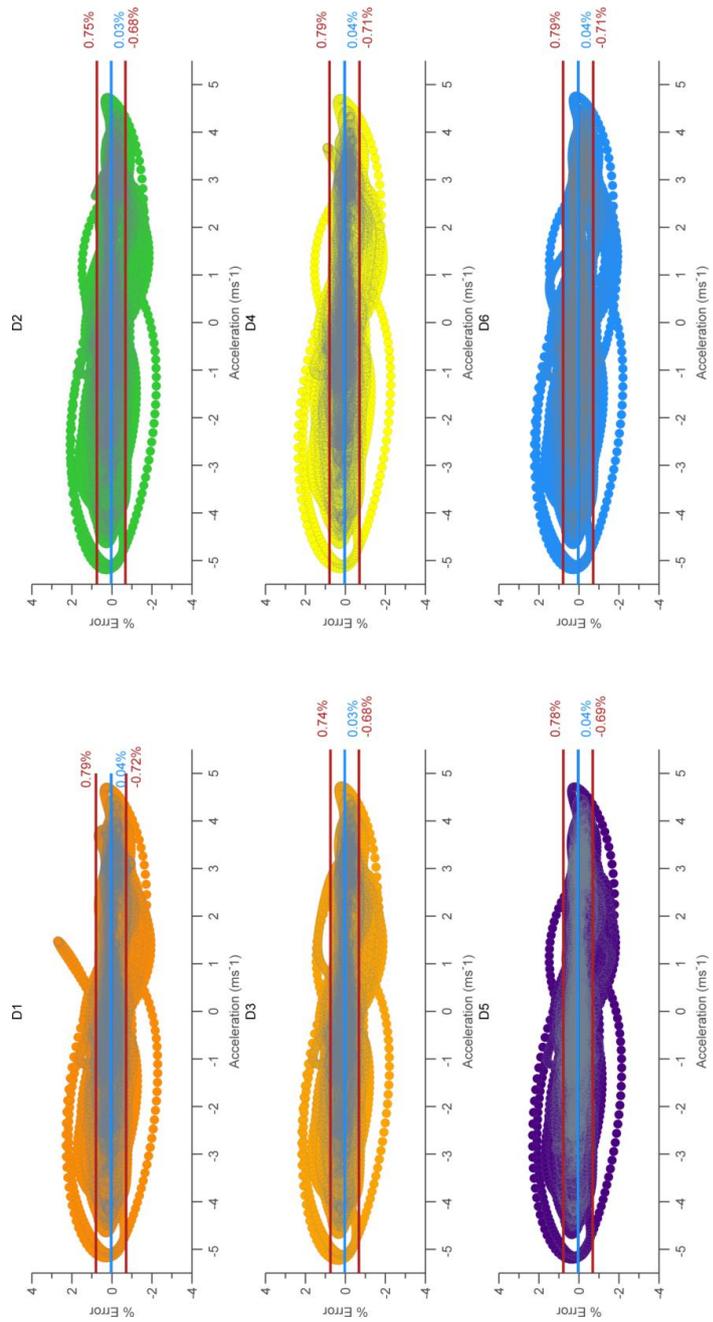


Figure 64: Bland-Altman Plot of X axis for each device

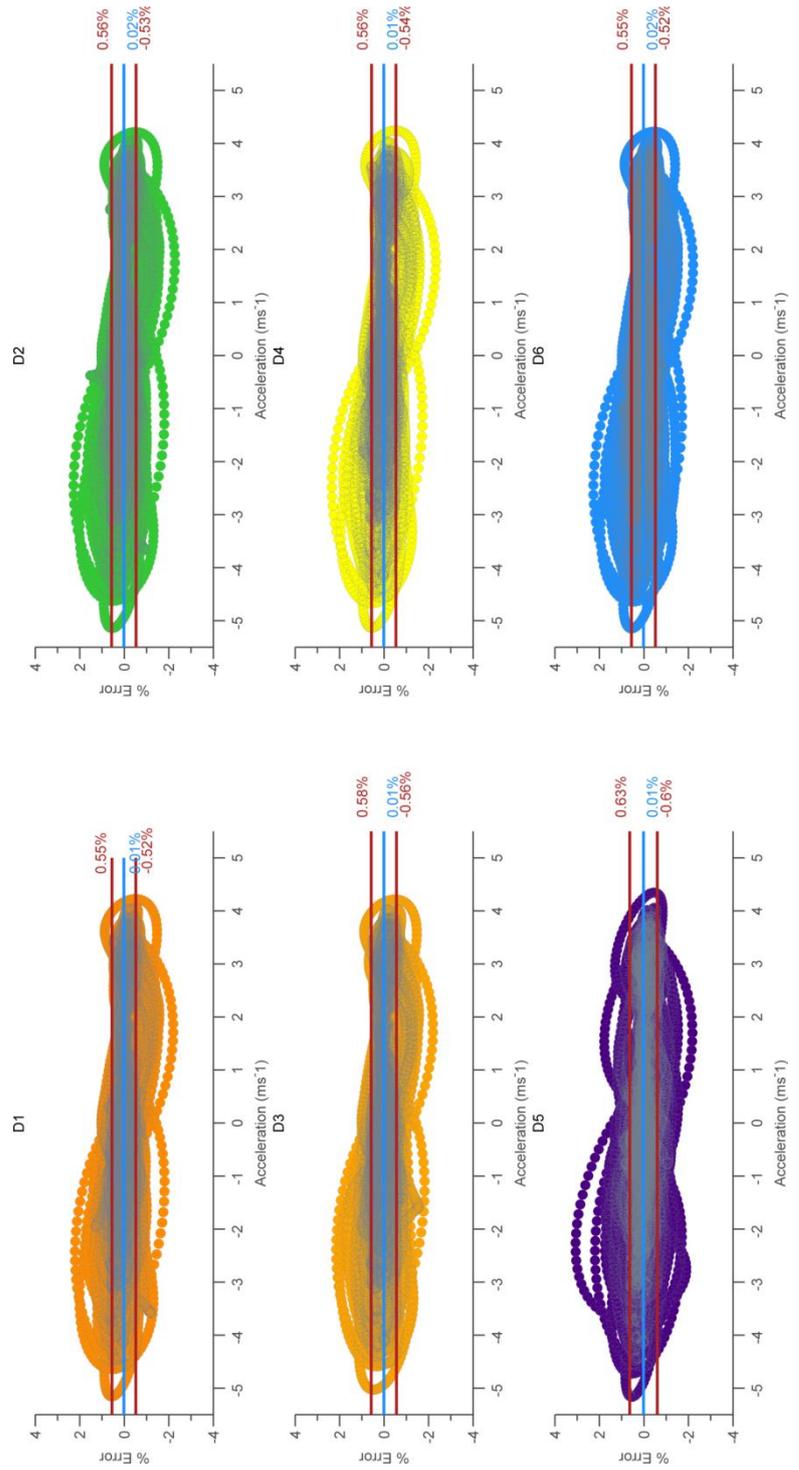


Figure 65: Bland-Altman Plot of Y axis for each device

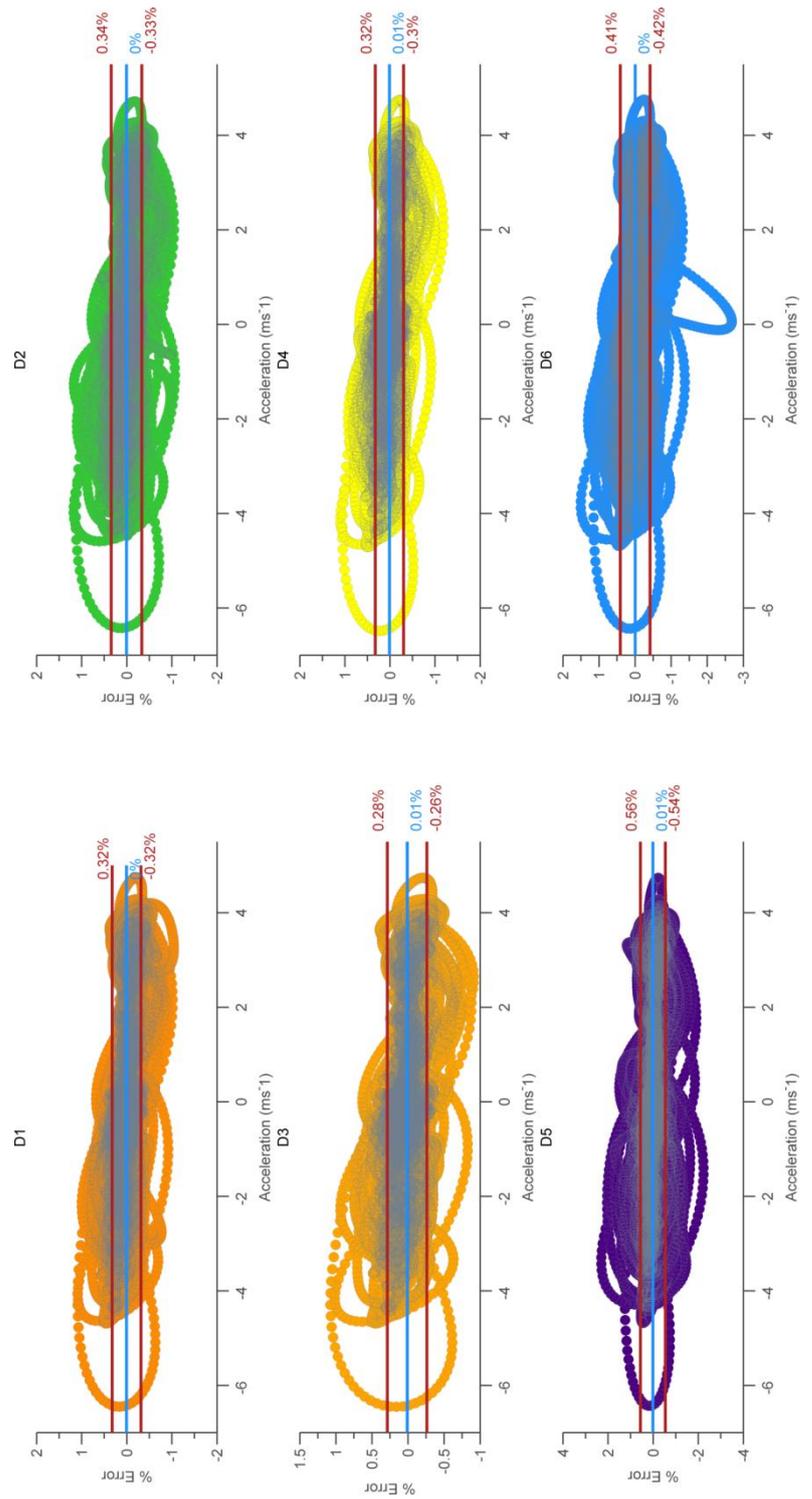


Figure 66: Bland-Altman Plot of Y axis for each device

RMSE between each instrument over >7000 data points in each test on each axis.

The average RMSE for each axis is shown in Table 14, Table 15 and Table 16.

The results show that error averaged over all instruments was 0.09ms^{-2} for the X axis, 0.14ms^{-2} for the Y axis 0.1ms^{-2} for the Z axis. The error derived from all the instruments against the Quintic data showed a slightly higher error with 0.18ms^{-2} for the X axis, 0.25ms^{-2} for the Y axis and 0.17ms^{-2} .

<i>X Axis</i>	<i>Instrument 1</i>	<i>Instrument 2</i>	<i>Instrument 3</i>	<i>Instrument 4</i>	<i>Instrument 5</i>	<i>Instrument 6</i>	<i>Quintic</i>
Instrument 1		0.094 ± 0.06	0.094 ± 0.07	0.106 ± 0.04	0.106 ± 0.05	0.111 ± 0.04	0.197 ± 0.05
Instrument 2	0.094 ± 0.06		0.072 ± 0.03	0.086 ± 0.01	0.087 ± 0.01	0.090 ± 0.01	0.175 ± 0.05
Instrument 3	0.093 ± 0.68	0.072 ± 0.03		0.086 ± 0.01	0.086 ± 0.02	0.090 ± 0.01	0.175 ± 0.05
Instrument 4	0.105 ± 0.05	0.085 ± 0.01	0.086 ± 0.01		0.093 ± 0.00	0.097 ± 0.02	0.186 ± 0.06
Instrument 5	0.105 ± 0.05	0.086 ± 0.01	0.086 ± 0.02	0.093 ± 0.01		0.100 ± 0.01	0.189 ± 0.06
Instrument 6	0.111 ± 0.04	0.089 ± 0.00	0.090 ± 0.01	0.097 ± 0.02	0.100 ± 0.01		0.188 ± 0.05
Quintic	0.197 ± 0.05	0.175 ± 0.05	0.175 ± 0.05	0.186 ± 0.06	0.189 ± 0.06	0.188 ± 0.05	

Table 14: RMSE and SD of each instrument on the X axis presented as ms^{-2} .

<i>Y Axis</i>	<i>Instrument 1</i>	<i>Instrument 2</i>	<i>Instrument 3</i>	<i>Instrument 4</i>	<i>Instrument 5</i>	<i>Instrument 6</i>	<i>Quintic</i>
Instrument 1		0.087 ± 0.03	0.102 ± 0.04	0.086 ± 0.02	0.084 ± 0.00	0.087 ± 0.03	0.258 ± 0.10
Instrument 2	0.087 ± 0.03		0.101 ± 0.02	0.084 ± 0.01	0.086 ± 0.02	0.089 ± 0.02	0.262 ± 0.10
Instrument 3	0.102 ± 0.04	0.101 ± 0.02		0.093 ± 0.02	0.136 ± 0.04	0.105 ± 0.02	0.277 ± 0.07
Instrument 4	0.086 ± 0.02	0.084 ± 0.01	0.093 ± 0.02		0.0976 ± 0.0022	0.082 ± 0.01	0.265 ± 0.09
Instrument 5	0.084 ± 0.00	0.090 ± 0.02	0.136 ± 0.04	0.098 ± 0.00		0.100 ± 0.00	0.189 ± 0.09
Instrument 6	0.087 ± 0.03	0.089 ± 0.02	0.105 ± 0.02	0.083 ± 0.01	0.100 ± 0.00		0.259 ± 0.09
Quintic	0.258 ± 0.10	0.262 ± 0.10	0.277 ± 0.07	0.265 ± 0.09	0.189 ± 0.09	0.259 ± 0.09	

Table 15: RMSE and SD of each instrument on the Y axis presented as ms⁻².

Z Axis	Instrument 1	Instrument 2	Instrument 3	Instrument 4	Instrument 5	Instrument 6	Quintic
Instrument 1		0.073 ± 0.02	0.065 ± 0.01	0.059 ± 0.01	0.154 ± 0.14	0.102 ± 0.06	0.152 ± 0.01
Instrument 2	0.073 ± 0.02		0.073 ± 0.01	0.066 ± 0.02	0.147 ± 0.12	0.098 ± 0.05	0.159 ± 0.01
Instrument 3	0.065 ± 0.01	0.073 ± 0.01		0.054 ± 0.01	0.162 ± 0.16	0.106 ± 0.07	0.130 ± 0.01
Instrument 4	0.059 ± 0.01	0.066 ± 0.02	0.05 ± 0.01		0.155 ± 0.14	0.095 ± 0.07	0.149 ± 0.02
Instrument 5	0.154 ± 0.14	0.147 ± 0.12	0.162 ± 0.16	0.155 ± 0.14		0.134 ± 0.10	0.239 ± 0.14
Instrument 6	0.102 ± 0.06	0.098 ± 0.05	0.106 ± 0.07	0.095 ± 0.07	0.134 ± 0.10		0.192 ± 0.05
Quintic	0.152 ± 0.01	0.159 ± 0.01	0.130 ± 0.01	0.149 ± 0.02	0.239 ± 0.14	0.192 ± 0.05	

Table 16: RMSE and SD of each instrument on the Z axis presented as ms⁻².

4.2 Swimming System Validation and Reliability

This section describes the validity and reliability of the system covering lap time, stroke count, stroke rate as well as stroke duration. The algorithm developed to identify the durations of the phases of the stroke was also tested for reliability.

Factors, such as IdC and body roll consistency, are not validated due to their being summative calculations based on a validated input being body roll angle or phases of the stroke.

4.2.1 Lap Time Validity and Reliability

Lap times (n=95, 10 swimmers) were derived from video as the wall push off at either end of the pool from the global camera. Correlations between the times from

the video and accelerometer show a significant strong positive correlation ($r = 0.978$, $p = 0.00$) showing the validity of the system, with large effect size ($r > 0.9$) (Cohen, 1988). Paired Samples t-Tests also show that there was no significant difference between the video times ($M = 17.24$, $SD = 1.50$) and sensor times ($M = 17.28$, $SD = 1.51$) overall; $t(94) = -1.59$, $p = 0.115$. The reliability of the system is demonstrated using the Mean %Error. Results show that for all lap times this was calculated at 3.5% (± 2.77). The mean is within the 5% limits of agreement showing the reliability of the system, although on occasion the standard deviation shows this will step outside of this range.

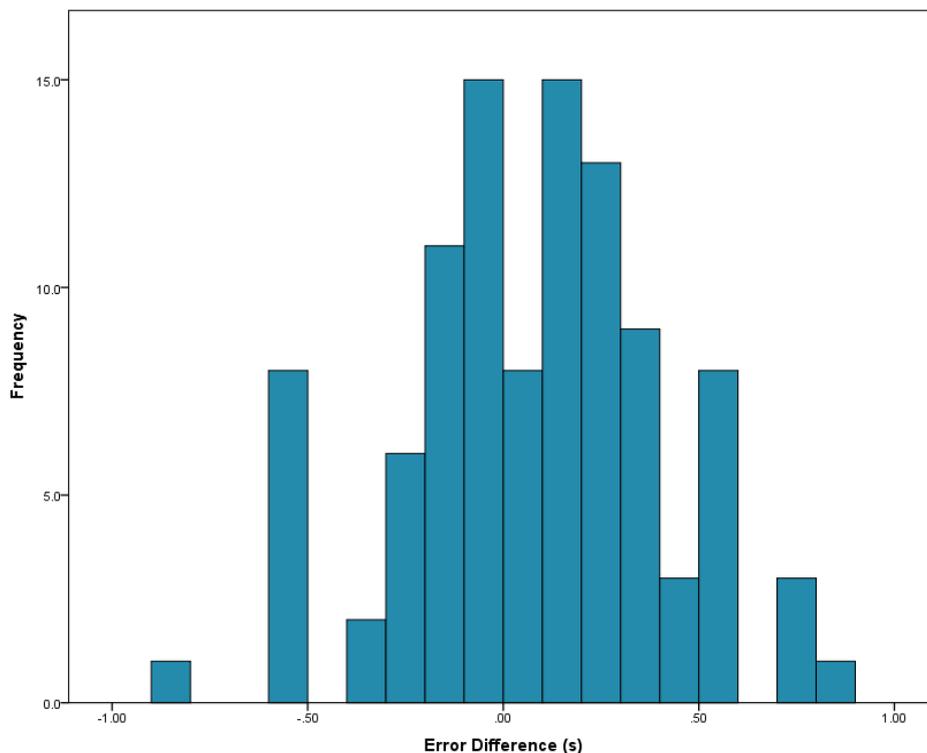


Figure 67: Lap time variation from Video recorded to Accelerometer (sensor) recorded

Each swimmer swam 4 length, pre and post fatigue. Of these, the start and end of the first and last length was manually selected, not automatically as with previous works (Davey et al. 2008). This was due to the nature of the non-wireless devices meaning there was excessive data at the start of a lap which would not allow for an

automatic retrieval of the lap start. It could be that previous works had not fully reported that data was trimmed before analysis to allow for the wall push off to be automatically detected. The 2nd and 3rd lap times, from the sensor were automatically detected. Figure 67 shows that generally lap times tend to be longer using the accelerometer over the video timings. Further analysis was conducted to explore whether there were greater errors in the manual selection method in the sensor data, or automatic detection in the sensor data.

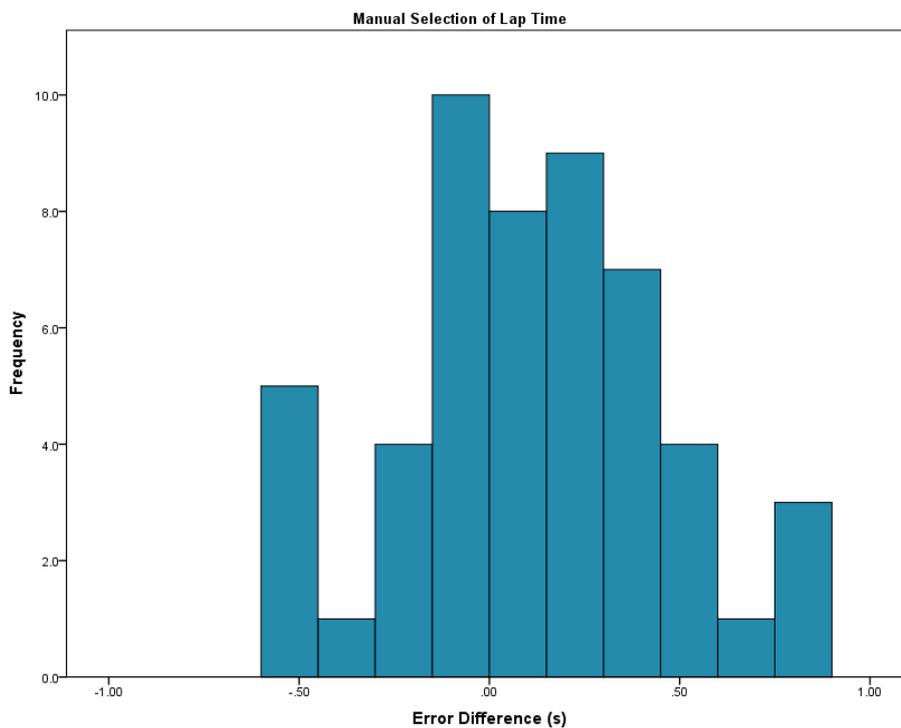


Figure 68: Analysis of only manual selected lap starts and stops

With the manual selection of laps (Figure 68), there was no significant difference between the video times ($M = 16.99$, $SD = 1.55$) and manually selected sensor times ($M = 17.06$, $SD = 1.57$) overall; $t(47) = -1.558$, $p = 0.126$. Mean %Error for manual lap times ($n = 47$) was calculated at 3.78% (± 2.88). The mean is within the 5% limits of agreement showing the reliability of the system, although on occasion the standard deviation shows this will step outside of this range.

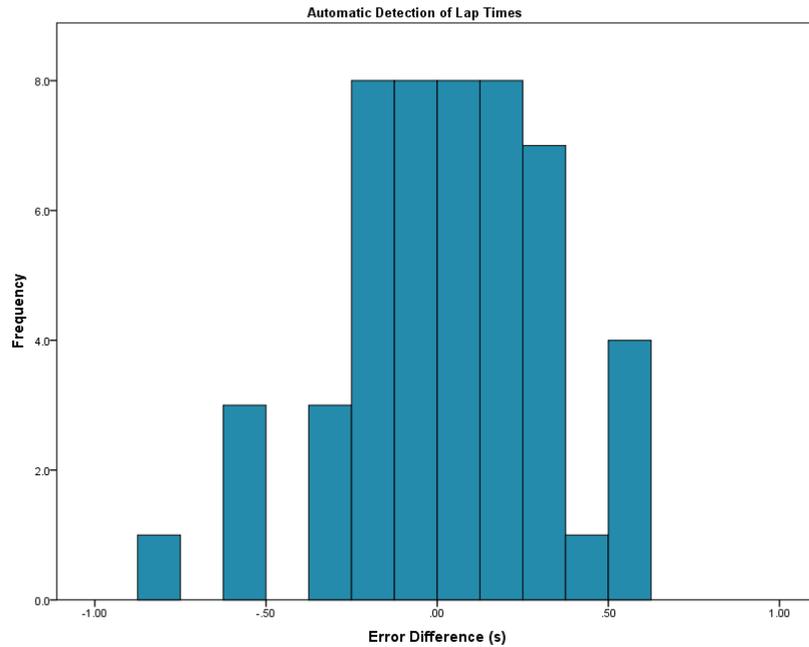


Figure 69: Analysis of only automatically selected lap starts and stops

There was also no significant difference between the video times ($M = 17.62$, $SD = 1.44$) and automatic lap times from the sensor data ($M = 17.65$, $SD = 1.39$) overall; $t(47) = -.719$, $p = 0.476$. Mean %Error for automatic lap times ($n=48$) was calculated at 3.51% (± 2.90). The mean is within the 5% limits of agreement showing the reliability of the system, although on occasion the standard deviation shows this will step outside of this range.

The results for the middle sections of the laps, the automatic detection, show a higher number of results within ± 0.2 seconds than with the automatic detection. However, there is one result showing a near -1s lap time error, which appears to be an anomaly. The differences in automatic lap time detection could be due to camera position not allowing for a clear observation of the wall push off.

4.2.2 Validation and Reliability of Stroke Count

Results showed a strong positive correlation ($r = 0.948$, $p = 0.00$) demonstrating the validity of the recorded information. Davey et al. (2008), using the lower back, are the only authors to validate their stroke count method. They used video data to count the strokes, and presented the accelerometer based data as the strokes counted which were different to the video cameras. The same process was replicated here to allow comparison, Figure 70.

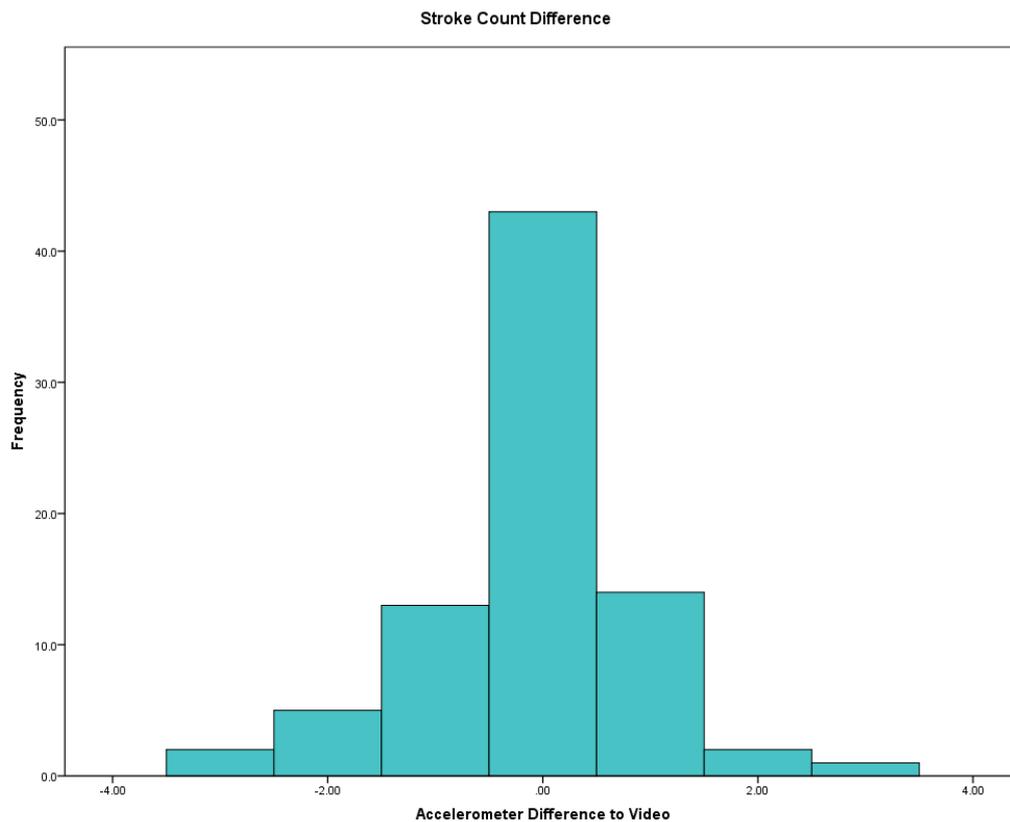


Figure 70: Stroke Count Difference

The results show a large number of counts with no difference to those counted from the video. The largest errors are shown with the accelerometer counting less counts than actually happened.

The reliability of this has been extended from Davey et al. (2008) using the Cohen's Kappa (κ) (O'Donoghue, 2009) to determine if there was reliability of the agreement between the video and accelerometer system for judgment on stroke

count. The results show that there was moderate agreement between the two, $\kappa = .537$.

4.2.3 Validation and Reliability of Roll Angles

A total of 44 rotations were conducted on the video and all of these were all found on the data from the accelerometer. The results between the criterion; the video; and the accelerometers showed a strong positive correlation, $r = .994$, $p = 0.00$, Figure 71. This correlation demonstrated a large effect size ($r = 0.99$) (Cohen, 1988). Paired samples T-Tests were used to check whether there were any differences between the results, the results showed that there was no significant difference between the two data, Video ($M = 38.9^\circ$, $SD = 19.1^\circ$) and Accelerometer ($M = 39.2^\circ$, $SD = 3.0^\circ$), $t(43) = -.781$, $p = .439$.

Whilst there is no significant difference between the video and accelerometer presented here, there is a mean difference of 0.29° ($\pm 2.47^\circ$) compared to the video derived angles. Despite a lower error, regression analysis was conducted to assist with the reduction of error in the system (Hopkins 2004). The regression analysis produced a linear and quadratic equation (EQ 28 and EQ 29), which was used in the calculation of the body roll to ensure any offsets were removed.

$$y = 0.941x + 2.012$$

EQ 28: Linear Regression Equation for Angles using Accelerometers

$$y = 4.722 + 0.784x + 0.02x^2$$

EQ 29: Quadratic Regression Equation for Angles using Accelerometers

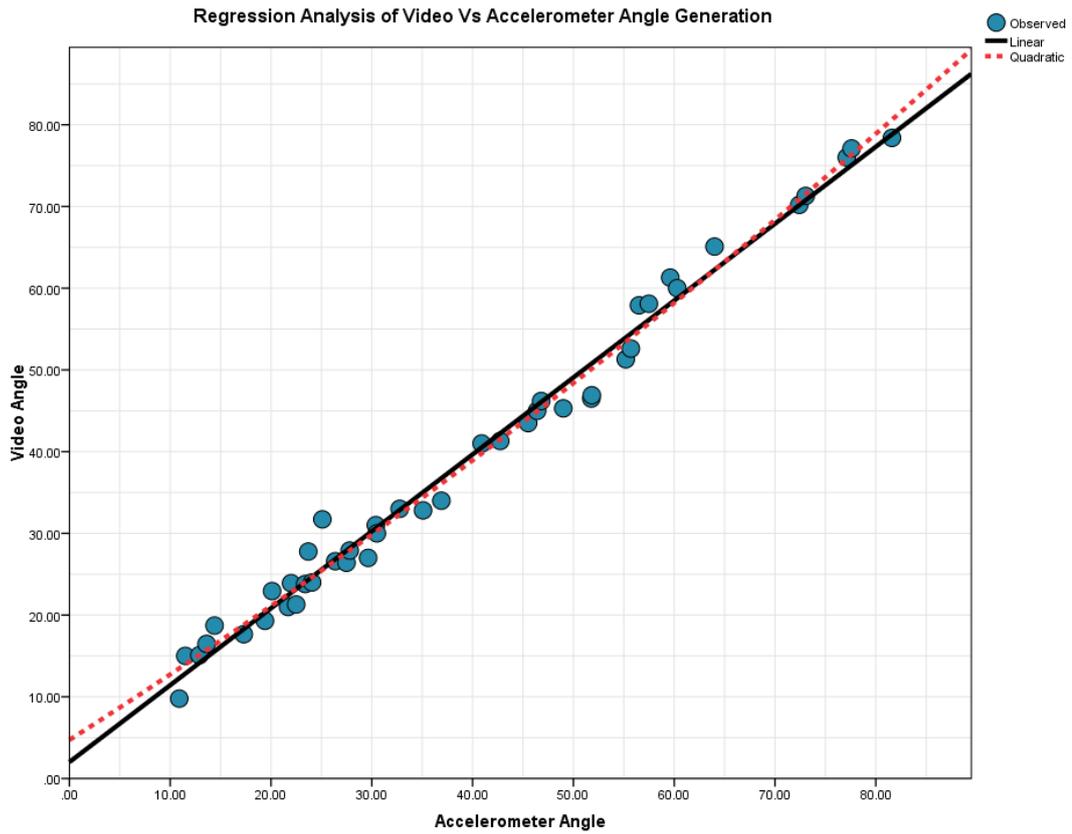


Figure 71: Regression analysis of Accelerometer vs Video for generating angles. Solid Black Line = Linear. Dashed Red Line - Quadratic.

Both of these equations (EQ 28 and EQ 29) were then tested on the data using a Bland Altman plot to show the percentage error associated with the original data to demonstrate the reliability of the system. The plots (Figure 72 and Figure 73), show the original accelerometer data (blue) with the error to the video angles.

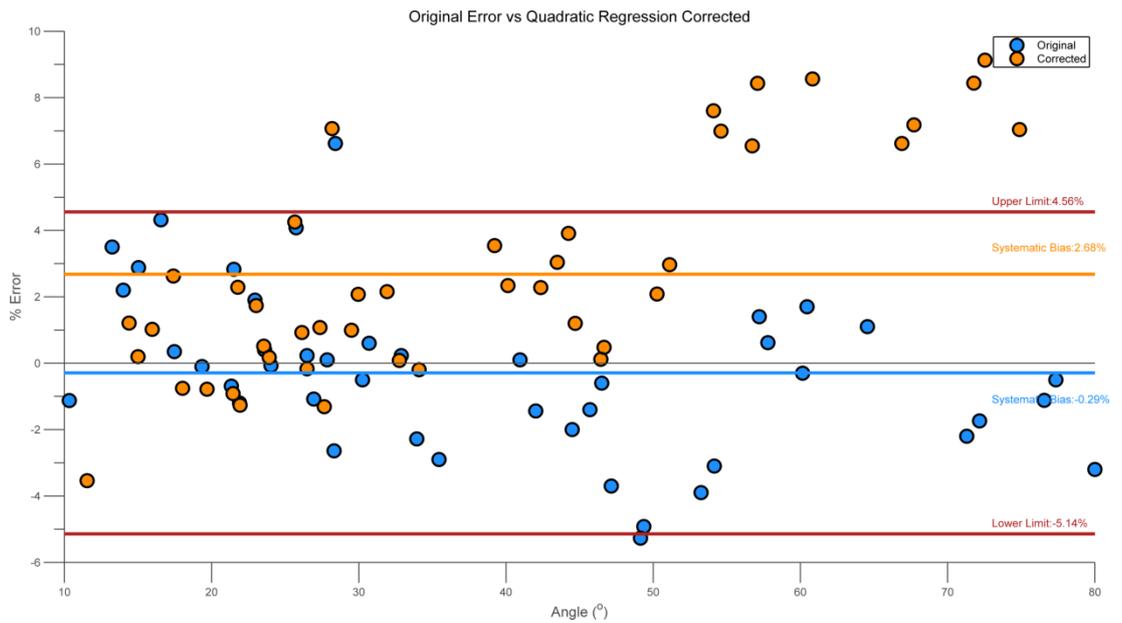


Figure 72: Bland-Altman plot of Original accelerometer to video error and Quadratic correction of accelerometer data

The plots show a systematic bias of -0.29%, showing the accelerometers generally under-estimate the angles. The accelerometer data were corrected using the quadratic equation and compared to the video data, Figure 72. This shows that the quadratic equation increases the systematic bias to 2.68% (from -0.29%) and also lifts a number of angles outside of the 95th percentile limits of 4.56% and -5.14%.

The Bland-Altman plot for the linear equation Figure 73, shows a reduction in the systematic bias from -0.29% to +0.01%, in addition to a tighter grouping of the data. The regression equation ($r = 0.99$) demonstrated a large effect size (Cohen, 1988).

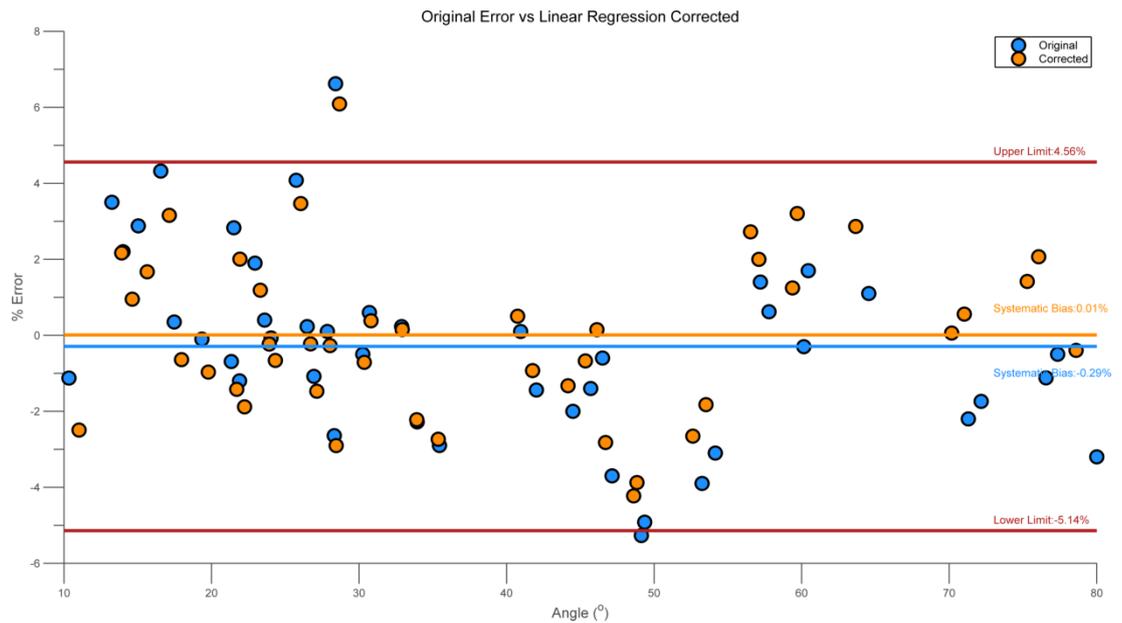


Figure 73: Bland-Altman plot of Original accelerometer to video error and Linear correction of accelerometer data

4.2.4 Validation and Reliability of Stroke Rate

Validation of stroke rate in previous systems have tended to focus on error reported as a frequency (Davey et al. 2008; Le Sage et al. 2011). However, considering the data type is scale, O'Donoghue (2013) and Sato et al. (2009) recommend the use of Correlations. Results show a very strong positive correlation, $r = 0.92$, $p = 0.00$, ($n = 80$ laps) and a large effect size (Cohen, 1988).

A Bland-Altman plot (Figure 74) shows that there is a mean error of -0.2% , where Le Sage et al. (2011) showed a similar error of -0.1% . Davey et al. (2008) used six swimmers to generate lap data which was also recorded manually and on video. They found that the manually calculated stroke rates had a higher error rate than the accelerometer, when compared to those derived by the accelerometer. Using a lower back sensor, the stroke rate error was shown to be between -1 and 2 cycles.

To extend on these previous works, the Bland Altman plot identified the outliers of the system, which were removed for regression analysis (Hopkins 2004). The regression analysis allowed for further correction in the system.

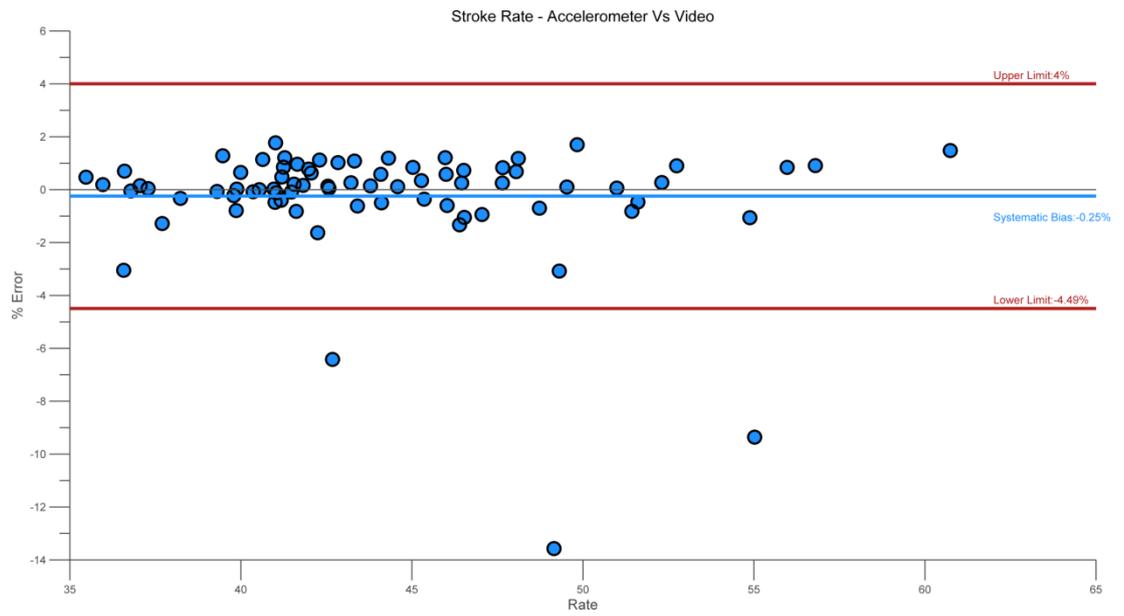


Figure 74: Bland Altman plot showing error in stroke rate

The Linear Regression analysis produced the equation (EQ 30),

$$y = 1.274 + 0.968x$$

EQ 30: Linear Regression equation for stroke rate correction

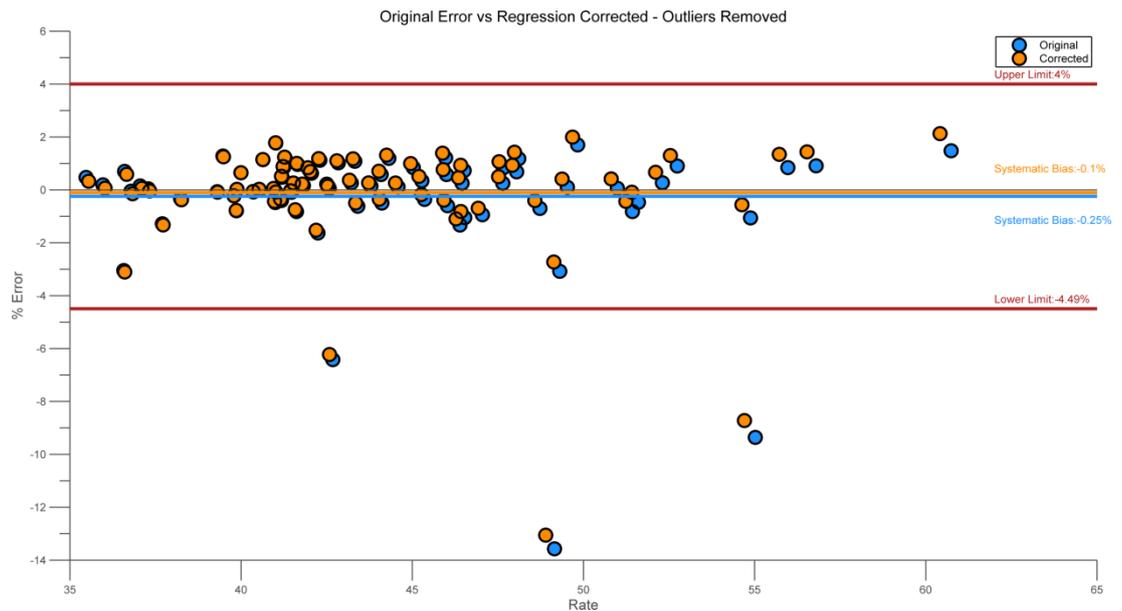


Figure 75: Bland Altman plot showing error in stroke rate after Regression correction

EQ 30 corrected the systematic bias for stroke rate identification from -0.2% to -0.1%, in line with that of Le Sage et al. (2011). The linear regression produced large effect size ($r = 0.99$) (Cohen, 1988).

4.2.5 Validation and Reliability of Stroke Duration

Stroke duration was defined as the time between consecutive hand entries. The accelerometer found the hand entry as the local LW_Y and RW_Y minima near the body being level. This identification of hand entry matched previous findings (Ohgi 2002; Ohgi and Ichikawa 2003), and was verified as the time from the initial synchronisation 'bumps' to the hand entry on the video.

The data type of stroke duration is scale. O'Donoghue (2013) and Sato et al. (2009) recommend the use of Correlations for validation. Stroke duration calculation between the video and accelerometers ($n = 1028$ individual entries) shows a strong significant positive correlation, $r = 0.637$, $p = 0.00$. Whilst the results show a strong correlation, Figure 76 shows that there are a number of outliers (outside 95% limits).

Whilst hand entry time is visually definable by the 'splash'; as the hand enters the water; and with these results being defined on a frame by frame basis, it can still be difficult to define the precise point of entry. This is particularly true from the video angle of the global camera used. The video angle occasionally limited the accuracy of the hand entry by the kick splashes obscuring the view. This however, does demonstrate the strength of the sensors in their ability to correctly and consistently identify the hand entry points using the minima LW_Y and RW_Y axes.

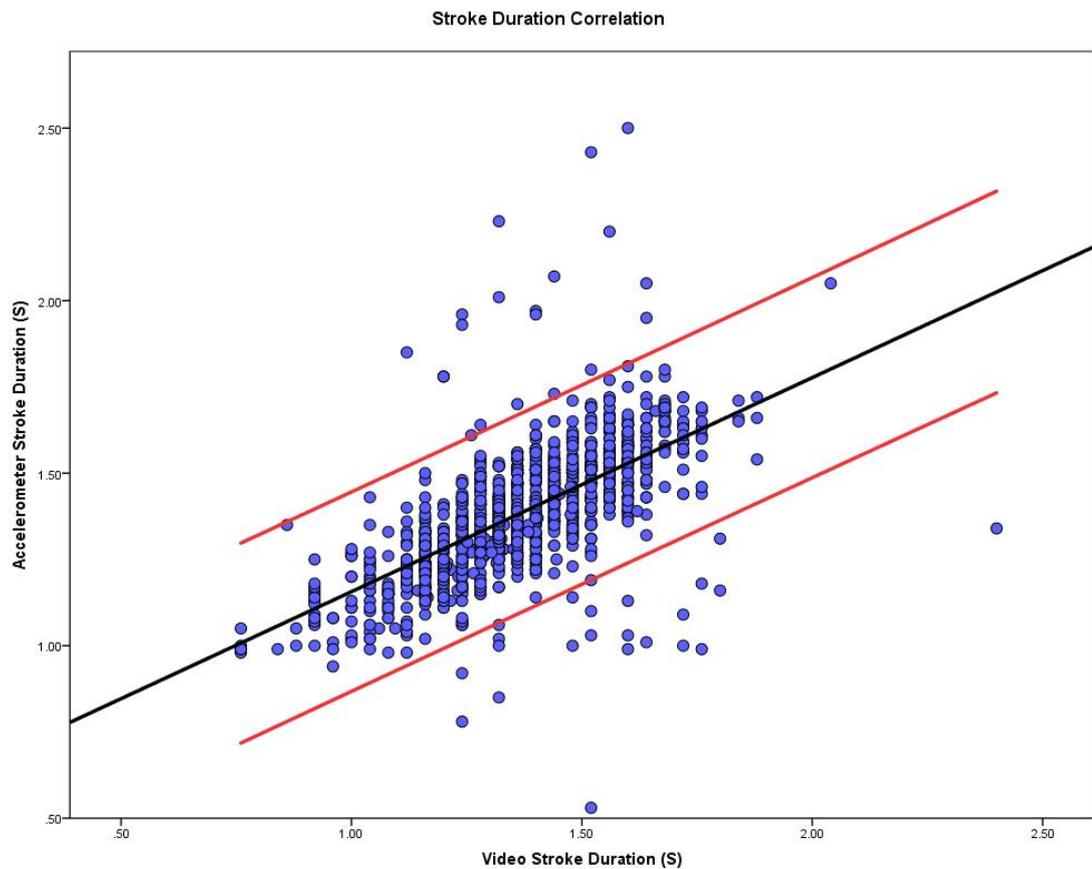


Figure 76: Stroke Duration Calculation. Black line shows correlation, red lines show 95% interval.

The phase identification mostly matched that of Ohgi (2002). Ohgi (2002) identified the hand entry as a sharp negative peak on the LW_X sensor (LW_X minima). The start of the downsweep (Figure 77) was defined as the next LW_Y minima. Whilst this was

not recorded here, it is visible in the data. The end of the downsweep (the catch) which leads to the start of the insweep/pull (Figure 77) was defined by Ohgi (2002) as a LW_X maxima (Figure 77, Purple Arrow). However, it was found that for the swimmers used here the duration was too short when compared to that derived to the video and that the LW_X minima after hand entry offered a better relation to the pull phase duration (Figure 77, Black Arrow).

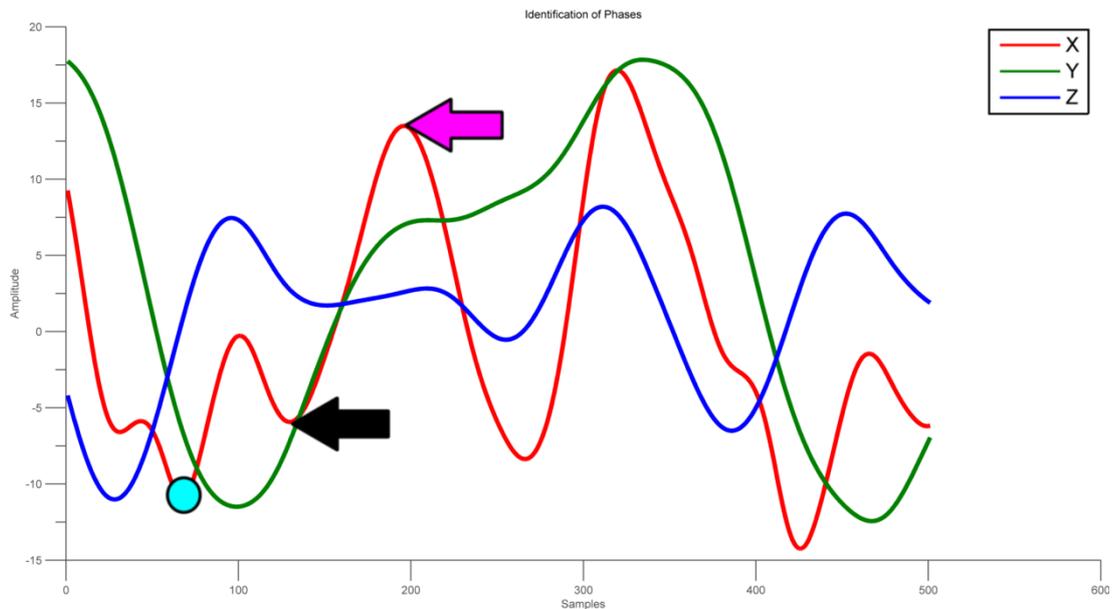


Figure 77: Differences in Pull Phase location. Purple Arrow, Ohgi (2002). Black Arrow, Current. Hand Entry identified by Cyan circle.

The algorithm developed was tested for reliability against the durations of the phases derived from the video. The video camera used for the underwater phases use a frame rate of 60Hz, resulting in an image being taken every 0.0166s. Results show (Table 17) that each phase has a relatively lower error. The Mean Absolute Error (MAE) of 0.06, 0.07, 0.06 and 0.08 seconds (respectively) also shows low error rates. There is little difference between the mean and MAE, which shows there is no major positive or negative difference, no positive or negative bias.

This error, in terms of an equivalent to video analysis, would relate to a difference between correct identification of a frame to within 3.6 frames (hand entry

and push) to 4.8 frames (for recovery), which could easily be a disagreement between coaches recording the phases from video.

	Mean Error (\pm SD)	Mean Absolute Error (\pm SD)	95th Percentile for Absolute Error	Root Mean Squared Error	SEM	Systematic Bias	Random Error
Entry (n = 78)	0.00 (\pm 0.08)	0.06 (\pm 0.06)	0.15	0.08	0.06	0.00	0.16
Pull (n = 78)	0.04 (\pm 0.10)	0.07 (\pm 0.08)	0.20	0.10	0.07	-0.04	0.19
Push (n = 78)	0.03 (\pm 0.07)	0.06 (\pm 0.05)	0.15	0.08	0.05	0.03	0.15
Recovery (n = 71)	0.05 (\pm 0.12)	0.08 (\pm 0.1)	0.33	0.13	0.08	0.05	0.23

Table 17: Reliability statistics for Phase durations. All results presented in Seconds.

It was found that, although every effort was taken using frame by frame analysis to determine each phase, and using cooperation from the coach to aid in this at the start, there is still error in the analysis. This is shown with random error in the reliability ranging from 0.15s to 0.23s. The phases of the strokes were found to be fairly subjective, in terms of 2D video analysis, with the swimmer making subtle movements during the pull and push which were at times directly towards the cameras and so it was difficult to quantify the exact timings of each phase. There was also occlusion of the arms during the entry and exit of the arm from the water at times, meaning the error in the recovery phase was doubly penalised by the air-water

interface. An error in the identification of the entry time also led to an additional error in the previous recovery phase.

Bland-Altman plots (Figure 78, Figure 79, Figure 80, Figure 81) showing the relative error in percentage terms shows that for each phase there are only 4 entry phases which were outside of the 95% limits, 2 for the pull phase, 3 for push and 5 for the recovery. This shows some promising results.

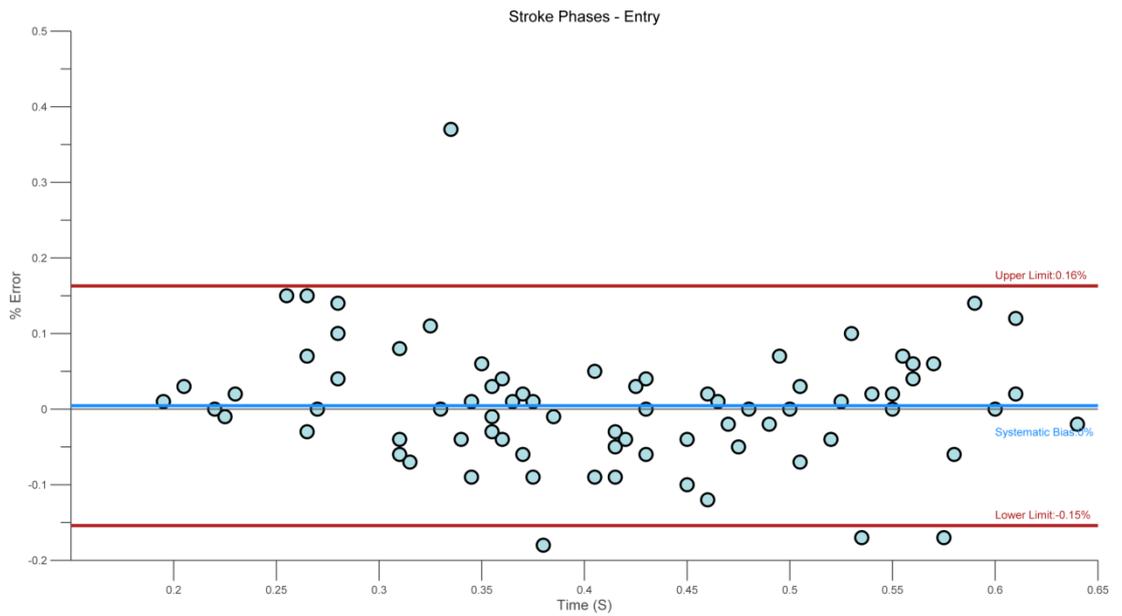


Figure 78: Bland-Altman plot of Entry Duration Error

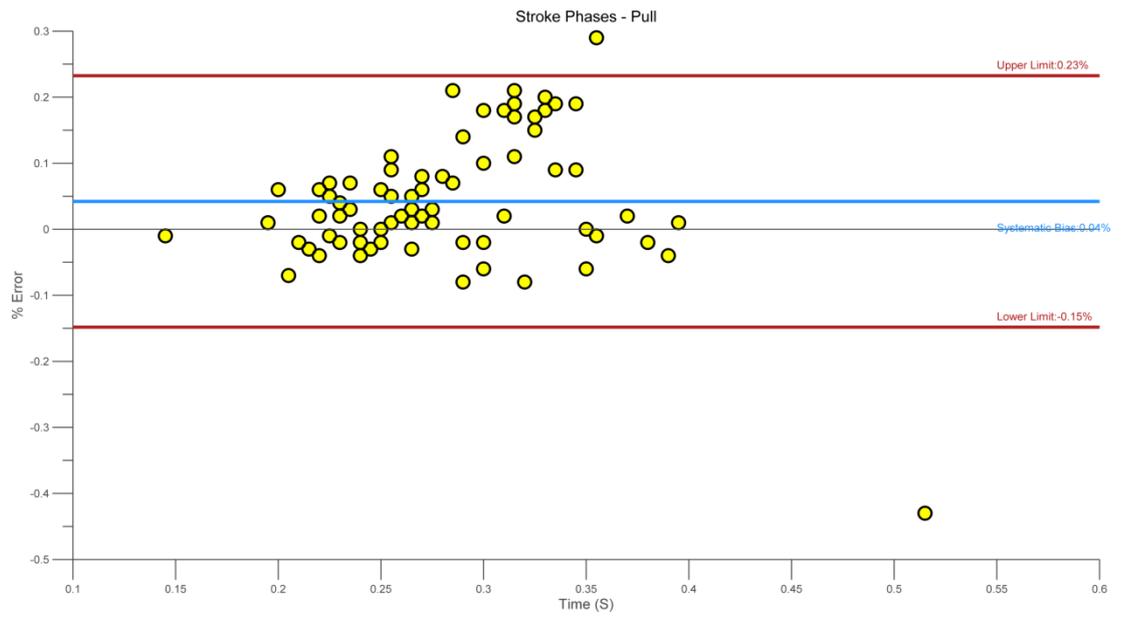


Figure 79: Bland-Altman plot of Pull Duration Error

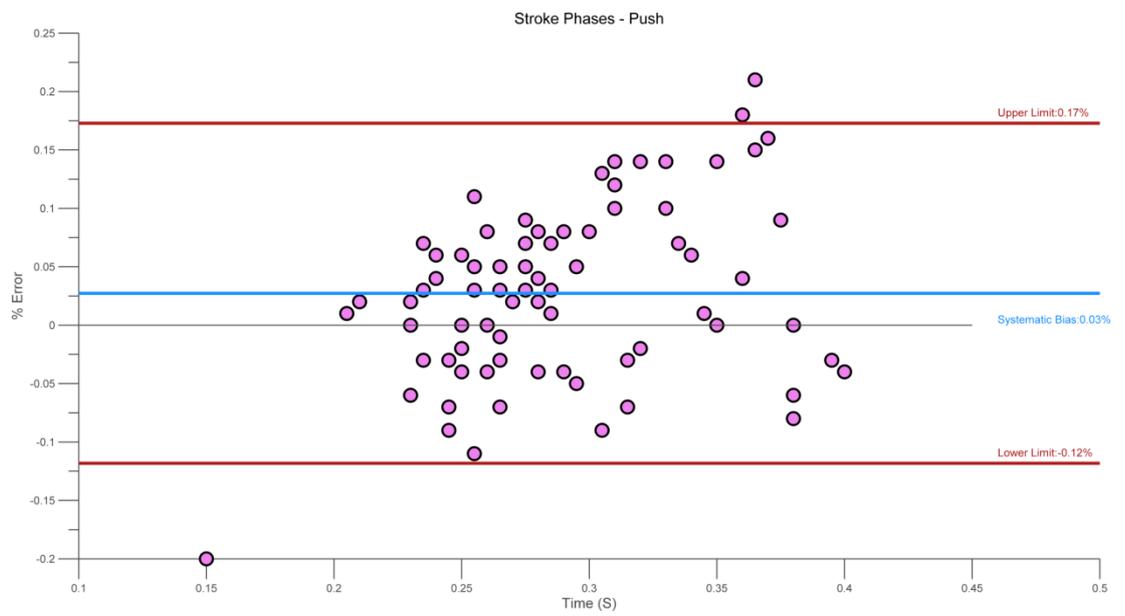


Figure 80: Bland-Altman plot of Push Duration Error

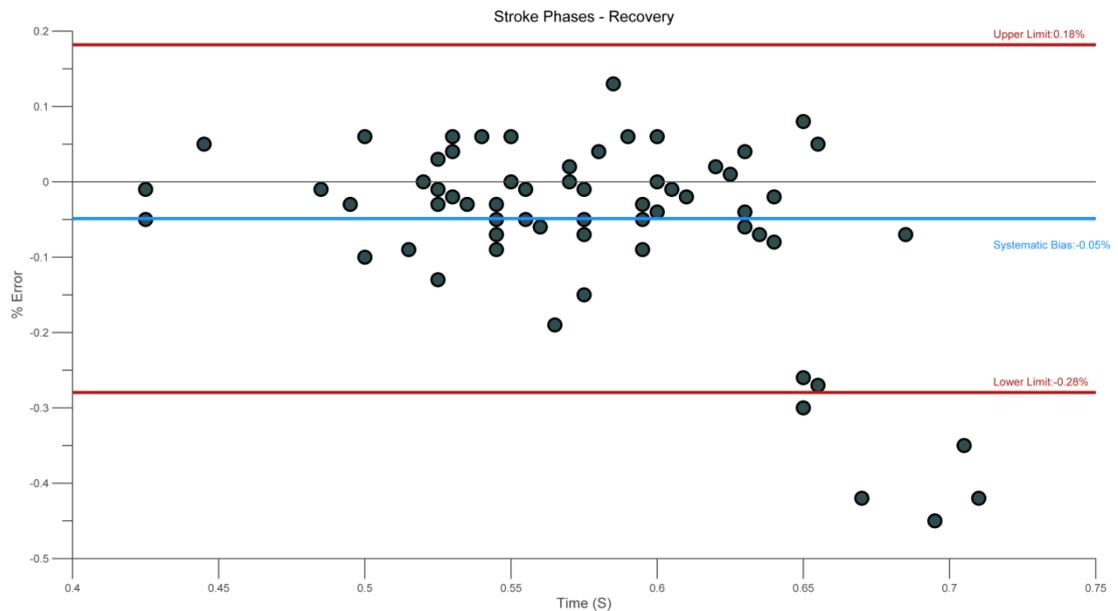


Figure 81: Bland-Altman plot of Recovery Duration Error

The results show positive relationships for the identification of the phases, with most results staying within a 5% limit of agreement. This resulted in most data ranging within 0.16% to -0.15% error for the Entry phase, 0.23 to -0.15% for the Pull Phase, 0.17% to -0.15% for the Push phase, and 0.18% to -0.28% error for the Recovery phase. There is some individualisation that is required per swimmer on the identification of the phases. This is discussed in section 5.2.5.

4.2.6 Usefulness for Coaches

With the visual profiles completed, the head coaches ER and SW were approached to determine the coaches thoughts towards the use of the profiles. The two other coaches, SL and CS, had moved away from the club by this time. The discussion was conducted informally in a quiet room where the researcher explained the validation process conducted to generate the results of the profiles.

The researcher explained the profiles to the coaches, with an overview of each section and its contents. This was to ensure that the coaches understood the diagrammatic representations of the information.

The core information, (lap time, velocity, stroke count, stroke rate, distance per stroke) was of great importance to them and easily understandable. The profiles display this in text format and graphically. SW and ER stated that this was useful in both formats. The numbers generated easily interpretable and recognisable information that they are used to. However, the visual information was also of use to allow visual patterns to be identified.

One of the most useful outputs, in the coaches perspective, was the break down of the phases of the stroke as a percentage (Figure 82). The head coaches (ER and SW) stated that this was a most useful way to display the information to the swimmers and would be of great use to them to explain the timings of the phases to the swimmers:

EW: "This is something I would definitely use with the swimmers, it's a clear image which I can talk through with my swimmers to show them where they are spending too much time [in a certain phase].. I would use Q&A [a question and answer approach]with them on how best to fix using their known drills"

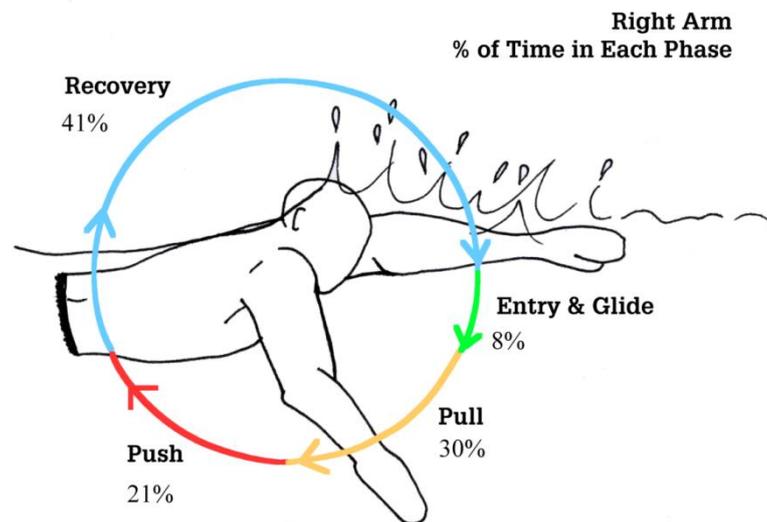


Figure 82: Percentage of Time per Phase

When the IdC process was discussed with the coaches, they understood the principle but acknowledged that this was not something they would actively use within the coaching process. This was also similar with the body roll angles and consistency. Both coaches did not seem interested in this, offering no discussion points or comments on its use. The symmetry table was met with comments of "*interesting*" from both coaches. However, it was observed by this stage of the profile that the coaches had already been met with too much information. This was also apparent with body roll angles, where the coaches did not seem to know how to fix any issues. EW did comment that with her training at GB level "*We never received this much information*". The suggestion was also made that there was a lack of understanding of how to use the information, generated by these profiles, to create meaningful changes to the swimmers techniques. Irwin et al. (2005) clearly stated that the responsibility of skill development rests with the coach, however, with an increasing ability to measure factors previously out of reach to the coach, there is the issue of information overload. Future work needs to not only consider the visual presentation of the work (Rowlands et al. 2014) to allow for accurate, meaningful interpretation, but, more importantly method on how to use this information wisely to create meaningful training programmes.

Chapter 5 - Discussion

Parts of this chapter have been published in the following papers:

Callaway, A., Cobb, J. E., & Jones, I. (2009). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *International Journal of Sports Science and Coaching*, 4, 139-153.

Callaway, A., & Cobb, J. E. (2012). Linear acceleration measurement utilising inter-instrument synchronisation: A comparison between accelerometers and motion based tracking approaches. *Measurement in Physical Education and Exercise Science*, 16, 151-163

5 Discussion

This chapter discusses the system implementation, starting with the discussion of the synchronisation method, followed by the discussion of the developed system. The swimmers results are also briefly discussed to show the principle of the system and individual adaptations to fatigue.

The future potential of the system in recording biomechanical variables for research purposes is then considered, with additional future work highlighted.

The interviews with coaches, covering their experiences and education, understanding and use of performance analysis and barriers to the use of performance analysis based systems, as identified from the thematic analysis is shown at times. The full interviews and discussion of these interviews can be found in Appendix 1.

5.1 Synchronisation Discussion

The correlation test results between devices and video cameras show a strong positive correlation, which is supported by previous literature (Sato et al., 2009). The instruments showed relatively low RMSE across all instruments on all axes. This shows that the developed instruments produces measures that correlate well with video derived kinematic data. This demonstrates that the implemented methods, using the peak detection and axis offset removal, work well in practice.

The RMSE across all instruments and all axes was very similar. However, the Quintic output compared to the Y axis in particular showed an error increase up to 0.25ms^{-2} , whereas the difference between inter-instrument and Quintic is 0.11ms^{-2} . Although this is a relatively small error (0.4%) compared to the full range of the device ($\pm 6\text{g}$, $\approx 58\text{ms}^{-2}$). It should be noted that the camera, calibration and processing procedures did not change across each data collection. There may be a slight deviation in the Y axis of these instruments however this appears very consistent between devices. This slight increase in error can be attributed to tolerances on the

accelerometer chip itself rather than fabrication issues in alignment of the devices on the circuit board. Accelerometer chips can have different levels of nonlinearity on different axes. Depending on the manufacturer and model, there can be a variation from 0.2% (Analog, 2008) to $\pm 1\%$ (Freescale, 2008). The devices used showing a variation between axes of $\pm 2\%$ (X and Y) and $\pm 3\%$ (Z) (Gulf Coast Data Concepts, 2010).

Although it has not been specifically investigated here, it is interesting to note that before any filtering was performed on the raw data, the accelerometer produced a more stable rest state than the video camera data, as shown in Figure 6. The lack of stability from the video kinematic data was removed using the automatic filter settings from Quintic. The filter setting from Quintic were also used on the accelerometer to ensure the data was filtered consistently in comparing the data. As shown in the method, these were 2nd Order Butterworth filter with a cut-off frequency set at 3Hz, and is similar to that of Le Sage et al. (2011) and Pansiot et al. (2010) who used 5Hz.

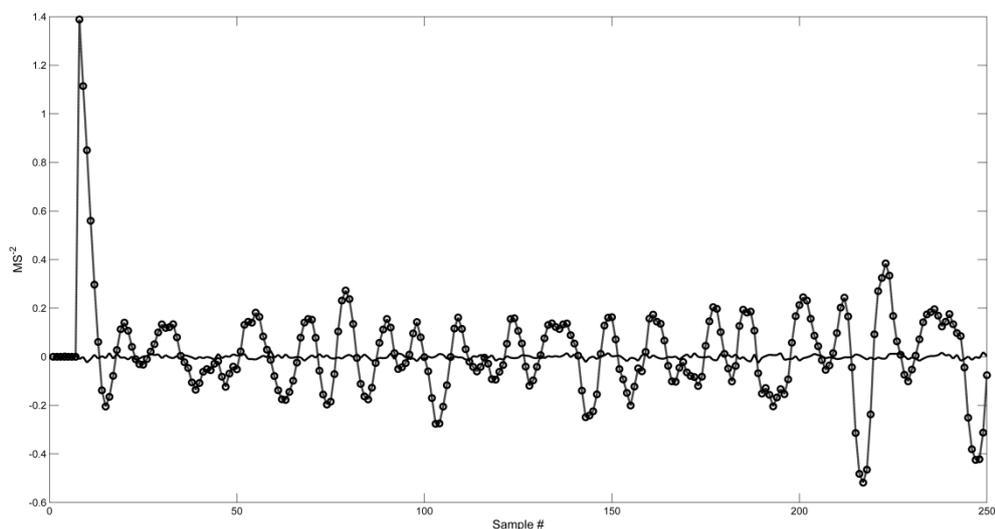


Figure 83: Showing the static comparison of raw accelerometer data (solid line) and raw video derived kinematic data (dashed with circles)

Some data loggers have the ability to record data only above a pre-set threshold. This principle can be slightly modified to allow the devices to be turned on and positioned on the person/equipment. A single movement is then generated which would break that threshold on all the instruments and recording on all of them would then commence. This would effectively synchronise the devices without the need for post collection analysis.

5.2 Swimming System Validity and Reliability

5.2.1 Lap time

The start of lap one and end of lap four were manually selected from the data set. The results for lap time reliability show that there was a variation in the difficulty of placing a marker for the start and end of laps manually. This was due to swimmers having slightly different wall push off techniques. Some dipped under the water and pushed off, others completed a twisting motion where they started almost facing out of the pool and then pushed off facing sideways, gradually rotating before the first stroke. Previous work, such as Davey et al. (2008), used an algorithm to detect the wall push off, in the same manner as used here. Whilst they also found a larger error with the first lap than with the subsequent lap identification, they may have been more strict with the swimmers wall push off strategy for this work as there is little identification of any issues of this nature being found.

Overall, Davey et al. (2008) did find that the error rates for their accelerometers to videos ranging +/- 2 seconds, but more within +/- 0.5 seconds. Those results are similar to the present system, however Davey et al. (2008) show a larger range. Davey et al. (2008) identified lap time variation was due to swimmers finishing the laps in a weak manner, with a soft touch, rather than a competition hard finish. This was also observed with the swimmers in this study, so it would seem that a manual selection method produces a better discrimination of those minor finish peaks, rather than a computational method.

Whilst the identification of lap times from the camera have been shown to be valid and reliable using inter-rater reliability, there is still error in the identification of the lap times. Using an underwater pressure pad at either end of the pool, as shown by Le Sage et al. (2011), synchronised to the cameras and accelerometers could allow for more exacting lap time at both ends of the pool to be recorded and would remove any error in the inter-rater reliability of lap times. The purpose of this is to create a more precise data set to compare the accelerometer lap times with.

5.2.2 Stroke Count

Results of stroke count calculation show that in the majority of cases there is no difference between accelerometer and video derived calculations. In the data from the upper body, the peaks of the body roll are counted as strokes. On 9 occasions, double peaks occurred. This resulted in three laps which were over counted by three strokes difference per lap.

Davey et al. (2008), the only other research group to clearly validate their work, show limits within ± 1 count. This could be because they are using the lower body, compared to upper body in this work.

The software has been written to remove any double peaks, however, sometimes there may be a double peak which is not found in this algorithm, which will result in an extra stroke count(s) being recorded.

5.2.3 Angles from Accelerometer

Bächlin et al. (2009) are the only authors to show the use of the accelerometer for body roll angles, however only validated their devices for the body pitch, not the body roll. For this reason, an experiment was developed to establish the validity of their use to determine angles (3.3.9.3). The results showed that there is no significant difference between the video and accelerometer presented here, there is a mean difference of 0.29° ($\pm 2.47^\circ$). The assumption that the acceleration generated by a swimmer would not impair the results, shown by Bächlin and Tröster (2012), under initial investigation, shows that they were correct. The results show strong

correlations and no significant differences between the two demonstrating that this method produces a true angle. Whilst there was a strong correlation between both, using a regression analysis shows a non-zero crossing showing a systematic bias (Figure 72), but this has been reduced from -0.29% to +0.01% improving the systems output. The linear equation generated here was used in the software to correct the body roll angle output for each swimmer to produce a true body roll angle.

5.2.4 Stroke Rate and Stroke Duration

Stroke rate was validated using a Pearson Correlation, with results showing a very strong positive correlation. A Bland-Altman plot showed a bias of underestimating the stroke rate, compared to video, by -0.2%. Le Sage et al. (2011) showed a similar error, but lower, of -0.1%. The regression analysis showed that this error could be reduced from -0.2% to -0.1%, showing the same error for two separate systems.

This shows that stroke rate can be accurately calculated using accelerometers to collect the data. Whilst the error is very small, the error seen here would be due to the use of the upper back sensor to identify the stroke count (as previously discussed), as the times between the stroke counts are used as part of the equation to determine stroke rate.

Stroke duration was a necessary variable to record as it formed the basis for part of the phases of the stroke calculation. The results show a strong positive correlation with regard to the times derived from videos. There were some outliers in the data however. The hand entry point was visually definable by the splash in the water, but this was often obscured by other splashes from kicking or changes in arm angle of the swimmer leading to no discernible splash. However, this is not to say that the results are not positive. They highlight the strength of the devices, where even unobservable hand entries can still be calculated. There was very little issue with the algorithm in detecting the hand entry phases of the stroke.

5.2.5 Stroke Phase Identification

The phases of the stroke were determined using the video (frame by frame) and the accelerometer, where the results gave a percentage error. The results show most data ranging within 0.16% to -0.15% error for the Entry phase, 0.23 to -0.15% for the Pull Phase, 0.17% to -0.15% for the Push phase, and 0.18% to -0.28% error for the Recovery phase.

Dadashi et al. (2013) are the only other authors to have attempted to identify the phases of the stroke automatically. They use a combination of peak detection and slope detection on accelerometer and gyroscope data to identify the Pull, Push and Recovery, and compared their results to a 50Hz video camera. Their results showed an error (in video terms) of less than 2.7 frames (0.054s). It is unclear what recording speed they used, as they state their observers viewed the video at every 0.04s for the duration of the swim, suggesting 25Hz cameras, not the 50Hz stated. The current system, using 60Hz cameras, showed slightly higher error for hand entry and push of 3.6 frames (0.06s), an error in pull of 4.3 frames (0.07s), and 4.8 frames (0.08s) for recovery. A portion of this error could quite easily be attributed to simple disagreement between two sequential frames in the video. Yeadon and King (1999) note that when synchronising two video sources, there can be an induced error of 0.02s further demonstrating that the error in this system is relatively small, emphasizing the benefit of the maxima detection method developed.

Whilst positive results were shown for the phase detection, there was some need for personalisation of the identification process for the swimmers. The algorithm was initially developed on one swimmer, Swimmer R (Figure 86a), as this swimmer showed a 'smooth' body roll with clear zero crossing and peaks and was identified by the coach as a consistent swimmer. The phases were also clear with little variation. This was also found to be a fairly consistent feature throughout the 10 swimmers used and the algorithm worked well. However, there were three swimmers, shown in Figure 86 (b, c, d), where individualisations in the algorithm were needed in determining the pull and recovery phases. The customisation process entailed

extending the windows of searching for maxima and minima relative to the body roll peak or zero crossing.

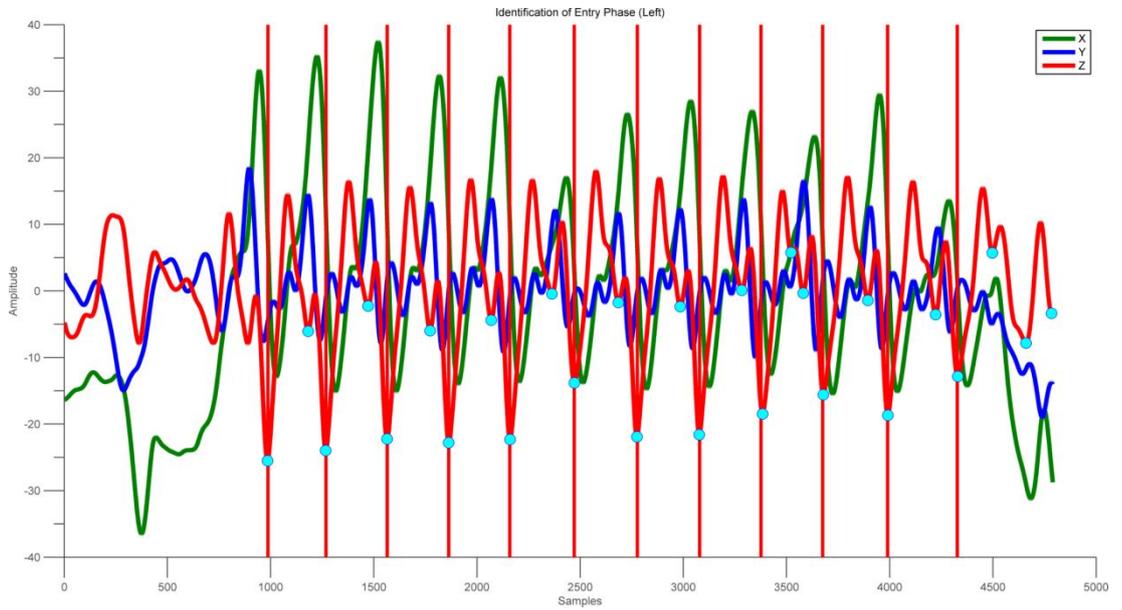


Figure 84: Swimmer L Hand Entry (Cyan) close to Zero Body Roll (Red Vertical Line) before fatigue

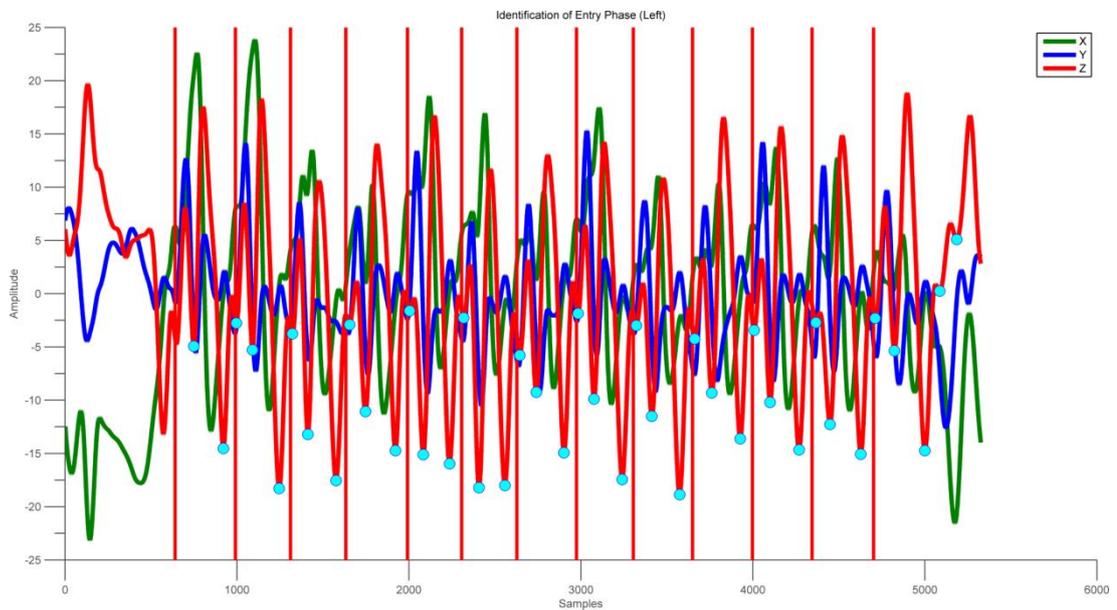


Figure 85: Swimmer L Hand Entry (Cyan) close to Zero Body Roll (Red Vertical Line) when fatigued

Visually, the strokes look fairly similar from swimmer to swimmer which demonstrates phases are similar from swimmer to swimmer. However, swimmers I, L and S (Figure 86b, c, d), all show the start of the pull phase is undetectable with no discernible minima.

Swimmer Ka has a similar push phase to swimmer R (Figure 86a), that being, very close to or on the zero crossing line, but the recovery for swimmer Ka occurs just before peak body roll. This was confirmed by video. With this swimmer, there is a subsequent peak in the X axis (unlabelled) after the recovery. The standard search algorithm also found this peak and moved the push and recovery points too far to the right in time.

This is in contrast to swimmers O and M (Figure 86c,d), where the push phases are both after the body roll peak and also not as well a defined minima for search purposes. This required changes to the code, but for only these swimmers. For swimmers Ka and M the pull phase is before the body roll, and swimmer O is after showing a large variation.

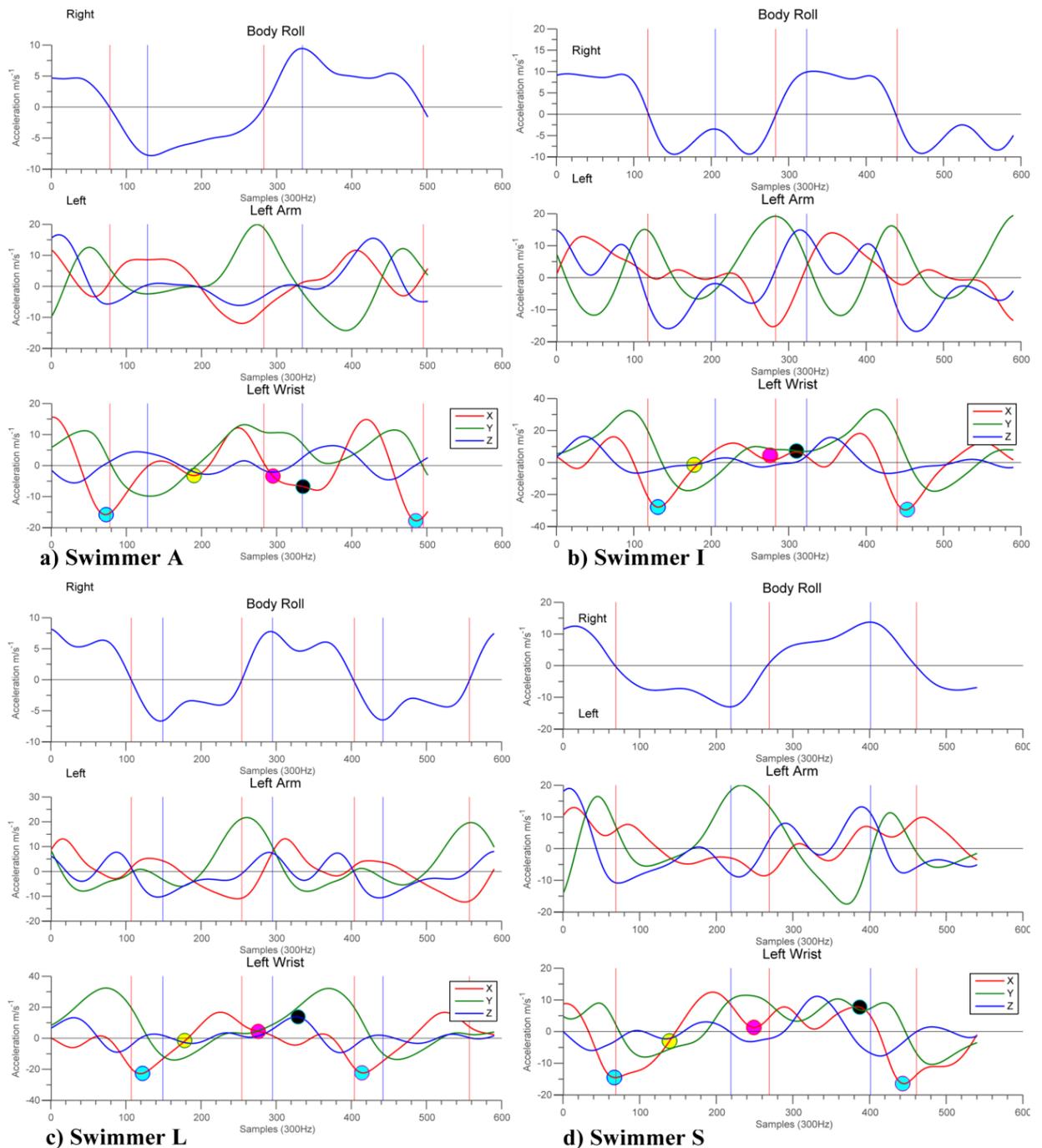


Figure 86: Examples of variations in phases of 4 different swimmers. Cyan = Entry, Yellow = Pull, Magenta = Push, Black = Recovery. Red vertical line shows a zero crossing line for body roll, and blue a peak body roll

Dadashi et al. (2013) did not find the same need to individualise their stroke phase algorithm. This could be due to them using seven well trained national

swimmers, which all exhibited similar stroke techniques. That is in relation to the swimmers used here, which were slightly younger with less national level experience, in general. It could also be due to the use of the gyroscope. In the same manner as the body roll (UB_X , LB_X) has been used here to assist with a search algorithm for the correct phases, the gyroscope has been used to assist with the identification of the phases. Future work should consider the same approach used in this present work using the lower body sensor, with a gyroscope, to assess whether this could expand on the results, particularly for lower level swimmer who may not exhibit the classical stroke phases seen by more experienced individuals.

5.3 General Discussion

Improving performance is better achieved through increasing the quality of a training session which can only be created by knowing the specific training requirements of the athlete (Mueller et al. 2000). Swimming coaches will run a training session using no technical equipment and this will lead to missing the opportunity of developing small improvements to their technique (Stamm et al. 2012). Monitoring based equipment can help identify these changes, of faults in technique and allow the coach to create training specific drills of training sessions.

Performance data and in-the-field assessment can be captured by placing small hermetically sealed electronic devices on the swimmer that measure linear acceleration or with an accompanying gyroscope to measure angular velocity and over recent years there have been some progression in this method (Bächlin and Tröster 2012; Davey 2004; Ichikawa et al. 2002a; Ichikawa et al. 1999; Ichikawa et al. 2002b; Le Sage et al. 2011; Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2003; Slawson et al. 2008; Stamm et al. 2012; Stamm et al. 2011). However, with systems such as this, Maile (1999) discusses the need for coaches to understand the data gathered in order to act upon it. Bartlett (2008, p124) states that there is a need to find new measurement methods to overcome the difficulties associated with movement variability, before any implications can be addressed '*in a context that would be truly meaningful for sports practitioners*', reiterating Maile (1999) comments. With the advances in monitoring technologies, which permit the

measuring multiple variables, unobtrusively during or post sporting performance, this can now become a possibility (Baca et al. 2009; Jobson et al. 2009; Johnstone et al. 2012; Liebermann et al. 2002). The present work has successfully achieved this demonstrating the ability to monitor a range of technical aspects of the front crawl stroke.

Previous works (Bächlin et al. 2009; Bächlin and Tröster 2009, 2012; Dadashi et al. 2013; Daukantas et al. 2008; Davey et al. 2008; Ichikawa et al. 2002a; Le Sage et al. 2011; Le Sage et al. 2010; Ohgi 2002; Ohgi et al. 1998; Ohgi et al. 2002; Ohgi and Ichikawa 2002; Ohgi and Ichikawa 2003; Ohgi et al. 2000) have relied on a single swim protocol. That is, attach the devices, swim, remove and analyse the data. It should also be remembered that the present system uses a test-retest protocol, where the devices are worn, removed and then reattached. All of the results presented have been calculated using that same method, showing the repeatability of the system.

The factors used in this work have been based on a deterministic model, which provides a strong theoretical structure for the examination of various factors interactions and influences on the outcome of the task, and have been extensively used in research (Chow and Knudson 2011). However, Glazier and Robins (2012) criticize the use of these models, proposing that these models have in fact assisted in the lack of progression in biomechanical research due to their use of a *product-oriented* approach, rather than a *process-oriented* approach. This is, they are models of performance and not of technique describing to us *what* performance parameters are important, but not *how* they are generated. This can be demonstrated using a kinetic chain as an example, as shown by Glazier and Robins (2012), where the deterministic model would describe the body segments *which* should be used, but would not specify *how* the body segments should interact, to generate a meaningful end value. This demonstrates a potential lack of the detail provided by a deterministic approach, where a different sequence of body segment movements could equally present very similar end values. Glazier and colleagues (Glazier et al. 2003; Glazier 2010; Glazier and Davids 2009; Glazier and Wheat 2013; Glazier et al.

2006a; Glazier et al. 2006b) have generally been critical of the biomechanical methods employed, and particularly the link between biomechanics and motor control.

Bennett (2003, p.1) describes that both intra and inter-subject variability is often present in many performance measures, and that within this there are often '*underlying coordination pattern[s]*', that can be consistent within different skill groups. These patterns need to be recorded and understood in order for that individual to progress to the next level (Bennett 2003). Glazier and Robins (2012) add to this by helping direct the future work for sport biomechanics by focusing on alternative methodological approaches such as coordination profiling (Button et al. 2006) and multiple single-participant analyses (Bartlett 2008; Bartlett et al. 2007; Hiley and Yeadon 2012; James and Bates 1997). However, Preatoni et al. (2012) notes that currently there is no agreed standard method to approach measuring variability in relation to performance, which means there is no standard way to present this information to coaches. This shows a gap in the research which systems such as this can fulfill in future work.

Elements of swimming research have started to make a move towards coordinative, dynamical systems, approach. This has been demonstrated by investigations into IdC (Chollet et al. 2000b; Figueiredo et al. 2010; Osborough et al. 2010; Satkunskiene et al. 2005; Seifert et al. 2005b; Seifert et al. 2004; Seifert et al. 2007a; Seifert et al. 2007b; Seifert et al. 2010), which offer insights into parts of the coordinative nature of front crawl swimming.

Glazier and Wheat (2013) argue that research into biomechanical factors in cricket has not substantially enhanced knowledge, and has had little impact on coaching practices. This cannot be said for swimming, where knowledge of stroke rates and lengths, and the curvilinear arm movements can be seen to have directly contributed to changes and development in the coaching of the front crawl stroke (Counsilman 1968, 1977; Maglischo 2003).

Whilst this thesis has not attempted to address a dynamical systems approach to swimming, the system developed does show some strong links towards developing one. The developed system has shown the ability to identify individual coordinative structures. The results show that each swimmer has a different method for adapting to perform the task to the best of their ability with the addition of fatigue, which is supported by previous research (Cross 1999; Davids et al. 2003; Rushall 1985; Toussaint et al. 2006).

A concern over a dynamical systems approach in swimming, particularly for any use by coaches, would be the level of sophistication in the system. Requiring the measurements of multiple factors from body size and shape to physiological factors, would be unrealistic for a coach to use in any fashion.

Head coaches ER and SW were re-approached with the completed profiles to ascertain their use within their coaching. This was conducted informally before their training sessions with the swimmers in a quiet room where the researcher re-explained the process and of validation with the video cameras and how these profiles were formed. The data collection had taken place 8 months prior to this, due to the time to develop and validate the system. This meant the data was no longer of immediate use to the coaches as the swimmers had changed and developed. The purpose of this meeting was to understand how the profile could be used in their training sessions. The other two coaches, SL and CS, had moved away from the club by this time.

The researcher explained the outline of each section in turn to ensure they understood the diagrammatic representations of the information. The core information, lap time, stroke length, stroke rate, was of great importance to them and easily understandable. One of the most useful outputs, in the coaches perspective, was the percentage of time per phase (Figure 87). The head coaches (ER and SW) stated that this was a most useful way to display the information to the swimmers and would be of great use to them to explain the timings of the phases to the swimmers.

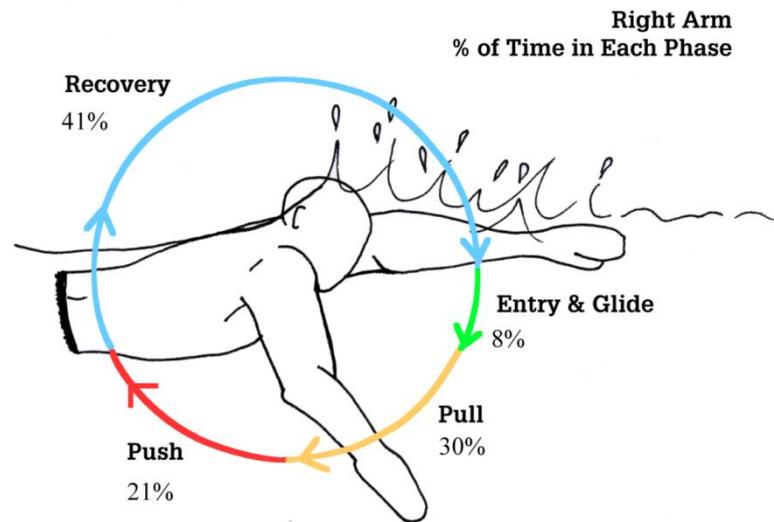


Figure 87: Percentage of Time per Phase

When the additional information presented in the profile; variation in body roll (upper and lower body), timing variation (upper and lower body roll), symmetry tables, IdC and body roll angles per phase; was presented to the coaches and was met with a little confusion by them. It appeared that there seemed to be too much information present for them to digest. In part, this could be because all of this information does not present the coach with an immediate solution to direct or create training programmes, but requires careful interpretation. The coaches did note that the body roll timing variation could be used as a diagnostic tool for use with their physiotherapist. However, the symmetry table was generally overlooked. This could simply be down to the ordering of the slides, and could appear to be more complicated than it is. Table 18 shows an example of a swimmer's symmetry information from a profile. This was designed to be interpretable by the coach, rather than showing a number which determined the dominant side, this was automatically changed into either Equal, Left or Right side dominance.

Symmetry: Dominant Side								
Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Equal	Equal	Left	Equal	Left	Equal	Right	Left
L 2	Right	Right	Equal	Equal	Left	Equal	Right	Equal
L 3	Right	Right	Equal	Equal	Left	Equal	Right	Equal
L 4	Right	Right	Equal	Equal	Left	Equal	Right	Equal
L 5	Right	Left	Equal	Equal	Left	Equal	Right	Left
L 6	Right	Left	Equal	Equal	Left	Equal	Right	Equal
L 7	Right	Left	Equal	Equal	Left	Equal	Right	Equal
L 8	Right	Left	Equal	Equal	Left	Equal	Right	Equal

Table 18: Symmetry table for various variables of a swimmer

Table 18 should help coaches to modify the swimmers technique to allow a more balanced swimming style. This also shows how the swimmer changes through the duration of the trial, further identifying the potential move towards a dynamical systems approach. The coaches lack of enthusiasm regarding the detailed elements of the profile could be because there is a lack of methods to treat this type of information. This is an issue acknowledged by Preatoni et al. (2012, p.70) showing that,

"...there are currently no universally agreed guidelines for practitioners regarding the treatment of variability within experiments. The lack of such information becomes more serious when the focus of investigations is shifted from basic movements such as walking or running to the multiplicity of more complex sports movements"

Stamm et al. (2012) are the only researchers to move towards a movement variability system using an accelerometer based approach in swimming, but have not specifically stated this as the purpose. Using a lower back sensor, they measured the symmetry of the stroke duration. This based on the premise that the stroke duration

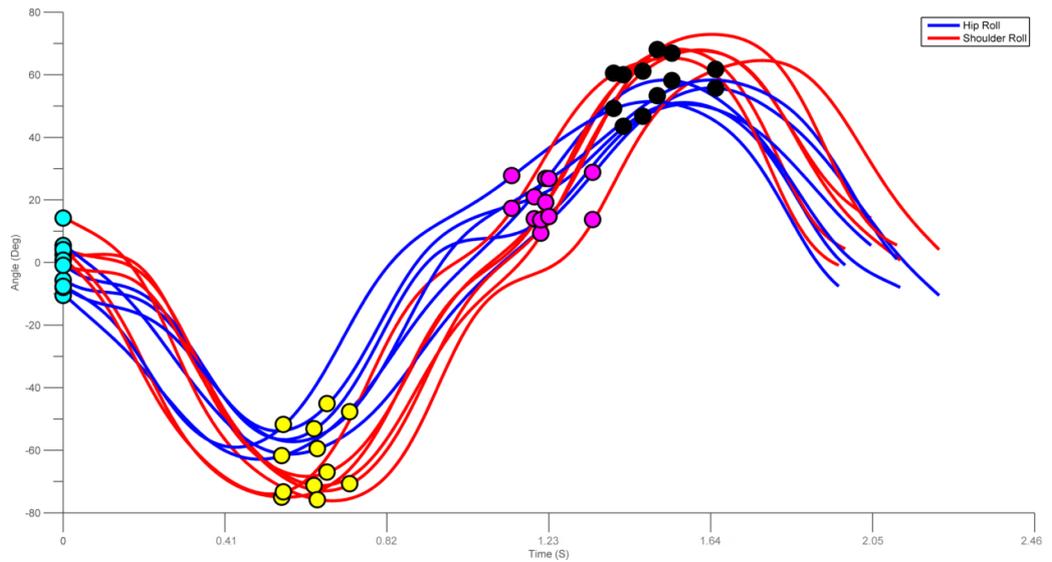
is directly related to the body roll (level body is hand entry, next level body is start of recovery). They verified this using video cameras.

Using Table 18 the duration of the stroke remains equal throughout the test, with dominant sides through the other phases, and variation in the recovery. This shows that to maintain stroke duration, the phases of the stroke change. The work of Stamm et al. (2012) has focused on the overall duration of the stroke with regard to body roll, but does not show these intricate changes in the phases by the swimmer. Table 19 shows the mean body roll angle, per phase of the stroke. This shows that there is some variation in the angle of the lower body angle compared for each phase, particularly over the duration of the laps.

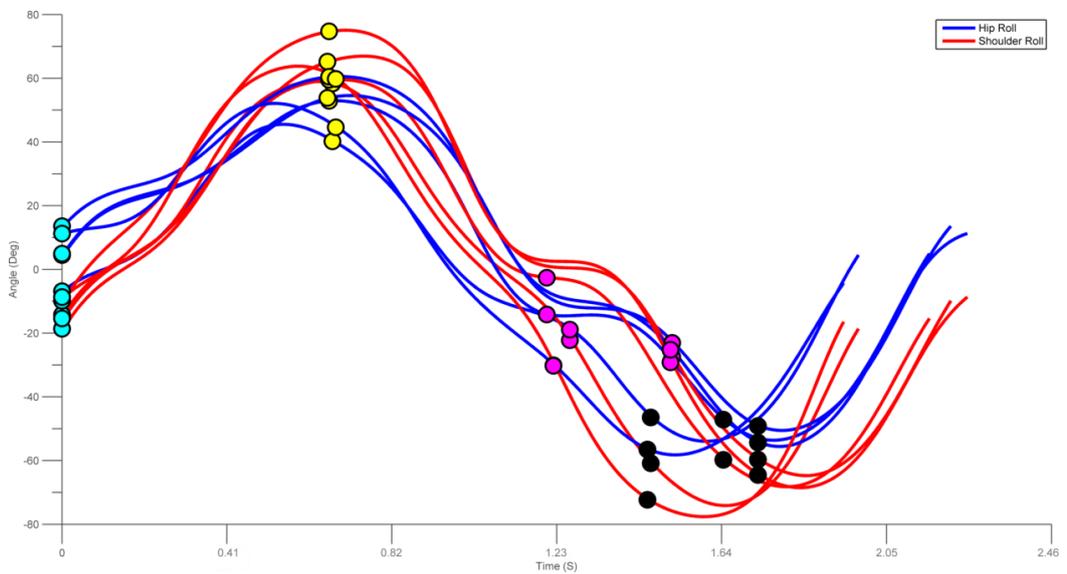
Body Roll Angles Per Phase, Upper Body, Left and Right								
Length	Entry	Push	Pull	Recovery	Entry	Push	Pull	Recovery
L 1	1.58	48.45	-13.53	-51.90	-17.69	-52.36	28.07	47.60
L 2	-2.22	48.99	-19.76	-46.54	-8.48	-49.45	19.81	50.31
L 3	-1.40	48.94	-26.16	-53.11	-6.61	-53.36	22.55	51.52
L 4	6.00	52.00	-21.15	-51.27	-5.46	-46.78	24.62	51.93
L 5	2.41	45.70	-29.88	-39.82	-5.28	-49.88	22.56	54.57
L 6	-6.82	37.30	-32.48	-58.97	-4.85	-56.93	20.05	52.52
L 7	7.67	48.48	-24.70	-56.01	-3.55	-49.13	22.96	51.94
L 8	7.72	49.17	-27.50	-59.32	-3.39	-55.01	24.74	53.08

Table 19: Mean body roll angles per phase of the stroke for the Lower body. Left side is left arm. Right side is right arm.

This demonstrates that Stamm et al. (2012), and others using a lower back sensor, will be limited in the data they can collect and should not assume symmetry in other limbs that they are not monitoring directly. This is further demonstrated in Figure 88.



(a)

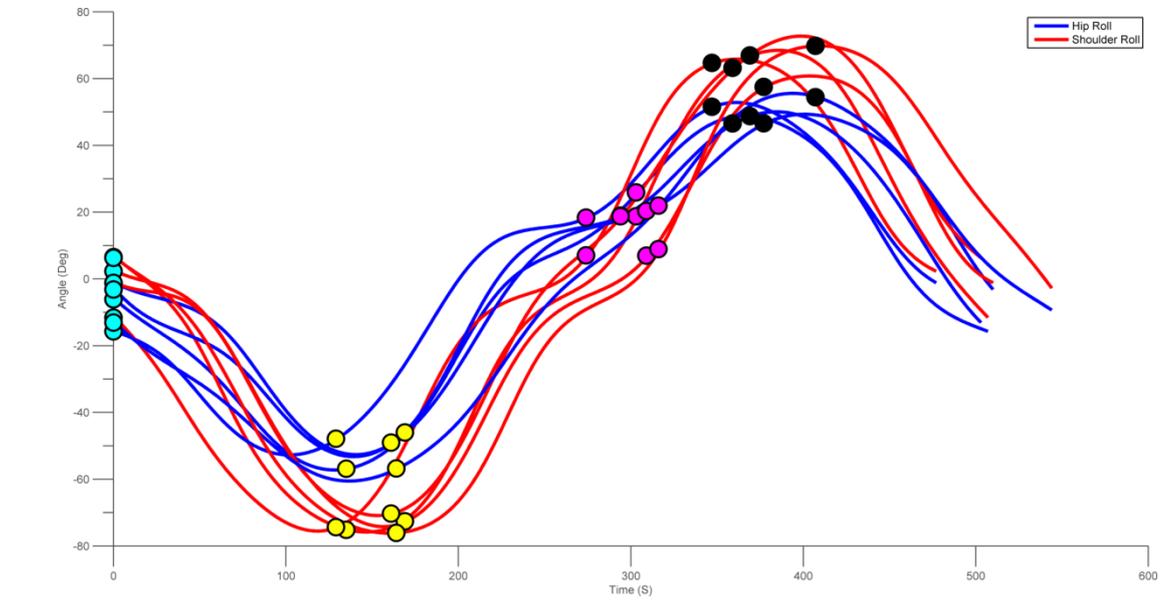


(b)

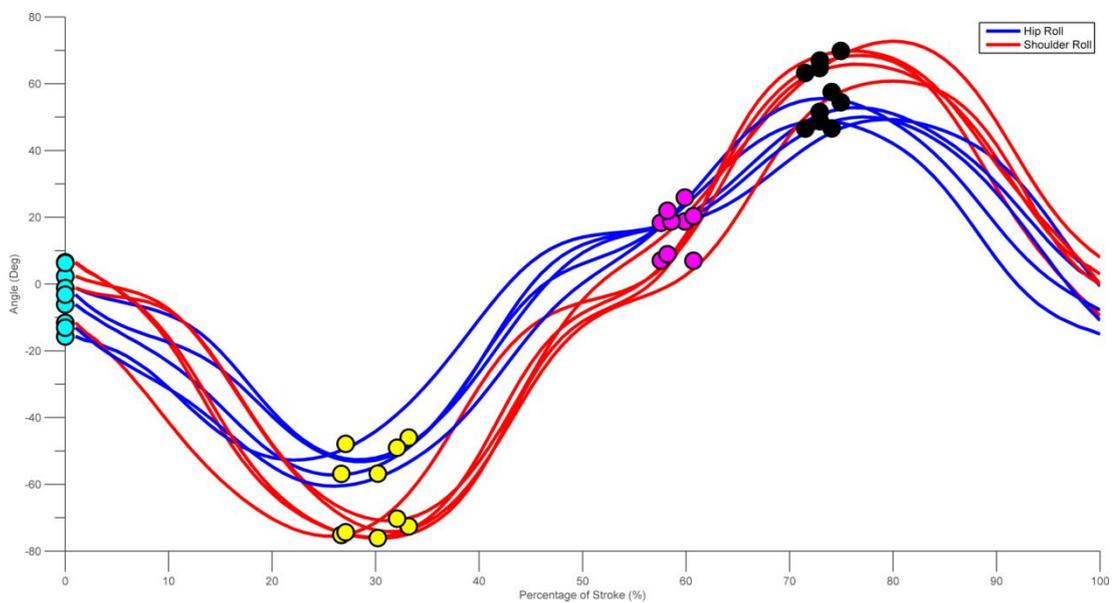
Figure 88: All strokes from one lap showing the phases of the stroke identified in relation to the body roll angles of hip and shoulder. a) Left stroke, b) Right stroke. Cyan = Entry, Yellow = Pull, Magenta = Push, Black = Recovery.

These (Figure 88) show that there is variation in the body roll in both the upper and lower body roll, for each phase of the stroke. This preliminary data shows a potential future for motor control work looking into the coordinative structures between the body roll and phases of the stroke. This can be further developed to

show the phases of the stroke as a percentage of a normalised (100%) stroke cycle (Figure 89).



(a)



(b)

Figure 89: All strokes from one lap showing normalisation to 100% stroke duration. a) Not normalised, b) Normalised to 100% stroke cycle. Cyan = Entry, Yellow = Pull, Magenta = Push, Black = Recovery.

These different ways to display information (Figure 89) demonstrate some interesting issues with movement variability which need future work. Normalising data to 100% of a cycle, is common practice in applications such as Gait analysis. However, this approach fails to consider time variability of a cycle. Figure 89a visually demonstrates time variability in the duration of the stroke with some variability in the overall duration of the stroke, and also in the start times of the pull, push and recovery. When this stroke is normalised to 100% (Figure 89b), visually there is an increase in the variability at the start of the pull, and a reduction in the variability for the push and recovery. There is variation in the stroke length, and the duration of the phases of the stroke. This variability will impact the time directed to the propulsive phases of the stroke and impact upon the coordination of this propulsion (IdC). There is a need to develop methods which are universally agreed to address consistent measurement of this variability, especially for complex movements (Preatoni et al. 2012).

Costill et al. (1985) and Chollet et al. (1997) have expressed that stroke length is the best indicator of performance. With the results presented here, the stroke length has remained constant for nearly all swimmers, showing high skill levels. The presentation of case studies has shown that there are different strategies for each swimmer when dealing with fatigue, of which this information should aid coaches in developing individual based training programs and drills, rather than group based drills. This can be shown particularly with swimmers R and O, where there was no significant difference between the lap times (and other core information) yet to maintain these times, they adapted elements of their technique. These adaptations include changes in body roll angle and changes in the duration of phases of the stroke. This however does demonstrate that the developed system has the potential to help record multiple variables simultaneously on a swimmer, but this level of detail is too advanced for the biomechanical knowledge which a coach should hold. However, it does show the potential future applications for recording, and analyzing data, using a dynamic systems approach in future research.

There are a multitude of methods available to record technique, so it would seem appropriate to extend the model demonstrated by Bartlett (2012) as none of the methods shown here would have been available without the underlying trend of sports technology and its ability to help develop each facet in the sports sciences, very few of these results would be available (Figure 90).

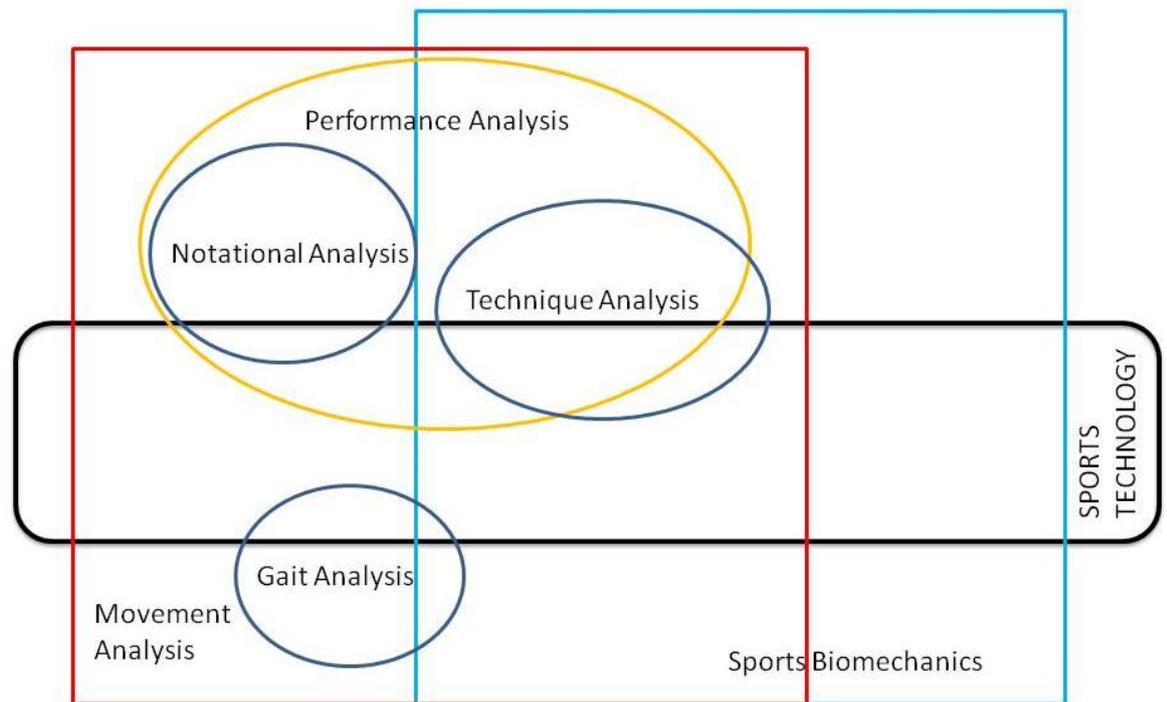


Figure 90: An extended version of Bartlett's (2012) model, showing the placement of performance analysis in the sports science environment, with the extension of sports technology running through every facet.

5.4 Contribution to Knowledge

The aim of the study was to increase the level of data available to swimming coaches. This study has made a contribution to this area by developing and validating a multi sensor system for swimming.

The research developed a method and computational process to allow the synchronisation of non-wireless sensors. This process was demonstrated to be reliable, and would allow for any number of non-wireless devices to be synchronised.

Previous systems have tended to focus on single sensor designs which can infer action of other limbs or technical factors. These sensors have also tended to process the data on the device. The present system was developed using a commercial datalogging devices, as opposed to a custom made sensor. This allowed a focus on PC based software for data processing which allows for graphical outputs for the coach, in addition to faster processing times and a greater range of factors to be extracted from the data. This method also allows future updates to software (i.e. to measure and record new factors in performance), to be developed and deployed in a single place (i.e. the PC software), rather than requiring updates and deployment on multiple devices.

The study has also added to current work by developing the number of factors recorded for the coach (Table 20). The outputs from previous systems have tended to be either too complicated for a coach to understand and interpret e.g. raw data (Ohgi et al. 2000), or quite basic in terms of output e.g. stroke rate and counts (Le Sage et al. 2011). Recent work (Rowlands, James and Lee, 2013) has demonstrated the importance of converting technical biomechanical data into meaningful outputs for coaches. This system is the first to demonstrate a wide range of factors (Table 20) which can be presented to the coach in a meaningful way.

Author(s)	Number of Sensors	Location(s)	Sensor Type	Lap Time	Velocity	Stroke Rate	Stroke Count	Distance Per Stroke	Stroke Duration	Kick Count	Fatigue	Hand Pitch at Entry	3D Display of Stroke	Upper Body Roll Angle	Lower Body Angle	Body Roll Timing	Body Pitch	Stroke Phases	IdC	Symmetry	Body Roll Consistency	Body Roll per Stroke Phase	Output for Coach
Holmér (1978)	1	LB	A		✓																		
Ohgi et al. (1998)	1	LW	A									✓						✓					
Ohgi et al. (2000)	1	LW	A									✓						✓					
Ohgi (2002), Ohgi and Ickikawa (2002)	1	LW	B								✓	✓						✓					
Ichikawa et al. (2002a)	1	LW	B																				
Ichikawa et al. (2002b)	1	LW	B																				
Davey et al. (2008)	1	LB	A	✓ ◇		✓ ◇	✓ ◇																
Daukantas et al. (2008)	1	LB	A			✓	✓ *																
Fulton et al. (2009)	1	Thigh	G							✓ ◇													
Bächlin et al. (2009), Bächlin and Tröster (2012), Bächlin and Tröster (2012)	4	LW, RW, UB, LB	A	✓	✓	✓	✓	✓	✓					✓*	✓*	✓*	✓*						
Pansiot et al. (2010)	1	Head																					
Nakashima et al. (2010)	1	LW	B										✓*										
Le Sage et al. (2011)	1	LB	B	✓ ◇		✓ ◇	✓ ◇																✓
Stamm et al. (2011)	1	LB	B		✓ ◇																		
Stamm et al. (2012)	1	LB	B																	✓ ◇			
Dadashi et al. (2013)	3	LW, RW, LB	B							✓ ◇								✓ ◇	✓ ◇				
Callaway (2013)	6	LW, LA, RW, RA, UB, LB	A	✓ ◇	✓	✓ ◇	✓ ◇	✓	✓ ◇		✓			✓ ◇	✓ ◇	✓ ◇		✓ ◇	✓	✓	✓	✓	✓

Table 20: Summary of previous works, with the addition of the contribution from this work. A = Accelerometer, G = Gyroscope, B = Both. ◇ = validity and reliability conducted. * = visually compared to video data.

6 Future Work

This thesis describes the development and use of an accelerometer based data logging system in front crawl swimming. The information is collected from multiple synchronised devices placed on the upper body and software has been developed to interrogate the accelerometer data to extract features which can be important to a coach and researcher. This is then output in a Powerpoint format for the coach.

The research focused on methods to synchronise non-wireless devices and validation of the system for lap time, hand entry, stroke duration and Index of Coordination.

6.1 Technology Development

A commercial sensor was used for the data collection. One limitation of previous works is the lack of opportunity to repeat the studies or develop the functionality due to the sensors being bespoke. These previous systems also tend to focus on the lower back where arm stroke information is inferred from those readings. This work utilised devices on the upper and lower back and upper and lower arms. This allowed for a greater range of features to be extracted over previous works.

Although the synchronisation method proved to be effective, there was a lot of information recorded which was not really needed (Figure 33). This could be reduced with the introduction of a wireless signal to synchronise the devices and reduce data load. Whilst this, in part, reduces the principle of using a commercial sensor, currently the commercial market is lacking a wireless, networkable, accelerometer device. Systems such as XSENS (Xsens Technologies B.V., Netherlands) offer full IMU (Inertial Measurement Unit) based devices, but this requires a large battery pack and magnetic source.

Work has started on an accelerometer based data logger which can utilise multiple devices on a ZigBee mesh network (Figure 91). This allows a controller to be connected to a PC and wirelessly synchronise up to 50 devices. The wireless signal may not carry sufficient bandwidth (less than Bluetooth) to wirelessly send the RAW data signals to the PC. It could however, process stroke count, stroke rate and lap times on the device. However, IdC and other factors would require a post-event download of the data. A circuit diagram can be found in the Appendix 6. As stated previously, only using software on a PC allows it to be updated in a single place, rather than on multiple devices. This also allows for the greater processing power of the PC to develop the movement variability methods for assessment of variables.



Figure 91: New sensor design

6.2 Data Analysis

At present the MATLAB based software does not offer a GUI (Graphical User Interface) to allow a user friendly interaction. It was identified that the coaches simply do not have the time to use a system to collect information (Appendix 1), and so rely on their perceptions of the events. This shows a need for analysts, in some form, to work with the swimming teams (and other sports) to help deliver the appropriate information to the coach. Adding a GUI to the system would allow for less experienced users to use the system and still generate the same output.

The analysis methods utilise peak detection and zero crossing algorithms. Some swimmers presented with additional peaks and troughs in their arm movements which were not expected, requiring slight tailoring for each swimmer. Within this, the upper arm sensor was added to the swimmer to attempt to find additional patterns to assist, however, preliminary investigations did not aid this. Future work will look further into zero crossing, and peaks and troughs in the upper arm devices in order to develop and refine the system.

The output of this system focuses on an immediate (within 10 minutes) output for the coach. Whilst this helps with the training session in hand, there is a need to develop a database of previous events. The basis for this is already present in the software with individual laps being stored ready to be interrogated in future in comparison to new data after a period of development.

6.3 Presentation of results

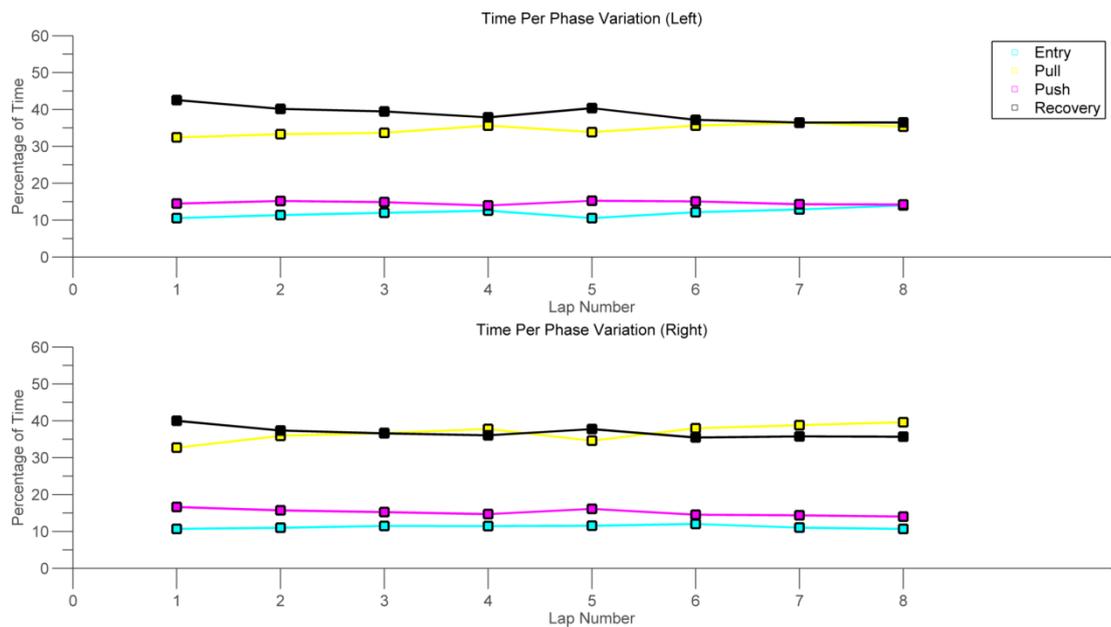


Figure 92: Time per phase - Swimmer A

Some of the graphics presented in the Powerpoint could potentially show mixed messages. Consider for example Figure 92 which shows the percentages per phase of swimmer A. At face value, the results seem to show little variation in the phase percentage over time. This could lead the coach, whilst quickly observing these

results, to discard the importance of these results. The statistics show the swimmer had a difference in the duration of nearly every phase, but this graph actually shows that whilst the whole duration of the stroke increased, the time spent in each phase was consistent, it does not show the coach that they actually fatigued.

The use of effect sizes could also be used here to help develop an 'intelligent' system. Effect sizes such as Cohen's d could be used to help a system prioritise technique changes which need attention from the coach. This would help satisfy the comment by Hughes and Bartlett (2008, p.9) who state that,

"further development of IT- and AI-based coaching tools by performance analysts is a high priority"

This would need attention and other constraints incorporated, such as the use of hierarchical models to help put the issues in order of function. That is, to express the linkages of improvement to the coach in the order to fix them. For example, an error with the phases of the stroke may stem from body roll issues (Psycharakis and Sanders, 2008). This could be an area for research, in addition to the variability considerations of the swimming stroke.

6.4 Scope for future research

On-body sensors offer the ability to inform the future of coaching knowledge and biomechanical research. This is capable through the collection of raw data, using various sensors in data logging devices, which can be stored and re-processed in the future as knowledge increases. If a relationship between several factors became established in the academic literature, existing videos would take a long time to re-process the correct data or the cameras may not have 'seen' the correct view of the swimmer making the data redundant. The raw data measured using on-body sensors can be re-processed as knowledge and processing technique improved. This offers some key advantages. Firstly, it offers larger datasets to academics for processing. Secondly, it can offer longitudinal analysis of their performance, which may help develop a more complete profile of the swimmer, their interaction with different

training patterns and methods, and also the potential of tracking the development of injuries.

Preatoni et al. (2012) states that there are no agreed guidelines for the treatment of movement variability within sport. Prior to establishing a treatment method or motor learning method for use within swimming, there needs to be investigation into whether variability within various factors of swimming is advantageous, unimportant or hindering in relation to performance. This can be assessed using synchronised on-body sensors where a multitude of factors can be simultaneously processed and correlated, over time, to identify these relationships.

The calculation process for various performance factors within front crawl swimming, presented here, can also be applied to other strokes within swimming. Previous work, such as Le Sage et al. (2011), have been able to identify the different stroke types using a lower back sensor. The process of development using multiple devices within this research would need to be repeated in order to validate the factors for other swimming strokes (breaststroke, backstroke etc). In addition to this, the system can easily transition to use in other sports, drawing on the same principles of analysis. Work is in progress to transition this to Archery. Whilst the performance factors require change, the principle of analysis, calculating temporal factors, remain the same. Using sports which are 'more stationary', such as Archery, will allow for additional factors to be calculated such as the aiming stability of the arm during the shot.

Whilst all of these future research areas will aid to better sports science, there is still a lack of translation from research to practice (Bishop, 2008). This work has started to render the biomechanical information in a useable manner for coaches. However, within the current work, once the data started to get a little more detailed, the coaches were not engaging. This raises two issues for future investigation. Firstly, as the biomechanical work becomes more detailed, how can this be appropriately presented to the coach. Secondly, rather than presenting facts and figures to the coach, there is scope for a system to intelligently suggest training

recommendations and drills to the coach. Each of these have implications which do require thorough investigation.

6.5 Summary

The research presented here has focused on swimming, however the devices can be utilised in other sports utilising the synchronisation methods demonstrated and using similar methods to identify temporal factors in sports.

The development of a ZigBee based wireless synchronisation system would offer ease of use for user, be that a coach (time permitting), analyst or researcher. With the progression of wireless and mobile technologies, such as Open Source operating systems, this system could be developed as a multi-sport tool where the system software will interrogate the data depending on the sport allowing an analyst to work over multiple sports with the same system.

6.6 Conclusions

Evaluating the performance of a swimmer is important for coaches and sport scientists alike. The monitoring methods for swimming typically utilise video camera technology, which has been shown to be time consuming. Le Sage et al. (2011) used an example of a swimmers dive being digitised, tracking the lower back. They state that this takes around 15 minutes to complete, for a relatively short sequence of video which is the dive. Their example concludes that 10 swimmers diving 3 times is 7.5hrs to retrieve relatively little data. If this is expanded to include factors such as stroke count, lap times, time per phase of the stroke, as well as others, this amount of time would increase dramatically. Although video cameras are considered to be a standard method for monitoring swimming, the coaches used in this study identified that they tended to observe their swimmers visually, which is known to be quite unreliable. Being able to measure numerous factors

simultaneously, and produce feedback to the coach quickly, would be of significant benefit in allowing them to develop their swimmers.

Generally with published works, nomothetic methods are utilised to determine whether the factors recorded can be related to the whole population of swimming. For coaches, using these previously defined factors (stroke rate, stroke length etc), the inter-individual variability of these factors could help a coach refine individual training programmes. Currently, the standard method of coaching involves large swimming groups of drill based training, with small amounts of inter dispersed specific coaching using observational methods, or the use of an iPad (camera). The system presented here does not try to replace the drill based training, but offers a more specific method of data collection and presentation to the coach for their one on one coaching to refine technique.

An electronic system was created using COTS (commercial off the shelf) micro electronic accelerometer dataloggers. Prior to this study, research had only recently started to use accelerometer data loggers on the swimmer to help determine lap time and stroke count, and observe the stroke phases. There were limitations in these works, mostly using singular data loggers, they could only monitor from a single wrist or lower back which does not allow for symmetry based factors, such as IdC, to be calculated. This study developed from single sensor systems allowing for the provision of additional factors, in order to help the coach make informed decisions, rather than relying on their visual observations or considerable time analysing video footage.

Monitoring human performance with miniature on the body sensors offers an exciting and evolving area of sports science. These sensors offer a non-invasive method for comprehensive simultaneous measurement of multiple factors of a swimmers stroke kinematics. However, to measure these factors the signals from the devices require the correct interpretation. The coaches defined factors which were important when coaching a swimmer. These matched the deterministic model presented by Hay (1993), including Stroke Length, Stroke Rate and Stroke Count. Methods to calculate these factors, as well as some extension factors such as

symmetry based variables and body roll, were created using the maxima and minima peaks in the data.

To develop the system, multiple non-wireless data loggers needed to be synchronised. A method was developed using maxima detection, where a series of tests were designed to show whether this is a reliable method for aligning an accelerometer dataset. The test was also to test the inter-instrument reliability of the devices, and to test the validity when compared to video derived kinematic data.

The maxima detection method was shown to be absolutely successful in 52 of 54 recorded data sets, where the 2 data sets which were not perfect showed a 0.04s error. The inter-instrument and instrument-video data correlations were all over .94 ($p < .01$) demonstrating the validity of using accelerometer based measurement as a reliable alternative to the established video based approach. Instrument precision (RMSE) was $0.09 \pm 0.02 \text{ ms}^{-2}$ for all three axes tested, and precision between accelerometer-video was $0.2 \pm 0.05 \text{ ms}^{-2}$ for all three axes tested. These results are relatively small in terms of kinematic data.

Making methods like this more available and accessible to researchers, coaches and students, it is hoped that instruments such as these will become more utilised within the sports setting, specifically in those areas measuring multiple kinematic aspects of sports. Sports science and coaching students should be encouraged to investigate the uses of technology so that they can put these into practice to develop the talents of future athletes.

The validity and reliability of any new technology against a criterion is important for sport science. Using the synchronised devices, six factors were tested for validity and reliability against video (criterion) derived data (Lap time, Stroke Count, Stroke Rate, Stroke Duration, Phases of the Stroke, Body Roll Angles). These six factors were chosen due to other factors being comprised of summation of various factors. The results showed a strong positive correlation and no significant differences between the lap time calculations from the sensors and video times. The stroke count and stroke rate results also showed no significant difference. The body roll angles

were validated, and a regression algorithm was successfully utilised in order to reduce any inherent errors present in the system. This method helped to reduce the error in angle detection for the body roll and extends upon previous work (Bächlin et al. 2009; Bächlin and Tröster 2009, 2012) by reducing this error where present. Phases of the stroke were successfully recognised in the swimmers, however, some personalisation was required due to the unique nature of some swimmers strokes.

Whilst this system has been shown to be valid and reliable, there is room for improvement in some of these results that need to be addressed in future refinements of the system and technology. In the identification of lap time, whilst there is no significant difference, the finish time of a lap tends to cause issue with the lap time. This is due to a "soft" finish when the swimmer touches the wall, the sensor does not record this touch very clearly in the data. There is also refinement required in the algorithm for the detection of the phases of the stroke. Whilst this generally worked well, some tailoring was required. Dadashi et al. (2013) recently highlighted that the use of a gyroscope with accelerometer produced stable identification of the propulsive and non-propulsive phases of the stroke, but did not identify all of the phases of the stroke. The current study extended upon this work by determining every phase of the stroke according to Chollet et al. (2000a), as well as presenting the percentage of time per phase and symmetry and IdC.

Six devices were used in the system, placed on each wrist and upper arm, upper back and lower back. This extended upon previous multi-device systems (Bächlin et al. 2009; Bächlin and Tröster 2009, 2012), which did not identify the phases of the stroke or variability within the factors. The presentation of these results has tended to be focused on the research side, rather than coaching based presentation. Le Sage et al. (2011), measuring stroke rate, presented this to the coach on a computer screen. This work has developed from this to produce a detailed report for the coach on the factors recorded from the system.

No previous work has attempted to use an upper arm sensor to allow a more robust method of identification of kinematic factors of the stroke. Consequently, the

upper arm sensor was not used for the detection of the phases of the stroke, or other factors. However, Rushall (2009, p17) states that,

“It is now time to extend the concept of the propelling surface to include the upper arm. No refereed papers have been produced about the upper-arm contribution to total propulsive forces generated by parts of the arm.”

This shows that, whilst currently the data has not been utilised, the upper arm sensor could play a future role in the identification of contributing factors of the upper arm. With future work there could be important factors to be measured from this location. The swimmers identified that none of the sensors and attachment methods effected their swimming strokes.

Eight swimming profiles were generated by the system utilising an experimental protocol to generate fatigue, under the coaches guidance. The results of this experiment highlighted how each individual swimmer compensated in the technique in order to maintain as fast a lap time as possible. This agrees with the proposal by Davids et al. (2003) that individuals will adapt to perform the task to the best of their ability. This highlighted the importance of systems such as this, where multiple coordination changes are unlikely to be accurately diagnosed by the coach visually, reiterating Burkett and Mellifont (2008, p.110) comment that,

“...the demands of the swimming coach and athlete, objective data on the swim performance is required”

In conclusion, this work has presented a valid and reliable system, which can still be enhanced in functionality. It has been presented as a system, greatly developing from previous systems in the degree of factors recorded and the presentation to the coach. It has also discussed how the current system can be enhanced to output additional biomechanical factors which could help to develop dynamic systems models of front crawl swimming in order to better enhance motor control and development understanding.

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1 Qualitative Data

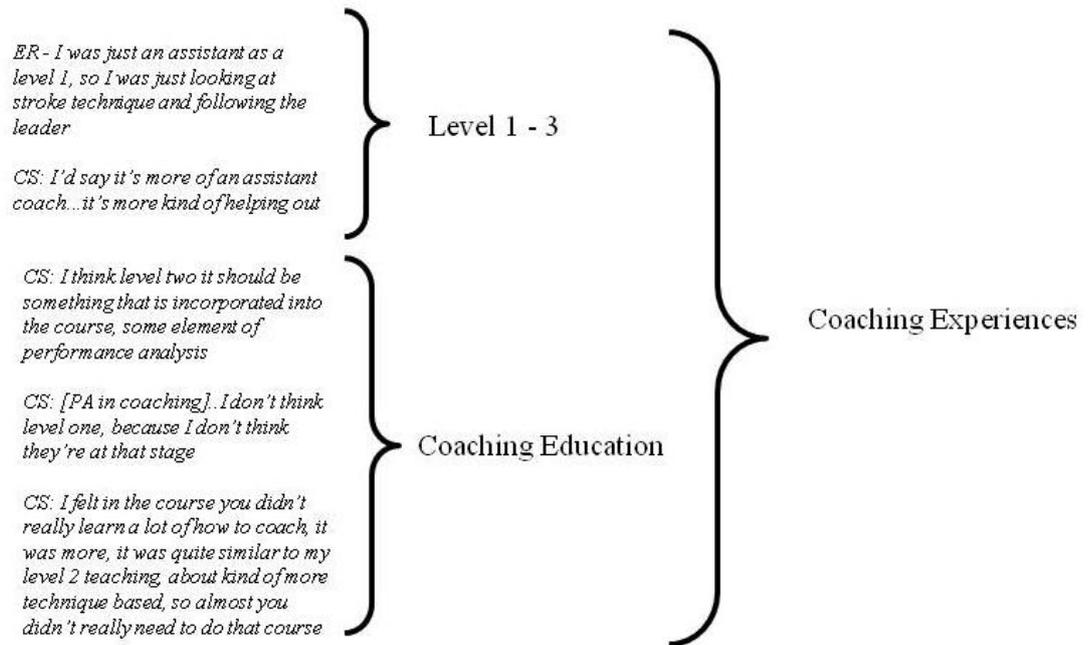


Figure 93: Thematic analysis showing coaching experience

CS: I guess it's trying to improve somebody's technique or performance using, kind of, you can use cameras or software to help analyse points which will make them better

ER: I would love to know lactate versus perceived exertion

SW: For me it's all about stroke efficiency so, as I said it's the distance stuff, so what their hands are doing under the water, any, you know, little things that could correct that to make them more efficient.

Understanding

CS: I think level two it should be something that is incorporated into the course, some element of performance analysis

ER: So it's more information for the swimmers because they understand it a bit more, so stroke counts and stroke rates, and can play a part far more, and they understand that so within training sets, using that data more rather than just understanding [assuming]I suppose

Benefits to Coaches

CS: In swimming there's not, I don't think there's any or much, especially, unless I think you're in a really elite, you don't see coaches using it at all.

ER: We've started to do a progression of the basics in sets so 50's on 40, 100's on 120, and then monitoring their heart rate and seeing if they are swimming aerobically, threshold or what is their body comfort and from that as the training progresses through the year we are looking at dropping the base time for them to see if they can still maintain a heart rate that's comfortable

Use in Swimming

ER: [On use of Video] now and again we will get the I-Pads out and quickly, you know, just film a start or if it's absolutely horrendous we can show them 'look, this is what you are doing, please correct it!'

Performance Analysis

Figure 94: Thematic analysis showing uses of Performance Analysis

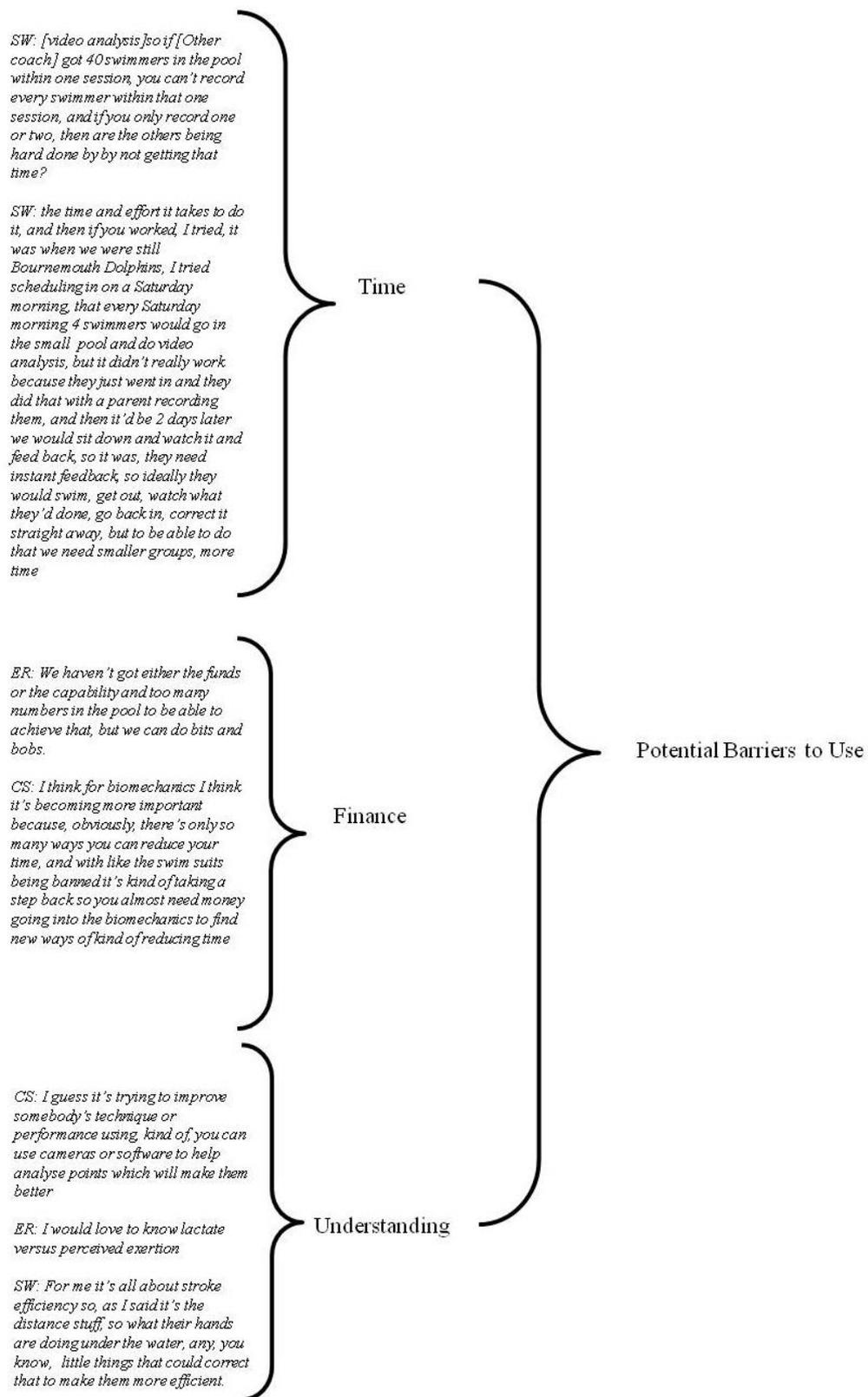


Figure 95: Thematic analysis showing potential barriers to use

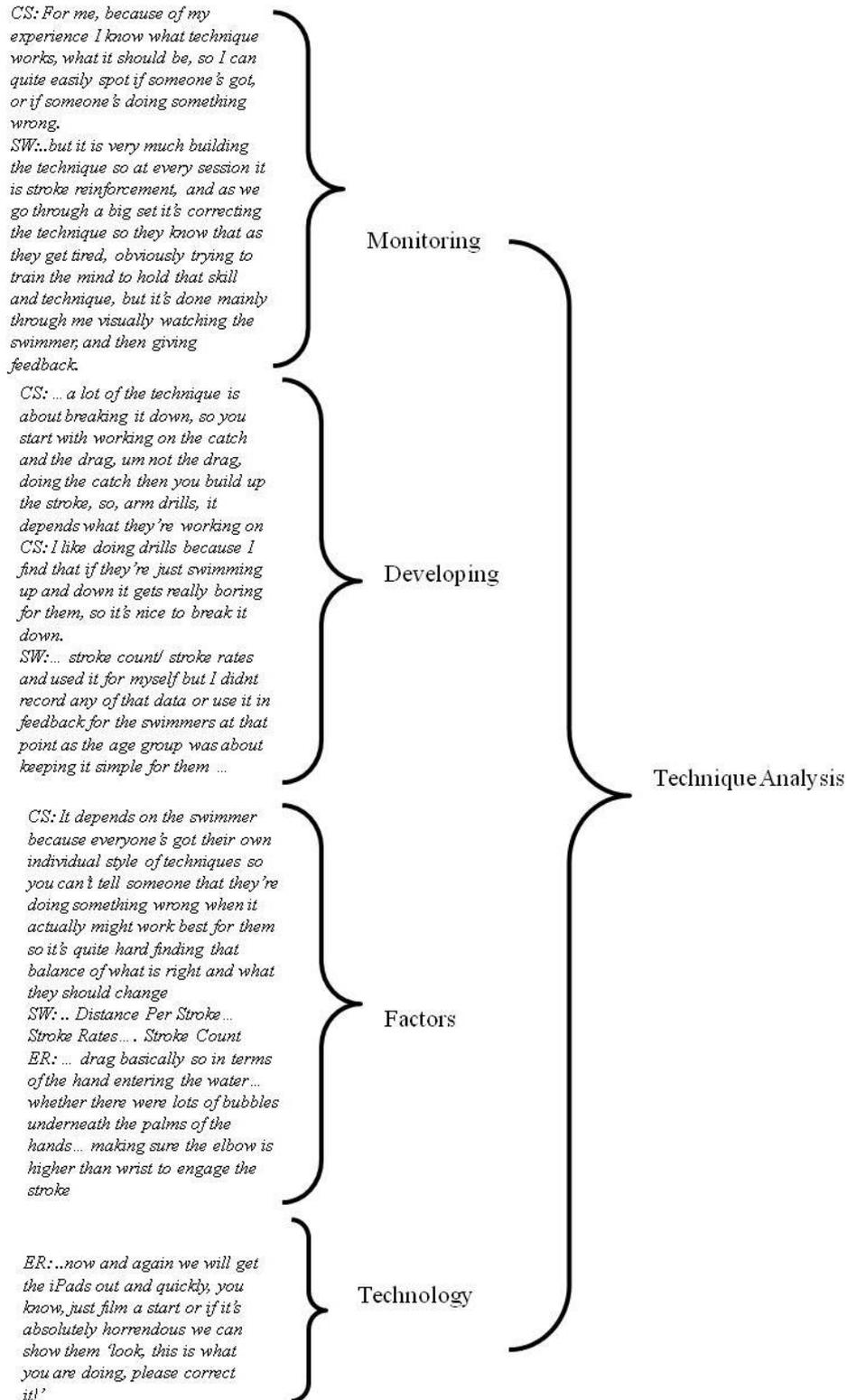


Figure 96: Thematic analysis showing what the coaches do for technique analysis

1.1 Interviews with Coaches

1.1.1 Coaching Experiences and Education

The coaches were asked to describe their job roles and experiences at Level 1-3 and what they saw their job role as. At Level 1 the feelings were that they were just an assistant to the main coach:

ER: I was just an assistant as a level 1, so I was just looking at stroke technique and following the leader, another coach on pool side

SW: guiding and assisting as far as coaching. Very much for myself learning off of a senior coach and often just feeding back to a smaller group within whole group..., technique, skills, and dealing with younger swimmers so just ensuring their skills were in place for when they get older.

CS: I'd say it's more of an assistant coach, it's not taking on the head, or it's more kind of helping out...if you kind of knew how to teach swimming, it's kind of they write something on the board and they get on with it. So I'd say it's more of an assistant, when I did it and I was helping out the head coach would tell me what sessions to do, what I was supposed to do, and I would just kind of tell my lane, a couple of lanes, what they would do and try to pick up on any technique that I saw was wrong

This was then progressed to Level 2 which showed some more factors to record and a need to take ownership, as noted by ER,

[in] Level 2 I had my own group so I had more control over what was actually being produced. Still at a lower age group level . Still making sure that skills are the foundation of everything.

SW also extended this to note that he would start to record,

...attendance, core turn-around times for various different sets,... 400s, 200s, 100s, what can they actually swim and turn around off of. Best effort times in training to then figure out what they should be turning off of compare to what they actually are doing. And then some very simple timed swims, so you'd have a record of timed 200 kick, 800 kicks,

that kind of thing. Didn't really record much, but was aware of stroke count/ stroke rates..

Importantly, the development from Level 1 to Level 2 demonstrates that young ages groups are important to develop the skills. SW noted that his ages groups were the 14-17 age range and ER noted that this is "*..more about technique..*" then as they progressed to Level 3, "*..now it's about educating.*".

From this, it can be seen that Level 1 and 2 coaches could be the potential users of the system, or the output of the system. Previous accelerometer based work (Bächlin et al. 2009; Bächlin and Tröster 2009, 2012; Le Sage et al. 2011; Ohgi 2002; Ohgi and Ichikawa 2002; Ohgi et al. 2000) has tended to focus on the researcher as the user of the system with the coach as the end user. However, Le Sage et al. (2011) is an excellent example of the cross over between system users. Their system shows that a researcher sets up the system, but the coach can then see the data (e.g. stroke rate) appear on the screen for the coach. This is a consideration in the development of a sports technology system.

The ASA Swimming coach education books for Level 1 and 2 as a guide, coach education was investigated (Cross and Wilson 2004; Hogarth 1998). CS noted,

I felt in the course [Level 1] you didn't really learn a lot of how to coach, it was more, it was quite similar to my level 2 teaching, about kind of more technique based, so almost you didn't really need to do that course

The coaching literature seems to offer limited work on the actual stroke mechanics or ways to monitor these, specifically for the coaches use. Yet, there is a general agreement regarding the basic knowledge required by coaches to work with athletes effectively (Reade et al. 2008). There has been a substantial development of scientific research in swimming, however, the transfer of knowledge between sport science and coaches is an area which still requires some development (Reade et al. 2008; Williams and Kendall 2007).

1.1.2 Performance Analysis: Understanding, Benefits and Use in swimming

The coaches were asked about their understanding and use of performance analysis, ER noted after the interview that she had been to some training sessions on Dartfish, a video analysis tool often used for technique analysis, but in the interview she noted "*I would love to know lactate versus perceived exertion..*". This showed a lack in the understanding of Performance Analysis and its purpose, but knowledge of Physiology within sports science. CS said,

I guess it's trying to improve somebody's technique or performance using, kind of, you can use cameras or software to help analyse points which will make them better

Whilst not a textbook definition, it is closer than the understanding of ER. Performance Analysis in its textbook form, noted by Hughes and Franks (2008) is objective measurement of performance and was developed as a joint working group with biomechanists by the BOA in 1998, but really only gathered momentum in the last decade or so as an independent area for investigation (Wright et al. 2012). With ER having more experience than CS and SL, it may be that it was not in the coaching literature or degree courses at that time.

With the amount of research conducted in swimming, it would be expected that this was common place in swimming. However, when asked about performance analysis use in swimming, CS stated that,

In swimming there's not [a lot of it being used], I don't think there's any or much, especially, unless I think you're in a really elite, you don't see coaches using it at all.

This was confirmed by ER:

We've both [SW and ER] been over to Australia and we've kind of seen how the AIS kind of operate, and seen what they do with analysis and been in awe of them. But in terms of actually putting it in practice at home programs, no.

and then extended later to include that,

...at performance centres and stuff like that, you know they've got nice LED screens on the side and, you know, within 10 second delays and all of a sudden they see themselves, you know.

This shows the their opinions of the use of Performance Analysis appears only at the top level. The coaches highlighted that Level 2 was more of a focus on technique than other levels, so it would seem logical to have more detail on how to analyse this in the coaching manuals provided by the ASA.

1.1.3 Potential Barriers to the Use of PA in Swimming

When asked how many swimmers each had,

ER: I've got 40.

SW: And I've got 3 squads of 20, so 60 in total.

CS: Coaching a normal squad, would probably have twenty, maybe twenty-five depending on who turns up for the session.

SL: 40

As noted by Stamm et al. (2009), Stamm et al. (2012) and Le Sage et al. (2011), digitising videos by the coaches can take a long time. Le Sage et al. (2011) uses an example of 10 swimmers completing 3 dives each with 15minutes to digitise each video, which they calculate at 7.5hrs to digitise, that doesn't then include time to change, develop and plan a strategy to change. That calculation also uses the dive start, which lasts a matter of a few seconds and tracks only the lower back (in the example by Le Sage et al. (2011)), most underwater analysis of stroke would analyse angles, stroke phases etc., which would involve yet more time. Given the number of swimmers that these coaches coach, it is unrealistic to expect them to use video analysis. As noted by SW and CS

SW: ...so if [we've] got 40 swimmers in the pool within one session, you can't record every swimmer within that one session, and if you only record one or two, then are the others being hard done by not getting that time? ... the time and effort it takes to do it, and then if you worked, I tried, ..., I tried scheduling in on a Saturday morning, that every Saturday morning 4 swimmers would go in the small pool and do video analysis,

but it didn't really work because they just went in and they did that with a parent recording them, and then it'd be 2 days later we would sit down and watch it and feedback, so it was, they need instant feedback, so ideally they would swim, get out, watch what they'd done, go back in, correct it straight away, but to be able to do that we need smaller groups, more time

CS: [I would]try[and record] as many as you can, but I guess the one-to-ones, I know from when I used to swim and the head coach would get maybe three swimmers out and have a one-on-one with them during the session, so it would take a few weeks to get through everyone. So if you were to give a load of video footage of all the swimmers it would take a while because obviously you've got, you've not got, most coaches don't just have one squad, they've got several, they've got morning and evening sessions, they've got competitions at the weekend, they have to do all the filing and paperwork for that as well, so it's quite a lot of work that would need to be done, it would probably take a while to get through it all.

They did attempt video feedback, but the feedback to the athletes too close to competitions to see a necessary benefit. It does also sound as though they did not go through the lengthy process of any digitisation, but only trimming videos for the athletes which could provide very limited information to the athlete.

An automatic or semi-automatic system would be ideal for a coach to use. The evidence presented seems to demonstrate a need for an analyst to work with them full time. However, would they have the finances available to afford either a system or an analyst's time?

ER: We haven't got either the funds or the capability and too many numbers in the pool to be able to achieve that, but we can do bits and bobs.

Some previous studies (Bampouras et al. 2012; Wright et al. 2013) have investigated the role of an analyst within a team. However, none of these identified the need of funding as an issue or barrier to their use. This is to be expected, with the

level of coaches within swimming not being equal in terms of finance compared to soccer teams or elite sports.

1.1.4 Technique: Monitoring and Developing

The coaches were asked about how they monitored and developed technique in their coaching sessions. The coaches mentioned that they monitored technique and corrected it, but did not generally offer much more information. CS did go into more detail stating that she would,

...tell my lane, a couple of lanes, what they would do and try to pick up on any technique that I saw was wrong

...I'd be on the pool side, but often I quite like, if there's someone that I know does something really well, I'd sometimes get the swimmer out of the pool, watch someone who's doing it correctly, and then get them to do it again, give them a few drills to help them build up...obviously you can see if they're streamlined, if they're in that right shape, but it would be more kind of distance, their breakout to their stroke, not necessarily the technique underneath the water

When asked how they then monitor from the "pool side" the underwater phases..*the underwater, that's quite hard really, because you can't see everything under water.* However, the coaches also talked about how,

CS: a lot of the technique is about breaking it down, so you start with working on the catch ... then you build up the stroke, so, arm drills, it depends what they're working on

This shows a contradiction which is amplified through the coaching literature for swimming, where it promotes pool side analysis with the addition of video analysis, but no detail on how to use this (Cross and Wilson 2004). The coaches therefore tend to work on the technique underwater without being able to see it. Cross and Wilson (2004) does suggest for underwater analysis that the coach "*don a snorkel and mask*

or goggles and view technique from all sides" (pg168). They generally have a 'gut feeling' about what is going on with very little evidence, most based on stroke count data

SW: ...on a stop watch we've got a mode for stroke rating but I don't actually use that as much as I used to, I used to use it a lot, I don't use it now I just go pretty much on stroke count and then visual perception

This was further heightened by SL when asked, if the insweep was different left to right arms what would you do?, She responded with,

SL: Probably a bit more doggy paddle. I'd [do] a lot of arm drills, with hundreds, fist front crawl, those kinds of things.

This shows that that the coaches have drills in place to correct issues, but have no way of monitoring these factors objectively in the first instance.

ER noted that swimmers in training needed to be swimming at a race pace. Glazier et al. (2006a) noted that competition speeds were often much faster than training speeds, which leads to fatiguing swimmers. It appears that ER has a very good training mentality for her swimmers here, but there is always the risk of over training with the athletes always working at the top few percent of their ability.

There is also a gap here showing that the coaches opinions are still based on observation from the pool side where they cannot see the underwater phases, so there is still merit in feeding back this information to the coach to allow them to choose the correct drill to implement. The next extension to this is also that a break down in technique due to fatigue could be very important to the coach, although not mentioned by the coaches themselves but noted by Glazier et al. (2006a) as being something of importance to coaches and research.

This does question some of the rationale for some of the literature presented through the review of literature. This literature generally presents differences between genders or speeds, however, coaches have identified that race pace is

essential in training, and that they developing athletes through drills. It does seem that there is a potential disconnect between the academic literature and the creation of drills to help implement the suggestions from the research. Whilst the research is of use to the coaches, the transition from research to practice seems lacking.

1.1.5 Technology

The coaches were asked about their current engagement with technology to measure or monitor their swimmers.

ER: [On Video] now and again we will get the iPads out and quickly, you know, just film a start or if it's absolutely horrendous we can show them 'look, this is what you are doing, please correct it!'

ER: we started doing a little bit of video analysis so that they can actually physically see X and Y

Kerwin and Irwin (2008) warned coaches of 'mindlessly' using technology as it can give a false impression of technique. This is also reiterated by the principles of 2D camera setup by Payton (2008) and Grimshaw et al. (2006), stating the need for consistent setups for technique evaluation. The methods suggested by the coaches do not suggest any measure of repeatability, leading to the potential for inaccurate coaching decisions to be made. Butterworth et al. (2012) describes that players seeing themselves doing the right or wrong actions in a performance are often believed to help reinforce positive behaviours, but these need to be delivered in the correct way at the correct point in their coaching process.

SW: The main thing is heart rates, now we've got nice heart rate monitors so we know what they're doing rather than just taking them as a guess

SW: on a stop watch we've got a mode for stroke rating but I don't actually use that as much as I used to, I used to use it a lot, I don't use it now I just go pretty much on stroke count and then visual perception.

SW mentions the use of heart rate monitors to show the level of engagement with the session, in terms of how hard they are working. The comment at the end of this, "*rather than...guess*" reiterates the earlier comments about their observation of technique under the water where they "*guess*" what is happening. This all links to either a lack of education in the analysis method available, but also links to the large time constraints faced by the coaches.

1.1.6 The need for change

It would appear from the results found here that the stakeholder for a system like this could potentially not actually be the swimming coach due to their lack of time and finance. As noted by Hughes (2004b) the coaching process includes multiple people, however, these coaches at a Level 3 (and below) do not seem to work with many of these other disciplines. It would seem however that the coaching model presented by Hughes (2004b) is a demonstration of coaches of level 4(+) range. Should the system be implemented with a level 4(+) coach, the system would need to be adapted. The terminology would need to change towards being more technical, particularly when having to interact with other sports science disciplines and act upon it. This would seem to potentially create a lot of additional pressure on the coach if this was implemented at the 1-3 coaching level.

There is the potential for a link here with institutions such as Universities to offer work based learning approaches. Consider students undertaking coaching or sports science based degrees that are in the need of experience and the coaches are lacking the time for engagement in analysis processes due to a high volume of athletes. This would change the user of the system to an academic, student or researcher leading to a dual output requirement to the system. The immediate use will need to be of use to the coach, and as identified needs to include stroke rate, stroke length (distance per stroke), and body roll. It was noted by the coaches that they provide drills for the underwater phases of the stroke, although have no way of monitoring these. With the identification of phases, there is also a clear link to the identification of the Index of Coordination (IdC) of the swimmer (Chollet et al. 2000b; Craig et al. 1985;

Osborough et al. 2010; Seifert et al. 2005b; Seifert et al. 2004; Seifert et al. 2007a; Seifert et al. 2007b; Seifert et al. 2010). Arm symmetry has been measured by Stamm et al. (2012) using a sensor on the lower back, and as previously discussed, this does not allow for the actual variation in the arms to be reported only suggested through non-direct measurement. Using a synchronised wrist mounted sensor on each arm, the IdC can be reported. This could then be of use to both coaches and researchers.

Any system developed for a coach, without a full analysis team behind them, will have the limiting factor of only being able to analyse a single swimmer at a time. Furthermore, current systems, be it cameras or walking along side the swimmer with iPads, have the limitation that only the lanes nearest the walls can be used. An on-swimmer system could help to free up the swimming resources associated with any lane restrictions.

It does have to be remembered however, as Smith and Cushion (2006) reminded us, that at the heart of the coaching process is the coach. It is their decision whether or not to request or use additional technical support, be it from an analyst of themselves, and then it is up to them on how to act upon it. It is the analysts job, to offer the information to the coach, not interpret it. It does appear to engrained in the coaches shown here that their gut feeling has a large part to play in the coaching process and it might take some time to change this view.

2 Case Study Examples

2.1 Case Study Results

The purpose of the system is to produce individual outputs of swimmers, for the coaches. Identified in section 3.1, was a secondary output of the system, a research output. This section presents case studies to demonstrate the output of the system and how the output for the coach is determined from a statistical view point.

Twelve swimmers were used in the generation of data for the validation of the system. From those twelve, eight profiles were generated. The four missing profiles were not complete due to misidentification of the correct minima and maxima in the phases of the stroke when these swimmers became fatigued. These four profiles did not allow for the complete profile to be created. This is discussed in section 5.2.5.

A summary of these is presented in Table 21. R2 was the only swimmer who had no significant change in any factor of his technique. In all other cases, there are changes in some form of technique during the tests. This shows that every swimmer reacts differently to compensate for fatigue, even if there is no change in overall lap time. Most prominent across the swimmers is the change in body roll angle and/or timings between hip and shoulder peak rotation time. Three case studies have been extracted to demonstrate the application of the system to highlight the ability to detect individual variation in technique.

		Core Info				
		Time	Velocity	Stroke Count	Stroke Rate	DPS
Swimmer	J	✗	✗	✗	✗	✗
	A	✓	✓	✗	✓	✗
	Ka	✗	✗	✗	✗	✓
	Ki	✓	✓	✗	✓	✗
	M	✗	✗	✗	✗	✗
	O	✗	✗	✗	✗	✗
	R1	✗	✗	✗	✗	✗

		Body Roll							
		Right Lower Angle	Left Lower Angle	Right Upper Angle	Left Upper Angle	Lower Back Symmetry	Upper Back Symmetry	Right Peak Timing	Left Peak Timing
Swimmer	J	✗	✗	✓	✓	✗	✗	✗	✗
	A	✓	✓	✓	✓	✓	✓	✓	✗
	Ka	✓	✓	✓	✓	✓	✓	✓	✓
	Ki	✓	✗	✗	✗	✗	✗	✗	✗
	M	✗	✓	✗	✓	✓	✓	✗	✗
	O	✓	✓	✓	✗	✓	✓	✗	✗
	R1	✗	✗	✓	✓	✓	✗	✗	✓

		Stroke Phases										
		Left Stroke Duration	Right Stroke Duration	Left				Right				IdC
				Entry	Pull	Push	Recovery	Entry	Pull	Push	Recovery	
Swimmer	J	✗	✗	✓	✗	✗	✗	✓	✗	✓	✗	✓
	A	✓	✓	✓	✗	✓	✗	✓	✗	✗	✗	✓
	Ka	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Ki	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗
	M	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗
	O	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗
	R1	✗	✗	✓	✗	✓	✗	✗	✗	✗	✗	✓

Table 21: Summary of individual results

2.1.1 Case Study 1 - R1

Swimmer R1 has reached a National Level. His coach noted that he is a very capable swimmer with a 'nice' stroke. It was noted through the trials that he maybe did not work as hard as he could have, and this was noted by the coach afterwards as well. His full profile is shown in Appendix 0.

2.1.1.1 Core Information

There was no significant difference between each of the core information components for Swimmer R1. There was no significant difference between lap times, Time Pre (M = 16.17, SD = 0.59), Time Post (M = 16.23, SD = 0.5), $t(3) = -0.90$, $p = 0.43$.

There was no significant difference between velocity, Velocity Pre (M = 1.54, SD = 0.05), Velocity Post (M = 1.54, SD = 0.04), $t(3) = 0.97$, $p = 0.40$. There was no significant difference between stroke count, Count Pre (M = 18.5, SD = 1), Count Post (M = 18.25, SD = 0.5), $t(3) = 1$, $p = 0.39$.

There was no significant difference between Stroke Rate, Rate Pre (M = 44.5, SD = 1.38), Rate Post (M = 43.64, SD = 3.85), $t(3) = 1.27$, $p = 0.29$. There was no significant difference between Distance Per Stroke (DPS), DPS Pre (M = 2.09, SD = 0.17), DPS Post (M = 2.13, SD = 0.13), $t(3) = -1.08$, $p = 0.35$.

2.1.1.2 Body Roll

There is no difference in the Left and Right lower body roll angles, Pre and Post fatigue; Right Lower Body roll angle Pre M = 52.11° (SD = 1.41°) and Post M = 53.99° (SD = 3.40°), $t(3) = -1.62$, $p = 0.20$ and Left Lower Body Roll Pre M = 48.98° (SD = 1.73°) and Post M = 47.99° (SD = 2.56°), $t(3) = 1.21$, $p = 0.31$.

However, there is a change in the symmetry index of the lower back angle ($<-10 =$ Right side dominance, $>10 =$ Left side dominance). Where, Pre M = -6.2 (SD = 2.0) and Post M = -11.72 (SD = 2.06). This shows that before fatigue R had symmetry in

his lower body roll (only values greater than 10 show asymmetry), but with fatigue he developed a right side dominance (asymmetry).

However, there is a significant difference in the upper body roll. Right Upper body roll, Pre M = 68.35° (SD = 0.97°) and Post M = 73.14° (SD = 2.06°), $t(3) = -4.82$, $p = 0.01$ and Left Upper body roll angle Pre, M = 55.33°, SD = 3.45° and Post M = 60.44°, SD = 2.89°, $t(3) = -8.31$, $p = 0.00$, showing that R rotates more in his upper body with fatigue. However, the Upper Body Symmetry index shows no significant change, Pre M = -21.17 (SD = 6.22) and Post M = -19.05 (SD = 2.64), $t(3) = -1.05$, $p = 0.37$. This shows that R has a Right side dominance, which does not change with fatigue.

Figure 97 shows how R1's lower back angle does not change over time, on either left or right sides, and that he is very close to the 50 degree angle suggested for lower body roll for skilled swimmers, by Kippenhan and Yanai (1995).

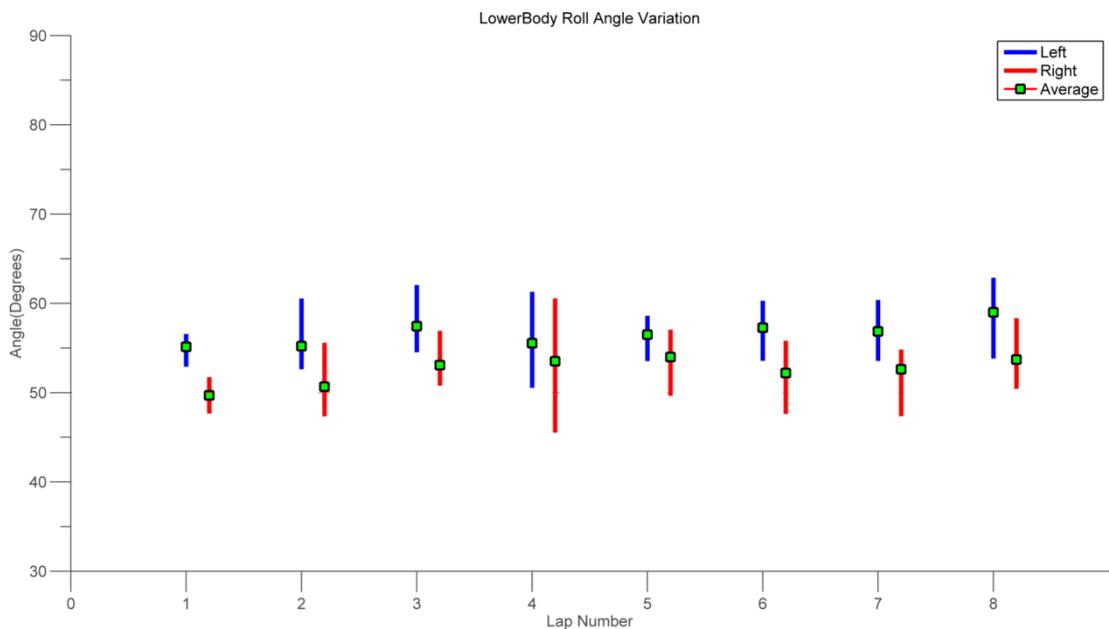


Figure 97: Lower body roll of Swimmer R1 showing average angle and range

Figure 98 shows R1's upper body variation over the 8 laps. His body roll on both sides is lower than a skilled swimmer, whilst his lower body is very good.

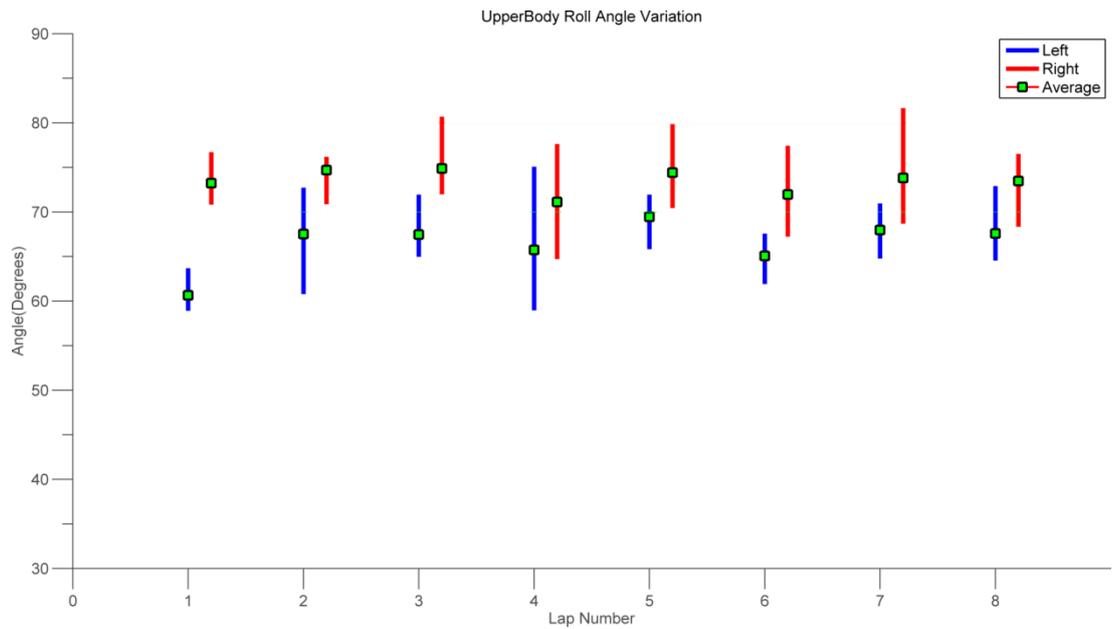


Figure 98: Upper body roll of Swimmer R1 showing average and range

Swimmer R1's body roll angles appear fairly consistent in Figure 98, this is met with a high level of body roll consistency Table 22.

Length	Left Angle	Right Angle	Right Con(%)	Left Con(%)	Left Angle	Right Angle	Right Con(%)	Left Con(%)
L 1	60.64	73.22	96.90	97.15	55.13	49.69	97.45	96.35
L 2	67.51	74.69	94.02	97.34	55.21	50.67	94.31	94.07
L 3	67.46	74.88	95.61	95.69	57.44	53.08	95.24	94.95
L 4	65.74	71.11	90.51	93.32	55.53	53.52	93.20	90.84
L 5	69.46	74.42	96.35	95.19	56.50	54.00	96.34	94.11
L 6	65.06	71.95	96.69	94.30	57.27	52.20	95.49	93.84
L 7	67.98	73.81	96.20	92.94	56.86	52.61	95.74	94.27
L 8	67.58	73.46	95.98	96.06	58.99	53.71	94.42	93.23

Table 22: Average angle for body roll (upper and lower) and the consistency (as a percentage) of Swimmer R1's body roll

There is also a difference in the timing between upper and lower body roll (Figure 99). This is, the timing difference when the upper and lower body both reach their peak angle. As the body roll timings are all above zero, the upper body peaks first, then the lower body follows. This is more pronounced on the right side (Red), although there is no significant difference Pre, $M = 0.04$, $SD = 0.001$ and Post $M = 0.06$, $SD = 0.01$, $t(3) = -1.96$, $p = 0.14$.

There is significant difference on the left side timing between the upper and lower body peak roll times, showing a significant increase in the timings between pre ($M = 0.018$ $SD = 0.003$) and post fatigue ($M = 0.04$, $SD = 0.006$), $t(3) = -4.59$, $p = 0.01$, which shows that the upper body is still rolling first, but the time before the lower body peak is increasing.

Figure 99 shows an increase in the range of the body roll on the left when compared to the right. However, both the left and right show very small standard deviations throughout all 8 laps showing this is a consistent change in the swimmers body roll timings. This could mean that this is heavily engrained in his swimming and could be hard to change through drills.

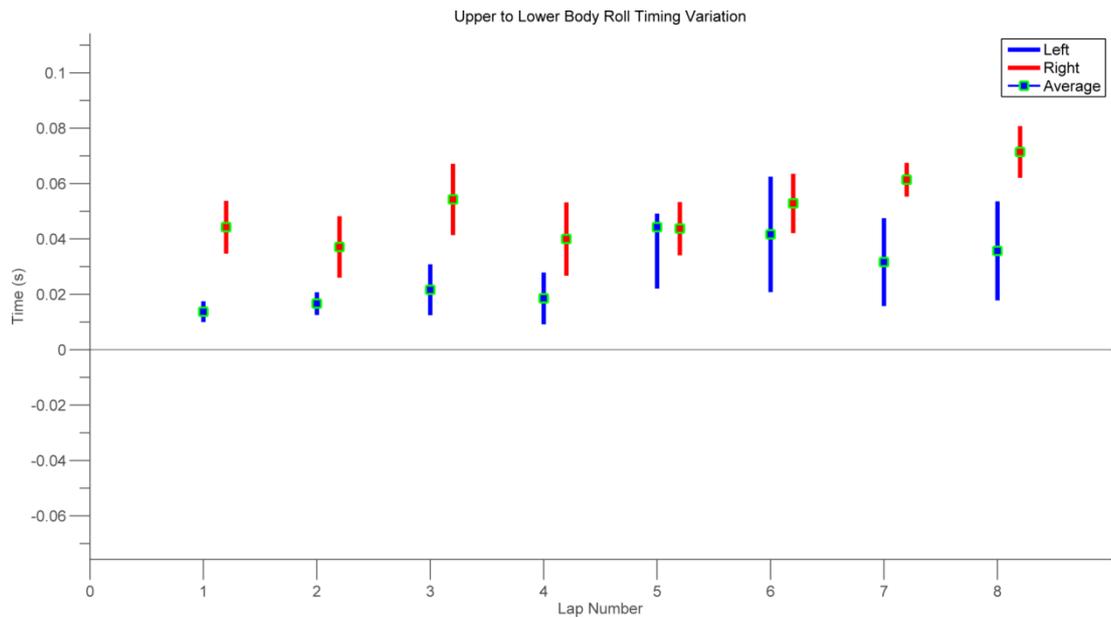


Figure 99: Variation in Upper and Lower Body Roll Timings for Swimmer R1

There does seem to be consistency between his Left and Right arms with similar mean durations per phase and very low standard deviations throughout. Using the symmetry index shows that there are dominant sides to the phases of his stroke. He is right side dominant for his entry phase, left side dominant for the push phase, but equal for the pull and recovery phase, shown in Table 23. There was no change in this with the addition of fatigue.

2.1.1.3 Arm Timings

R's Right stroke duration Pre $M = 1.38s$ ($SD = 0.12s$) and Post $M = 1.39s$ ($SD = 0.13s$) showed no significant difference, $t(3) = -0.8$, $p = 0.48$. This was also shown with no significant differences between each individual phase duration of the stroke. The duration of each phase as a percentage of the whole stroke is shown in Figure 100.

Entry, Pre ($M = 0.09s$, $SD = 0.03s$) and Post ($M = 0.09s$, $SD = 0.04s$), $t(3) = -0.07$, $p = 0.95$.

Pull, Pre (M = 0.40s, SD = 0.09s) and Post (M = 0.41s, SD = 0.09s), $t(3) = -1.08$, $p = 0.36$.

Push, Pre (M = 0.25s, SD = 0.01s) and Post (M = 0.61s, SD = 0.01s), $t(3) = 1.72$, $p = 0.18$.

Recovery, Pre (M = 0.40, SD = 0.09) and Post (M = 0.41s, SD = 0.09s), $t(3) = -1.08$, $p = 0.36$.

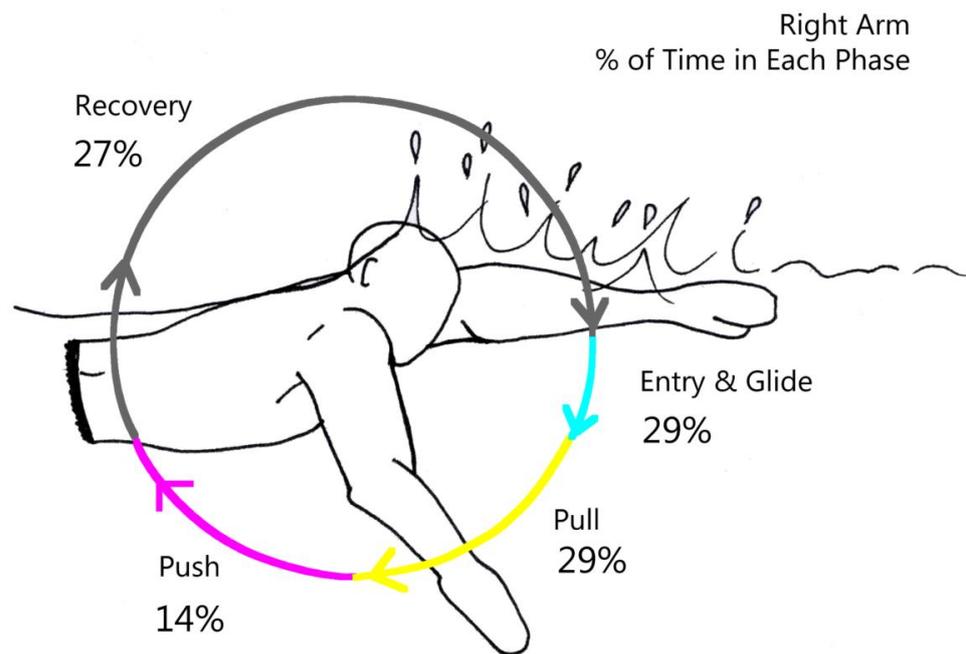


Figure 100: Swimmer R1's average phase duration of the stroke as a percentage of the whole stroke for the right arm

R's Left stroke duration (seconds) Pre (M = 1.37s, SD = 0.12s) and Post (M = 1.40s, SD = 0.11s) showed a significant difference, $t(3) = -3.44$, $p = 0.04$. There was a significant difference in duration on his Entry to Pull Phase, showing a significant decrease in time. There was also a significant increase in time of the Recovery

Phases. The duration as each phase as a percentage of the whole stroke is shown in Figure 101.

Entry, Pre (M = 0.16s, SD = 0.01s) and Post (M = 0.09s, SD = 0.03s), $t(3) = 8.70$, $p = 0.003$.

Pull, Pre (M = 0.4s, SD = 0.07s) and Post (M = 0.41s, SD = 0.05s), $t(3) = -1.37$, $p = 0.26$.

Push, Pre (M = 0.24s, SD = 0.02s) and Post (M = 0.26s, SD = 0.01s), $t(3) = -2.53$, $p = 0.09$.

Recovery, Pre (M = 0.57s, SD = 0.01s) and Post (M = 0.64s, SD = 0.02s), $t(3) = -39$, $p = 0.00$.

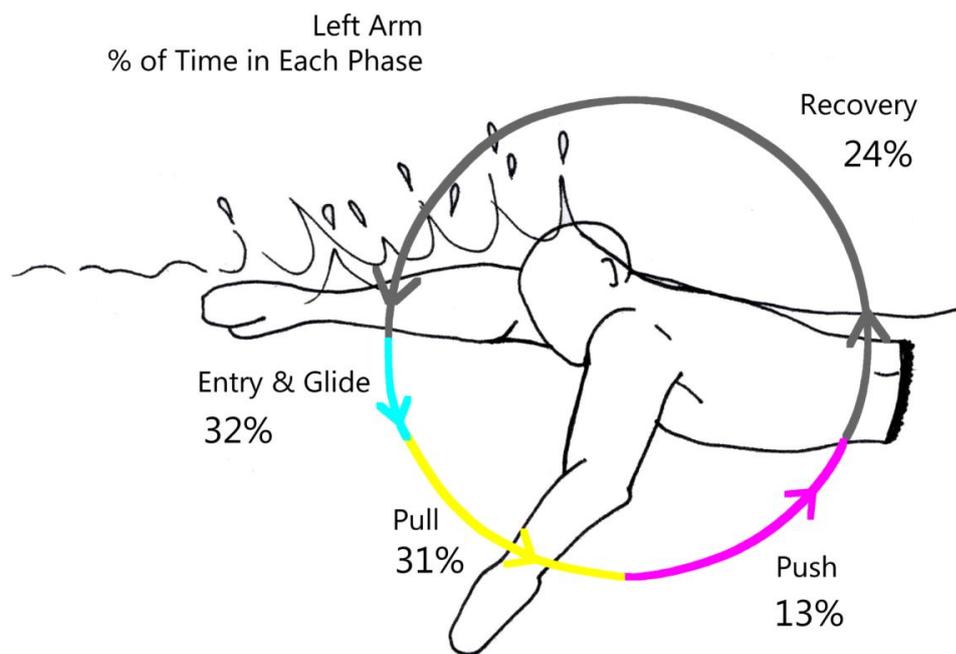


Figure 101: Swimmer R1's average phase duration of the stroke as a percentage of the whole stroke for the left arm

Other than those significant results, there does seem to be consistency between his Left and Right arms with similar mean durations per phase and low standard deviations throughout.

There does seem to be consistency between his Left and Right arms with similar mean durations per phase and very low standard deviations throughout. Using the symmetry index shows that there are dominant sides to the phases of his stroke. He is right side dominant for his push and recovery phases, left side dominant for the entry phase but this changes with fatigue to become equal. This is not found using the T-test method, shown in Table 23.

Symmetry of entry, Pre (M = 14.2, SD = 16.8) and Post (M = 3.5, SD = 14.7), $t(3) = 1.06$, $p = 0.36$.

Symmetry of pull, Pre (M = 3.2, SD = 9.5) and Post (M = 7.1, SD = 10.9), $t(3) = -0.6$, $p = 0.58$.

Symmetry of push, Pre (M = -12.9, SD = 24.8) and Post (M = -11.8, SD = 4.3), $t(3) = -0.09$, $p = 0.93$.

Symmetry of recovery, Pre (M = -17.3, SD = 11.5) and Post (M = -9.4, SD = 5.5), $t(3) = -1.22$, $p = 0.30$.

A used an IdC of -5.4 (SD = 2.7) on the left, utilising an 'opposition' method. With the induction of fatigue, the classification stayed as an 'opposition' style (M = -6.5, SD = 0.9) with no real move from this coordination, $t(3) = 0.69$, $p = 0.53$. On the right side, R1 used an IdC of -5.9 (SD = 2.8), utilising an 'opposition' method. With the induction of fatigue, the classification stayed as an 'opposition' style (M = -6.75, SD = 1.1) but, as with the left, no real change, $t(3) = 0.44$, $p = 0.68$. This also led to no significant change in the symmetry of IdC, Pre (M = -8.7, SD = 7.6) and Post (M = -2.3, SD = 12.5), $t(3) = -0.96$, $p = 0.40$, showing no dominant side for IdC.

Symmetry: Dominant Side

Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Equal	Right	Equal	Equal	Left	Right	Equal	Equal
L 2	Equal	Right	Left	Equal	Left	Equal	Right	Equal
L 3	Equal	Right	Left	Equal	Equal	Equal	Right	Left
L 4	Equal	Right	Left	Equal	Equal	Equal	Right	Equal
L 5	Equal	Right	Right	Equal	Equal	Equal	Equal	Equal
L 6	Right	Right	Equal	Equal	Equal	Equal	Equal	Equal
L 7	Right	Right	Equal	Equal	Right	Left	Equal	Left
L 8	Right	Right	Equal	Equal	Right	Left	Equal	Equal

Table 23: Symmetry of Swimmer R1

2.1.1.4 Summary

R1 maintained his stroke count, length, velocity and stroke rate as well as distance per stroke, with no significant change to lap times.

There was however a change in his upper body roll angle on both left and right sides. On both sides there was an increase of 5°, but there was an asymmetry with a right side dominance in the upper body angle throughout the test. Without fatigue, there was no dominant side in the lower body, but in the second test there was a right side dominance.

There is a significant decrease in the entry-pull duration and increase in the push duration on the left side with fatigue. However, on the right side there is no change with fatigue. This suggests that with an increase upper body roll, and these increased timings, there is an increase in the breathing time of this swimmer suggesting that his cardio vascular side could be lacking in development.

2.1.2 Case Study - Swimmer A

Swimmer A is an Olympic level sprinter, with qualifying times for the London 2012 Olympics but did not quite make the final cut. He is hoping to compete in Rio 2016. His coach has commented on his impressive speed over 25 and 50 m, but his lack of cardio vascular strength and endurance lets him down. It was observed that this swimmer worked very hard during the testing. His full profile is shown in Appendix 4.

2.1.2.1 Core Information

There was a significant difference between lap times, Time Pre M = 15.33 (SD = 0.99), Time Post M = 16.8 (SD = 1.8), $t(3) = -3.62$, $p = 0.036$. This change in time, then led to significant decrease in velocity, Pre (M = 1.64, SD = 0.10), Post M = 1.49 (SD = 0.12), $t(3) = 3.8$, $p = 0.03$.

There was however no significant difference in stroke count, Pre M = 18.25 (SD = 2.06), Post M = 18.5 (SD = 2.08), $t(3) = -1$, $p = 0.39$. And no significant difference in DPS, Pre M = 2.10 (SD = 0.06), Post M = 2.13 (SD = 0.06), $t(3) = -1.86$, $p = 0.15$. There was a significant decrease in stroke rate Pre (M = 46.6, SD = 0.06), stroke rate Post (M = 41.9, SD = 3.77), $t(3) = 5.43$, $p = 0.01$.

2.1.2.2 Body Roll

A's lower back roll increased significantly during the laps, on both the right and left sides. Right Pre M = 41.9° (SD = 2.88°) and Post M = 47.5° (SD = 3.49°), $t(3) = -4.69$, $p = 0.01$. Left Pre M = 40.7° (SD = 2.34°) and Post M = 43.9° (SD = 2.59°), $t(3) = -3.79$, $p = 0.03$.

Figure 102 shows that he is slightly lower than the 50° of body roll for a 'skilled' swimmer, but he progresses towards this as he fatigues. There is a significant difference in the symmetry index, Pre M = -2.82 (SD = 1.68) and Post M = -7.73 (SD = 2.57), $t(3) = 4.79$, $p = 0.01$. This shows that the difference between the body roll on each side is starting to increase, which can be seen in Figure 102, with the right side starting to roll further than the left side. However, both of these symmetry

values are less than -10, so whilst there is a right side dominance, this is not of immediate concern, but the overall body roll angles need to be increased.

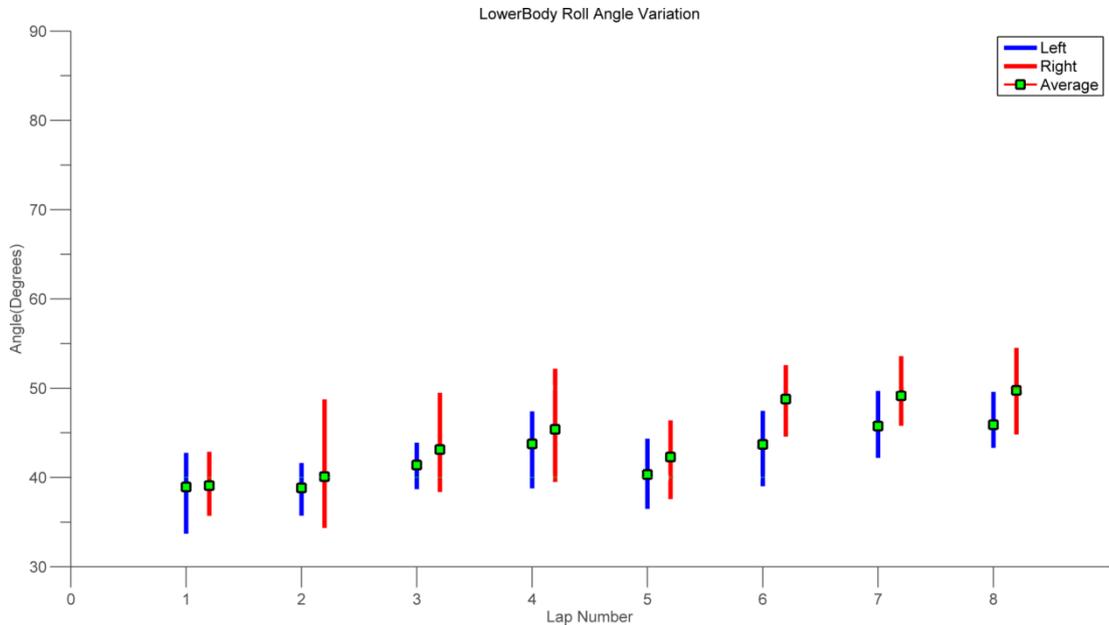


Figure 102: Lower body roll of Swimmer A showing average angle and range

A's upper back roll also changed significantly during the laps. On his right side there is a significant increase, Right Pre M = 48.6° (SD = 1.87°) and Post M = 65.0° (SD = 0.66°), $t(3) = -23.06$, $p = 0.00$. Whilst on the left there is a significant decrease, Left Pre M = 79.7° (SD = 3.66°) and Post M = 62.1° (SD = 6.57°), $t(3) = 10.38$, $p = 0.00$. With a range difference of nearly 30° it is unsurprising to also see a significant difference in the symmetry of the upper back, Pre M = 48.53 (SD = 6.18), Post M = -5.03 (SD = 11.5), $t(3) = 13.05$, $p = 0.00$, showing a dominant left side pre fatigue, and good symmetry (less than -10) with fatigue. Figure 103 shows a large variation in the first 4 laps between left and right side. This seems to settle down with fatigue.

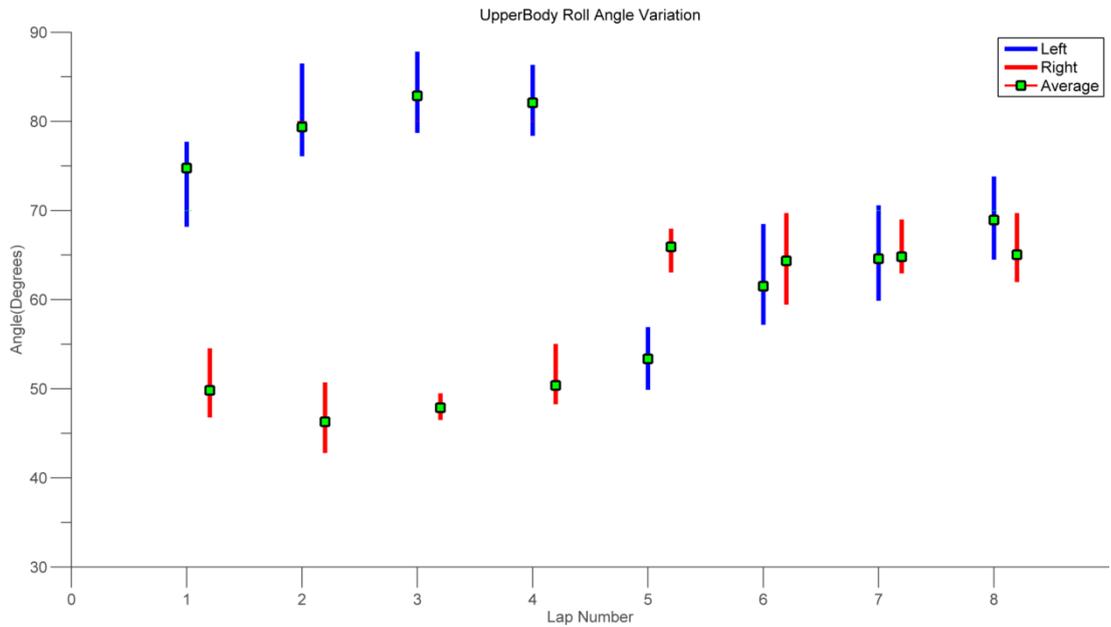


Figure 103: Upper body roll of Swimmer A showing average and range

Swimmer A appears to have very large variation in his body roll angle, however, he is consistent with attaining this average angle, per lap, showing typically over 90% consistency for both left and right side of the body (Table 24).

Length	Left Angle	Right Angle	Right Con(%)	Left Con(%)	Left Angle	Right Angle	Right Con(%)	Left Con(%)
L 1	74.76	49.81	95.44	94.36	38.93	39.08	92.26	91.52
L 2	79.37	46.29	95.72	94.15	38.84	40.09	93.87	87.76
L 3	82.87	47.87	96.05	97.55	41.39	43.13	95.25	89.44
L 4	82.08	50.37	96.38	95.23	43.77	45.39	94.26	90.84
L 5	53.35	65.91	94.17	97.46	40.33	42.30	92.80	92.69
L 6	61.50	64.34	93.93	94.54	43.70	48.77	93.96	94.43
L 7	64.58	64.81	94.38	97.06	45.76	49.16	95.14	93.78
L 8	68.93	65.04	95.94	96.27	45.91	49.76	95.21	94.06

Table 24: Average angle for body roll (upper and lower) and the consistency (as a percentage) of Swimmer A's body roll

In spite of the large variations in the angles shown by A, his timing remains fairly consistent between peak upper and lower body rolls (Figure 104). There is no significant difference on the left side, Pre M = 0.002s (SD = 0.009s), Post M = -0.001s (SD = 0.013s), $t(3) = 0.86$, $p = 0.45$. There is however a significant difference on the right side, Pre M = 0.019s (SD = 0.007s), Post M = 0.01s (SD = 0.006), $t(3) = 5.06$, $p = 0.01$.

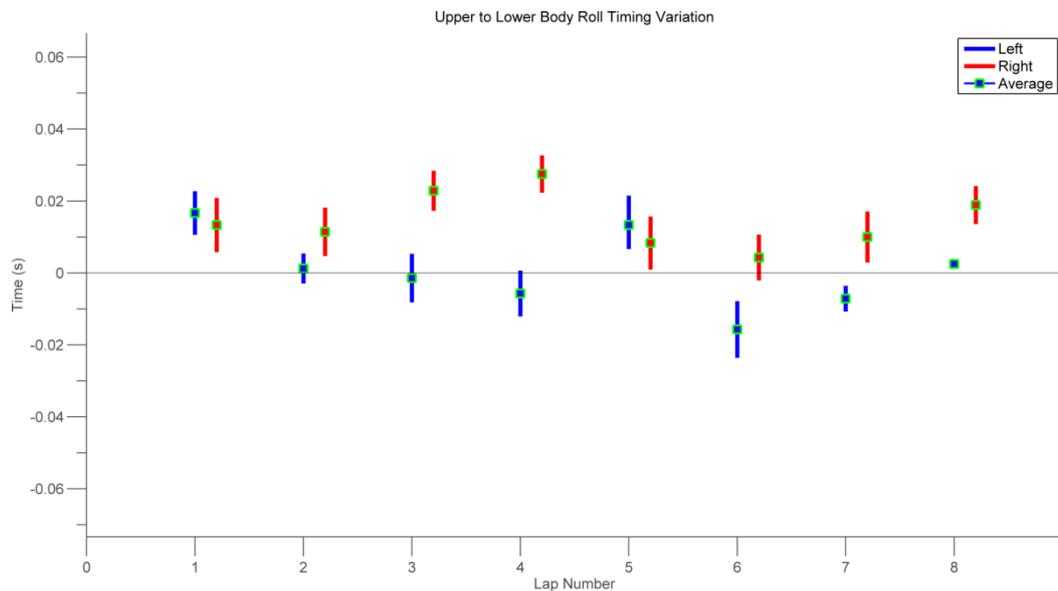


Figure 104: Variation in Upper and Lower Body Roll Timings for Swimmer A

2.1.2.3 Arm timings

A's Right stroke duration Pre M = 1.29s (SD = 0.09s) and Post M = 1.43s (SD = 0.12s) showed a significant difference, $t(3) = -4.99$, $p = 0.01$. This duration increase was shown to come from the entry and push phase of the stroke, with no significant changes from any other phases. The duration as each phase as a percentage of the whole stroke is shown in Figure 105.

Entry, Pre (M = 0.38s, SD = 0.06s) and Post (M = 0.50s, SD = 0.08s), $t(3) = -8.00$, $p = 0.00$.

Pull, Pre (M = 0.23s, SD = 0.03s) and Post (M = 0.21s, SD = 0.00s), $t(3) = 0.98$, $p = 0.39$.

Push, Pre (M = 0.25s, SD = 0.00s) and Post (M = 0.30s, SD = 0.02s), $t(3) = -4.22$, $p = 0.02$.

Recovery, Pre (M = 0.41, SD = 0.00) and Post (M = 0.41s, SD = 0.122s), $t(3) = -0.03$, $p = 0.98$.

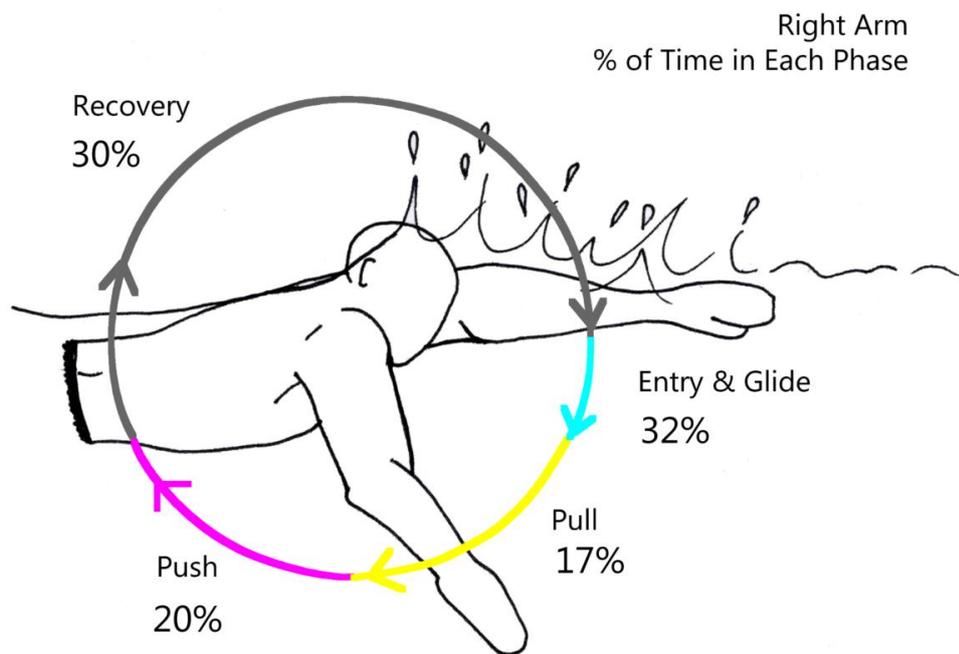


Figure 105: Swimmer A's average phase duration of the stroke as a percentage of the whole stroke for the right arm

A's Left stroke duration (seconds) Pre (M = 1.29s, SD = 0.09s) and Post (M = 1.45s, SD = 0.08s) showed a significant difference, $t(3) = -8.95$, $p = 0.00$. This was attributed to significant increases in the duration of the entry and push phases of the stroke. The duration of the phases is shown in Figure 106.

Entry, Pre (M = 0.36s, SD = 0.08s) and Post (M = 0.46s, SD = 0.09s), $t(3) = -5.05$, $p = 0.01$.

Pull, Pre (M = 0.22s, SD = 0.00s) and Post (M = 0.22s, SD = 0.00s), $t(3) = 0.29$, $p = 0.79$.

Push, Pre (M = 0.30s, SD = 0.01s) and Post (M = 0.35s, SD = 0.01s), $t(3) = -5.55$, $p = 0.01$.

Recovery, Pre (M = 0.40s, SD = 0.01s) and Post (M = 0.41s, SD = 0.03s), $t(3) = -0.79$, $p = 0.48$.

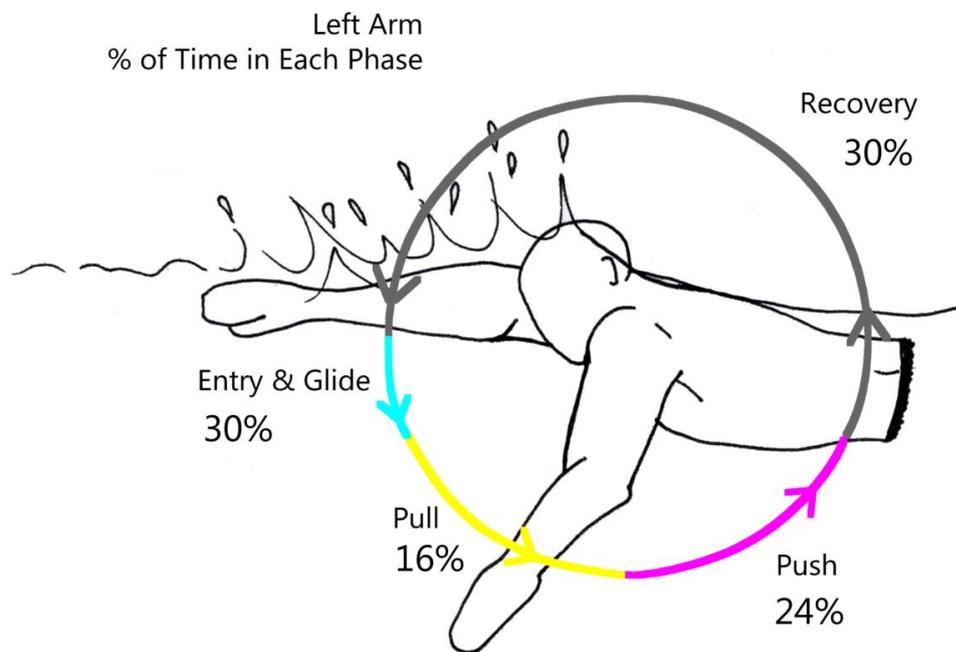


Figure 106: Swimmer A's average phase duration of the stroke as a percentage of the whole stroke for the left arm

There does seem to be consistency between his Left and Right arms with similar mean durations per phase and very low standard deviations throughout. Using the symmetry index shows that there are dominant sides to the phases of his stroke. He is right side dominant for his entry phase, left side dominant for the push phase, but equal for the pull and recovery phase, shown in Table 25. There was no change in this with the addition of fatigue.

Symmetry of entry, Pre (M = -7.5, SD = 7.41) and Post (M = -8.75, SD = 3.90), $t(3) = 0.47$, $p = 0.66$.

Symmetry of pull, Pre (M = -4.6, SD = 15.10) and Post (M = 2.20, SD = 1.84), $t(3) = -1.01$, $p = 0.39$.

Symmetry of push, Pre (M = 19.1, SD = 3.36) and Post (M = 15.18, SD = 4.49), $t(3) = 1.09$, $p = 0.35$.

Symmetry of recovery, Pre (M = -2.8, SD = 2.20) and Post (M = 0.5, SD = 8.39), $t(3) = -0.63$, $p = 0.57$.

A used an IdC of -10.5 (SD = 1.46) on the left, utilising an 'opposition' method. With the induction of fatigue, the classification stayed as an 'opposition' style (M = -11.69, SD = 1.89) but moving further away from 'catch-up' technique, with a significant change, $t(3) = 3.46$, $p = 0.04$. On the right side, K used an IdC of -10.5 (SD = 1.06), utilising an 'opposition' method. With the induction of fatigue, the classification stayed as an 'opposition' style (M = -11.61, SD = 1.65) but, as with the left, moving further from a 'catch-up' technique but there was no significant change, $t(3) = 3.57$, $p = 0.03$. This also led to no significant change in the symmetry of IdC, Pre (M = -0.68, SD = 5.83) and Post (M = 0.42, SD = 2.60), $t(3) = -0.48$, $p = 0.66$, showing no dominant side for IdC.

Symmetry: Dominant Side								
Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Equal	Left	Equal	Equal	Equal	Equal	Left	Equal
L 2	Equal	Left	Equal	Equal	Right	Equal	Left	Equal
L 3	Equal	Left	Equal	Equal	Equal	Equal	Left	Equal
L 4	Equal	Left	Equal	Equal	Equal	Right	Left	Equal
L 5	Equal	Right	Equal	Equal	Right	Equal	Left	Left
L 6	Right	Equal	Equal	Equal	Right	Equal	Left	Equal
L 7	Equal	Equal	Equal	Equal	Equal	Equal	Left	Equal
L 8	Equal	Equal	Equal	Equal	Equal	Equal	Left	Equal

Table 25: Symmetry table showing the dominant side for a variety of A's factors over each lap

2.1.2.4 Summary

He maintained his stroke count and length but because his lap times decreased, his stroke rate decreased. This shows, on the face of it, that technique appears to be maintained and there is just a temporal variation.

With his body roll, there is around 20° of variation in upper body roll angle with fatigue, although his timing of body roll (between upper and lower back) on the left side is very consistent. All of his right side results (Figure 104) show a positive value showing his upper body peaks before his lower body, however, the values of 0.007s are very small to realistically alter through drills. These values may naturally change with technique and endurance development and should be investigated again by the coach.

2.1.3 Case Study - Swimmer Ka

Swimmer K is a former national level swimmer. He took a two year career break and is building back up to competition level. He is hoping to compete in 2014/15. His full profile is shown in Appendix 4.

2.1.3.1 Core Information

There was no significant difference between each of the core information components for swimmer KA. There was no significant difference between lap times, Time Pre (M = 16.08, SD = 0.81), Time Post (M = 15.9, SD = 0.65), $t(3) = 1.27$, $p = 0.29$.

Whilst the mean velocity increased in the second test, there was no significant difference between them, Velocity Pre (M = 1.55, SD = 0.08), Velocity Post (M = 1.57, SD = 0.06), $t(3) = -1.14$, $p = 0.33$. There was no significant difference between stroke count, Count Pre (M = 14.25, SD = 0.5), Count Post (M = 15, SD = 1.4), $t(3) = -1.56$, $p = 0.21$.

There was no significant difference between Stroke Rate, Rate Pre (M = 37.67, SD = 2.55), Rate Post (M = 39.59, SD = 1.52), $t(3) = -2.64$, $p = 0.07$. There was a significant decrease in Distance Per Stroke (DPS), DPS Pre (M = 2.48, SD = 0.10), DPS Post (M = 2.38, SD = 0.04), $t(3) = 3.30$, $p = 0.04$.

2.1.3.2 Body Roll

Ka's lower back roll increased significantly on the right side during the laps. Right Pre M = 56.9° (SD = 3.7°) and Post M = 64.4° (SD = 3.4°), $t(3) = -31.58$, $p = 0.00$. But decreased significantly on the Left. Left Pre M = 55.6° (SD = 0.7°) and Post M = 51.0° (SD = 0.6°), $t(3) = 13.22$, $p = 0.00$.

Figure 107 shows that over the duration of the trial there is a steady deviation in the lower body roll angle. There is a significant decrease in the symmetry index, Pre M = -2.2 (SD = 7.39) and Post M = -23.03 (SD = 5.47), $t(3) = 16.41$, $p = 0.00$. This

only shows an increase in the use of his right side, where he with no dominant side (-2.2), this changed to show a dominant right side with fatigue (-23.03).

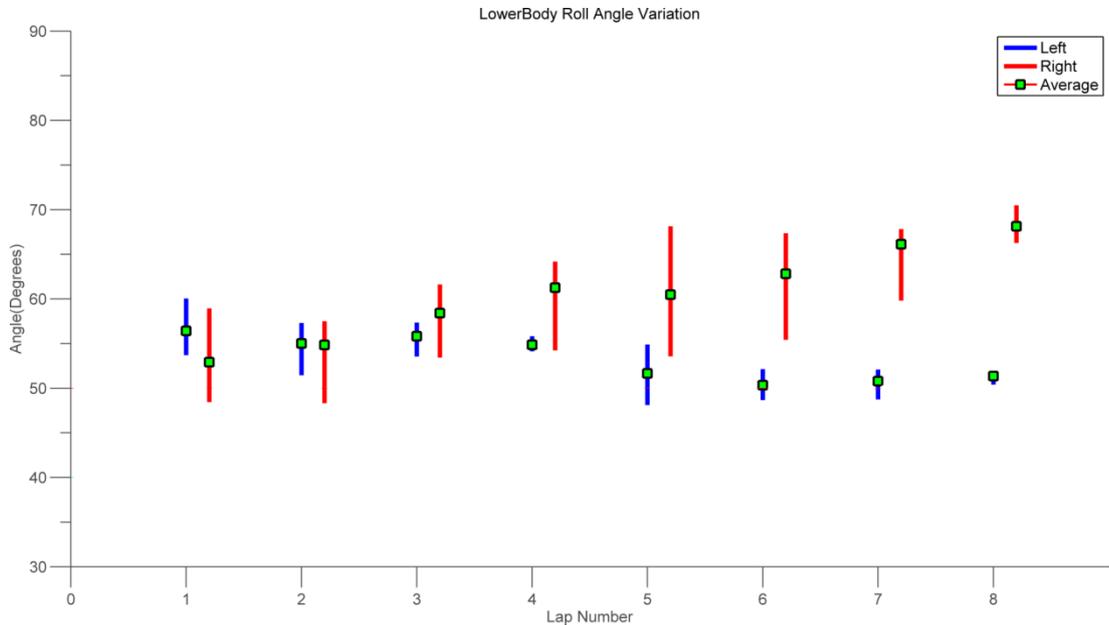


Figure 107: Lower body roll of Swimmer Ka showing average angle and range

Ka's upper back roll also changed significantly during the laps on both sides. On his right side there was a significant decrease, Right Pre M = 68.6° (SD = 1.2°) and Post M = 57.2° (SD = 1.2°), $t(3) = 13.64$, $p = 0.00$. Whilst on the left there was a significant increase, Left Pre M = 63.9° (SD = 1.2°) and Post M = 70.5° (SD = 1.5°), $t(3) = -5.3$, $p = 0.01$. With this difference between sides, there was also a significant change in the symmetry index for the upper back body roll. Pre M = -6.99 (SD = 3.38), Post M = 20.81 (SD = 2.05), $t(3) = -13.59$, $p = 0.00$, showing a shift in the dominant sides from no clear dominant side to Left dominant side. It should be noted that the Pre M score for symmetry does not exceed 10, which is required for a dominant side. However, there is an increase in the standard deviation, resulting in times where there will be right dominance.

Figure 108 shows that in the first 4 laps, Ka shows a 'good' level of body roll, within that stated by the literature, but perhaps on the high side, with 60° being a recommended upper limit (Newsome and Young 2012).

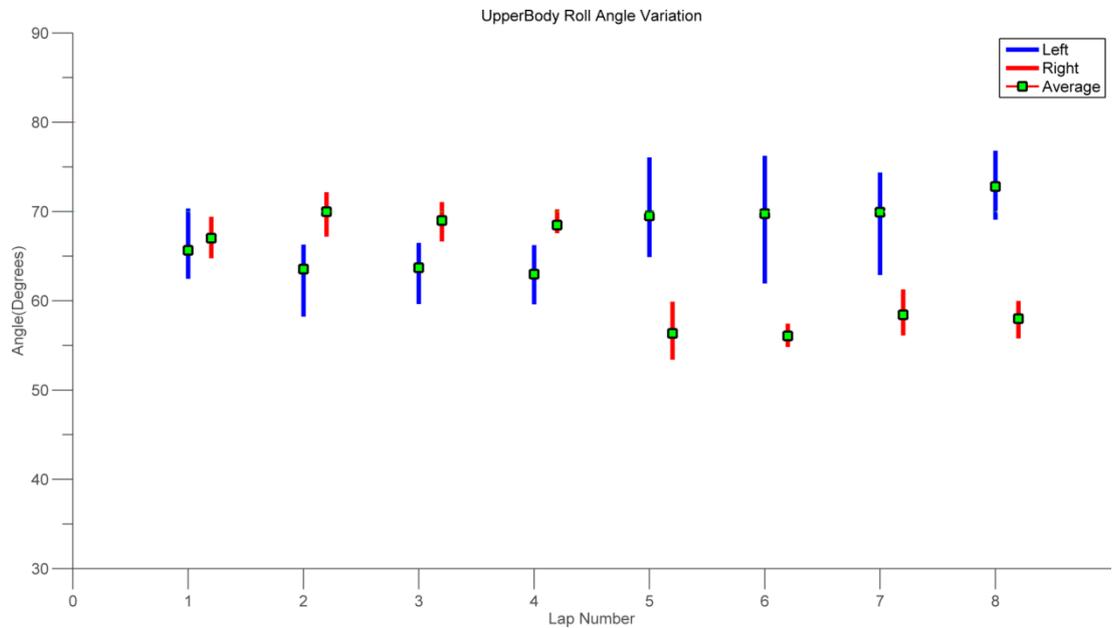


Figure 108: Upper body roll of Swimmer Ka showing average angle and range

Swimmer Ka also showed a great deal of consistency with his body roll for both upper and lower body, and both sides. Typically scoring well into the 90% consistency bracket Table 26.

Body Roll Angles and Consistency (%) (Upper, Lower)								
Length	Left Angle	Right Angle	Right Con(%)	Left Con(%)	Left Angle	Right Angle	Right Con(%)	Left Con(%)
L 1	65.65	67.01	93.97	96.79	56.42	52.91	95.51	91.40
L 2	63.56	69.97	94.30	97.44	55.01	54.84	95.82	92.05
L 3	63.70	68.99	95.47	97.70	55.82	58.41	97.19	94.75
L 4	62.98	68.47	95.79	98.46	54.86	61.26	98.71	94.11
L 5	69.51	56.35	92.12	94.97	51.65	60.48	94.55	89.61
L 6	69.76	56.06	89.97	97.96	50.33	62.82	97.37	91.07
L 7	69.92	58.43	93.90	96.75	50.78	66.13	97.17	95.30
L 8	72.80	57.99	95.35	96.84	51.35	68.13	98.58	97.60

Table 26: Average angle for body roll (upper and lower) and the consistency (as a percentage) of Swimmer Ka's body roll

With the variation in upper and lower body angles, swimmer Ka also experienced significant changes in the timing of the body roll peaks on both sides. On his right side there was a significant decrease, Right Pre M = 0.073s (SD = 0.01s) and Post M = -0.14 (SD = 0.01), $t(3) = 65.62$, $p = 0.00$. This decrease was also shown on the left side with a significant decrease, Left Pre M = -0.02 (SD = 0.02s) and Post M = -0.20s (SD = 0.01), $t(3) = 14.85$, $p = 0.00$. This is illustrated in Figure 109 showing that before fatigue, the upper body tends to roll first, with the lower body lagging. This more so on the right side than the left. On the left, before fatigue, there is a range of times where they are equal, or the lower body will roll first. With fatigue however, both side of the body result in the lower body rolling to its peak before the upper body. The left side also has larger standard deviations in this timing.

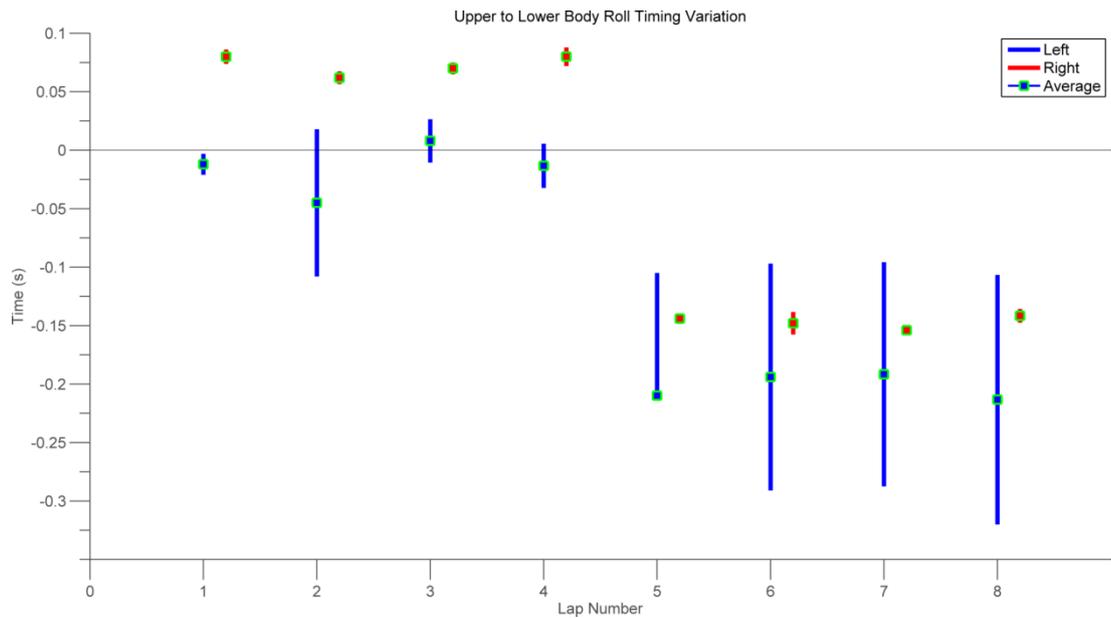


Figure 109: Body roll timings for Swimmer Ka

2.1.4 Arm timings

Ka's Right stroke duration Pre $M = 1.58s$ ($SD = 0.09s$) and Post $M = 1.51s$ ($SD = 0.06s$) showed a significant difference, $t(3) = 3.35$, $p = 0.04$. This duration increase was shown to come from the recovery phase of the stroke, with no significant changes from any other phases. The duration as each phase as a percentage of the whole stroke is shown in Figure 110.

Entry, Pre ($M = 0.47s$, $SD = 0.05s$) and Post ($M = 0.42s$, $SD = 0.03s$), $t(3) = -0.08$, $p = 2.48$.

Pull, Pre ($M = 0.27s$, $SD = 0.09s$) and Post ($M = 0.22s$, $SD = 0.00s$), $t(3) = 1.12$, $p = 0.08$.

Push, Pre ($M = 0.36s$, $SD = 0.09s$) and Post ($M = 0.42s$, $SD = 0.01s$), $t(3) = -1.29$, $p = 0.28$.

Recovery, Pre ($M = 0.46$, $SD = 0.01$) and Post ($M = 0.43s$, $SD = 0.05s$), $t(3) = -3.69$, $p = 0.03$.

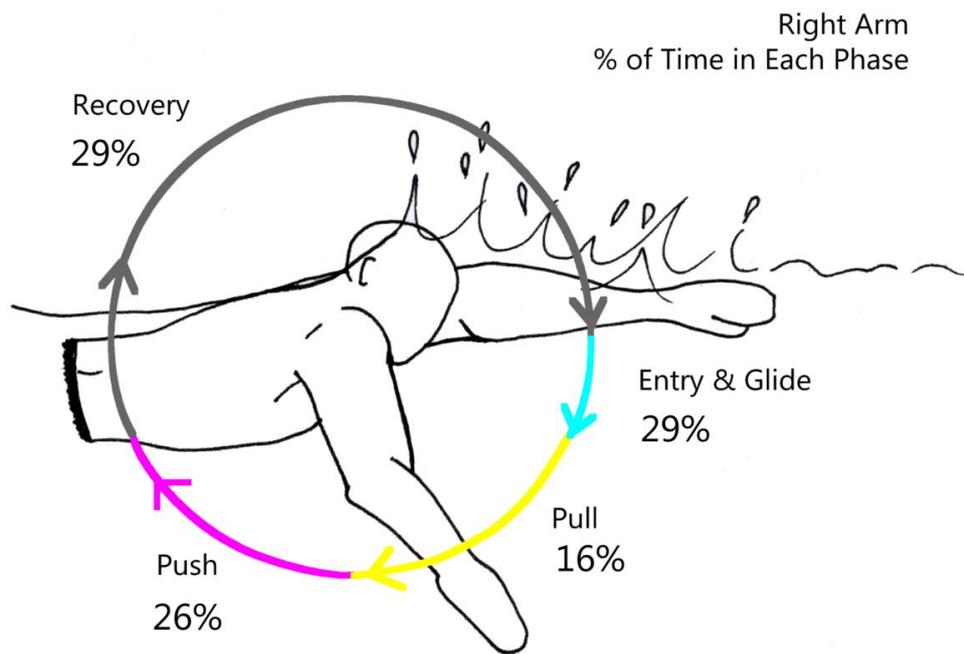


Figure 110: Swimmer Ka's average phase duration of the stroke as a percentage of the whole stroke for the right arm

R's Left stroke duration (seconds) Pre (M = 1.58s, SD = 0.09s) and Post (M = 1.50s, SD = 0.05s) showed no significant difference, $t(3) = 2.42$, $p = 0.09$. There was also no significant difference in any of the phases of the stroke. The duration of the phases is shown in Figure 111.

Entry, Pre (M = 0.28s, SD = 0.03s) and Post (M = 0.27s, SD = 0.02s), $t(3) = 0.85$, $p = 0.45$.

Pull, Pre (M = 0.31s, SD = 0.01s) and Post (M = 0.28s, SD = 0.01s), $t(3) = -2.76$, $p = 0.07$.

Push, Pre (M = 0.51s, SD = 0.11s) and Post (M = 0.51s, SD = 0.07s), $t(3) = -0.08$, $p = 0.93$.

Recovery, Pre (M = 0.48s, SD = 0.02s) and Post (M = 0.44s, SD = 0.03s), $t(3) = 2.2$, $p = 0.11$.

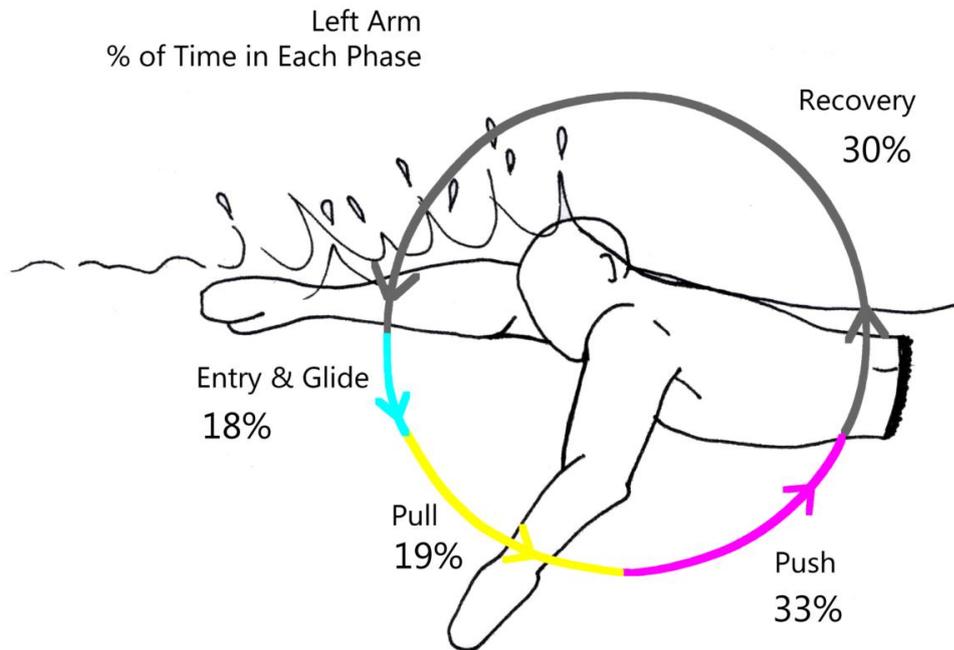


Figure 111: Swimmer Ka's average phase duration of the stroke as a percentage of the whole stroke for the left arm

Other than those significant results, there does seem to be consistency between his Left and Right arms with similar mean durations per phase and low standard deviations throughout. However, using the symmetry index shows that there are dominant sides to his stroke. He is right side dominant for his entry phase, left side dominant for the pull and push phases, but equal for the recovery phase, shown in Table 27. There is also no change in this with the addition of fatigue.

Symmetry of entry, Pre (M = -51.27, SD = 14.55) and Post (M = -46.35, SD = 3.58), $t(3) = -0.67$, $p = 0.54$.

Symmetry of pull, Pre (M = 13.17, SD = 33.14) and Post (M = 23.14, SD = 8.38), $t(3) = -0.77$, $p = 0.50$.

Symmetry of push, Pre (M = 34.61, SD = 40.45) and Post (M = 18.75, SD = 11.67), $t(3) = 0.99$, $p = 0.39$.

Symmetry of recovery, Pre (M = 2.65, SD = 6.84) and Post (M = 0.47, SD = 10.40), $t(3) = 0.89$, $p = 0.43$.

Before fatigue, Ka used an IdC of -4.0 (SD = 1.76) on the left, utilising an 'opposition' method. With the induction of fatigue, the classification stayed as an 'opposition' style (M = -1.9, SD = 1.34) but moving towards a 'catch-up' technique with a significant change, $t(3) = -3.84$, $p = 0.03$. On the right side, Ka used an IdC of -6.9 (SD = 6.40), utilising an 'opposition' method. With the induction of fatigue, the classification stays as an 'opposition' style (M = -2.13, SD = 1.19) but seeming to move towards a 'catch-up' technique but there was no significant change, $t(3) = -1.5$, $p = 0.22$.

Symmetry: Dominant Side

Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Equal	Equal	Right	Equal	Right	Left	Right	Left
L 2	Equal	Equal	Right	Equal	Right	Right	Left	Equal
L 3	Equal	Equal	Equal	Equal	Right	Left	Left	Equal
L 4	Right	Equal	Left	Equal	Right	Left	Left	Equal
L 5	Right	Left	Equal	Equal	Right	Left	Equal	Left
L 6	Right	Left	Equal	Equal	Right	Left	Left	Equal
L 7	Right	Left	Equal	Equal	Right	Left	Left	Equal
L 8	Right	Left	Right	Equal	Right	Left	Left	Equal

Table 27: Symmetry table showing the dominant side for a variety of Ka's factors over each lap

2.1.5 Summary of Results

Swimmer Ka shows a relatively stable arm stroking method, with little variation in the duration of the phases, and no changes in the symmetry of the arm phases. The coordination changes on the left side, but stays as a opposition method stroke. The largest variation is in the body roll. There are changes in the body roll angle between upper and lower body, and on each side with significant changes to the symmetry and timings between the peak rolls. Despite the changes in this body roll, he maintains his lap times.

3 Swimmer R1 Profile

R1

Swimming Profile 30/11/12

Training Notes:

4 x 25m (With devices on, Race Pace)
 Around 2 minutes to remove devices
 8 x 25m (Race Pace, no devices, to generate fatigue)
 Around 5 minutes to re-attached devices
 4 x 25m (With devices on, Race Pace)

Summary - Core Info

Time	Avg.Vel	Count	Rate	DistPerS(m)
No	No	No	No	No

Summary - Body Roll

Lower Angle (L)	Lower Angle (R)	Upper Angle (L)	Upper Angle (R)	Timing (L)	Timing (R)
No	No	No	No	No	No

Summary - Stroke Duration

Left	Right	Left IdC	Right IdC
No	No	No	No

Summary - Left Stroke Phase Duration

Entry	Push	Pull	Recovery
No	No	No	No

Summary - Right Stroke Phase Duration

Entry	Push	Pull	Recovery
No	No	No	No

Overview

These tables show if there is there a difference before and after fatigue.

If there is a differences in the core info, the tables below show where these changes occurred. If there is no difference in the core info, the tables show potential compensation strategies to ensure consistent lap times/rate etc.

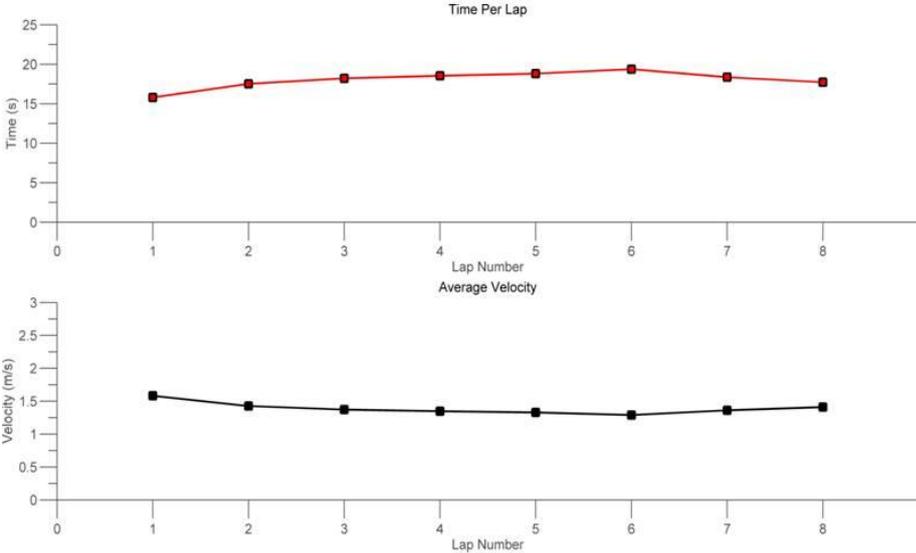
Overview



Core Info

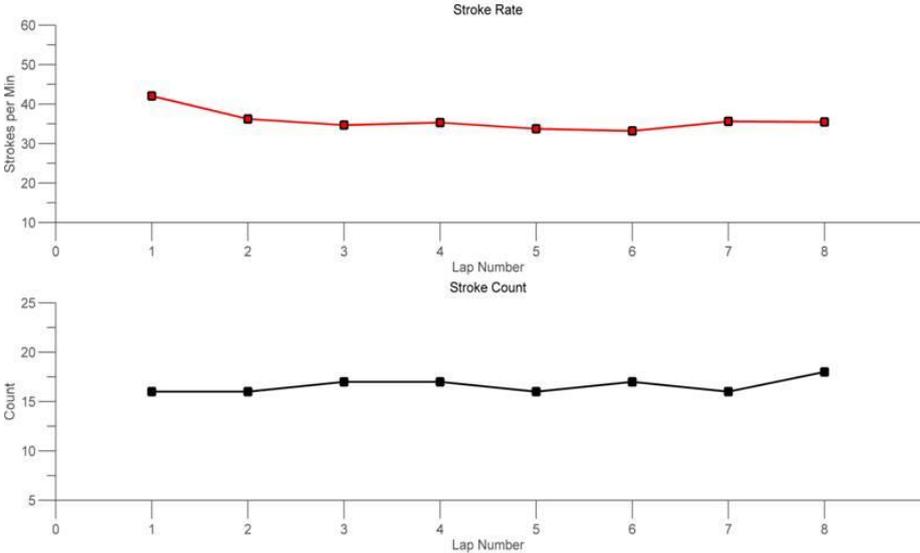
Length	Time (S)	Stroke Count	Stroke Rate	Avg.Vel(m/s)	DistPerS(m)
L 1	15.79	16	42.03	1.58	2.26
L 2	17.52	16	36.21	1.43	2.36
L 3	18.21	17	34.65	1.37	2.38
L 4	18.54	17	35.29	1.35	2.29
L 5	18.81	16	33.72	1.33	2.36
L 6	19.38	17	33.19	1.29	2.33
L 7	18.36	16	35.59	1.36	2.30
L 8	17.72	18	35.44	1.41	2.39

Overview

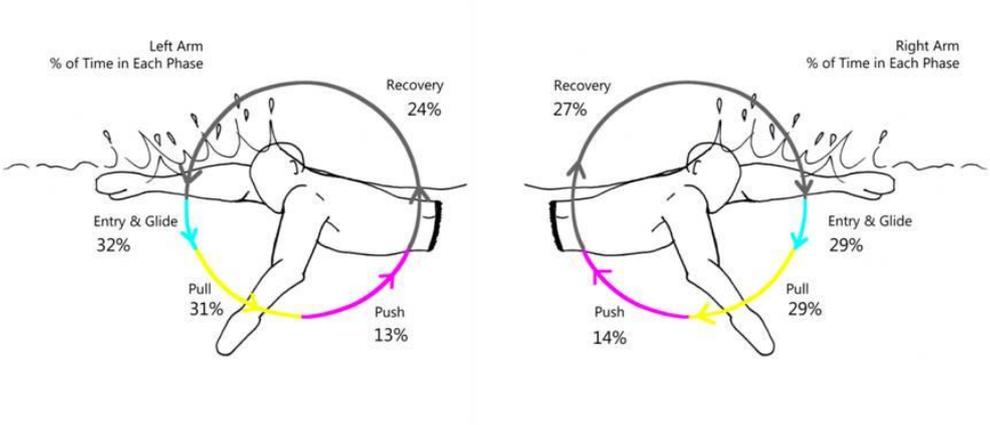


Overview

CORE

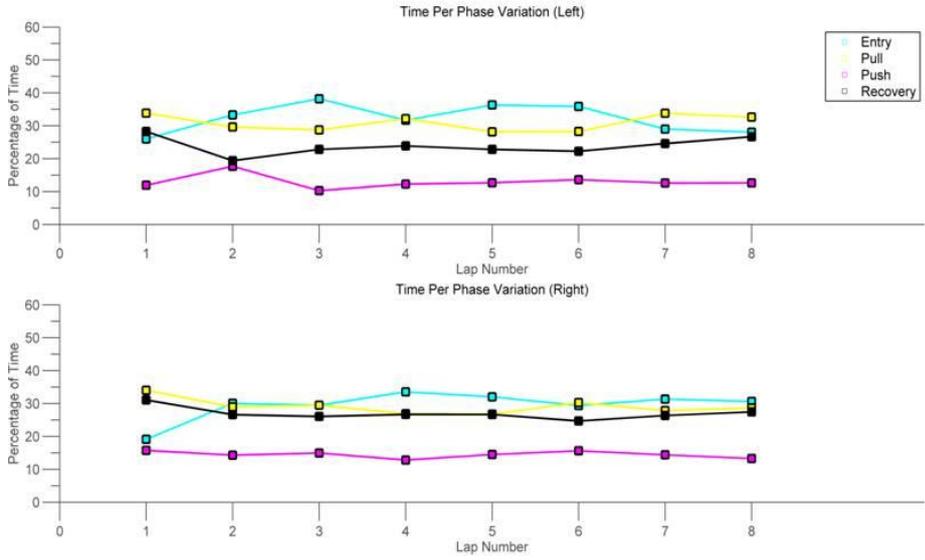


Average Stroke Phase Duration - Overall

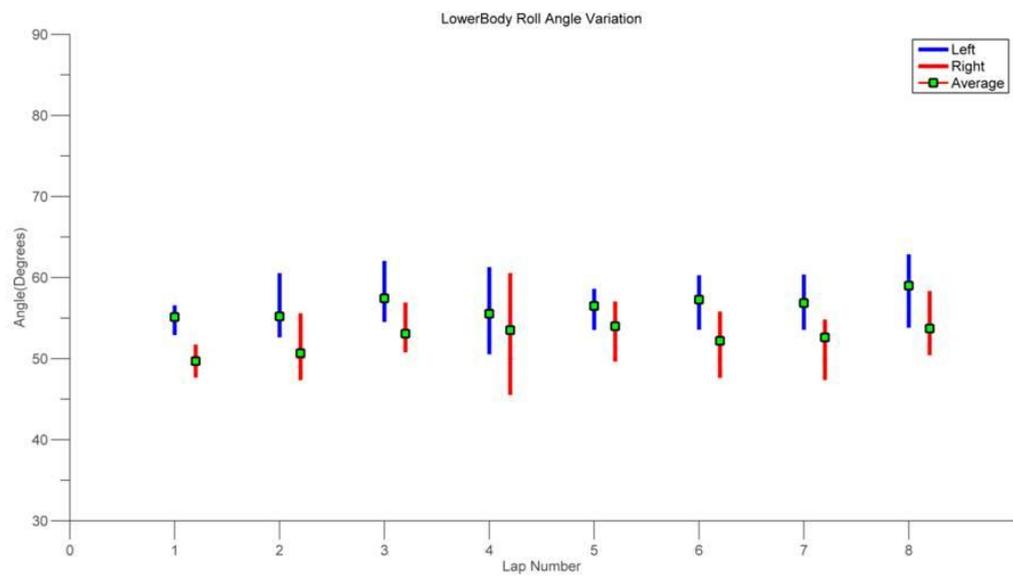


Stroke Phases

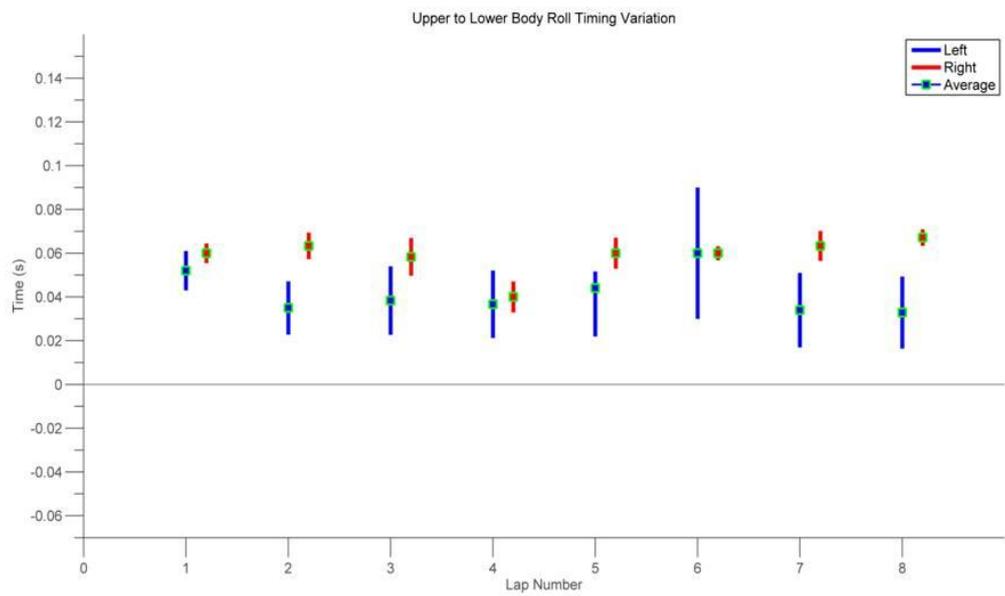
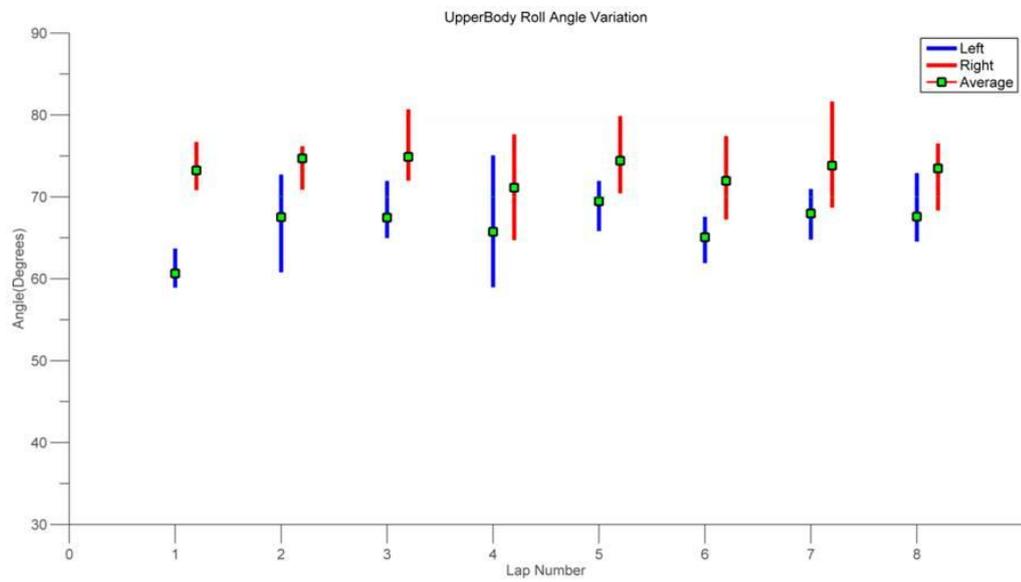
Stroke Phase Duration - Overview



Stroke Phases



Body Roll



Above Zero, Time from Upper body to Lower Body Peak (Upper body first, Lower body lags)

Below Zero, Time from Lower body to Upper Body Peak (Lower body first, Upper body lags)

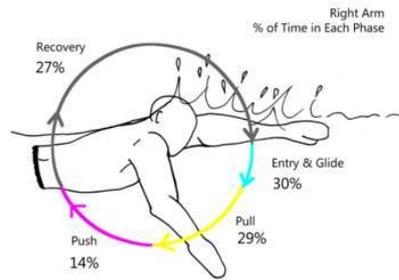
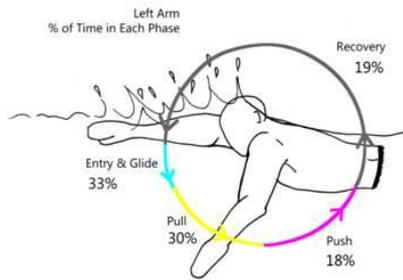
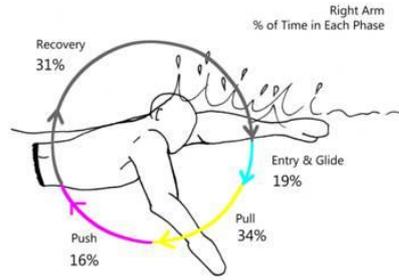
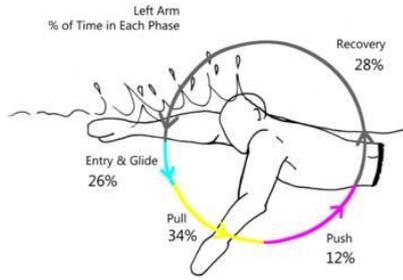
This table tells you which side is dominant showing potential asymmetry

Symmetry: Dominant Side

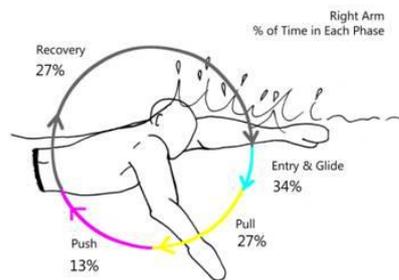
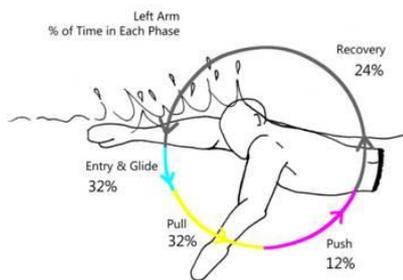
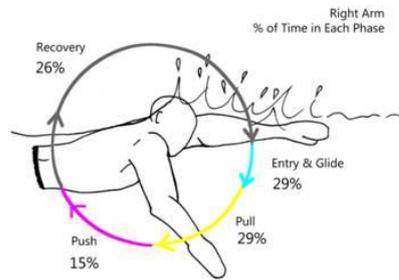
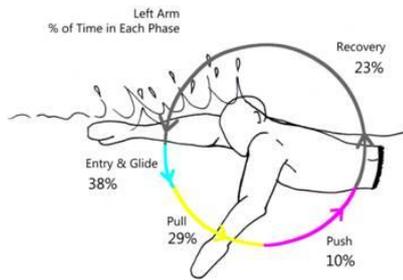
Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Left	Right	Right	Equal	Left	Equal	Right	Equal
L 2	Equal	Right	Right	Equal	Equal	Equal	Left	Right
L 3	Equal	Right	Right	Equal	Left	Equal	Right	Right
L 4	Equal	Equal	Equal	Equal	Equal	Left	Equal	Right
L 5	Equal	Equal	Equal	Equal	Left	Equal	Right	Right
L 6	Equal	Right	Right	Equal	Left	Equal	Right	Right
L 7	Equal	Equal	Left	Equal	Equal	Left	Right	Equal
L 8	Equal	Equal	Equal	Equal	Equal	Left	Equal	Equal

Detailed View

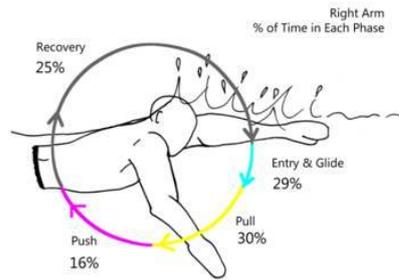
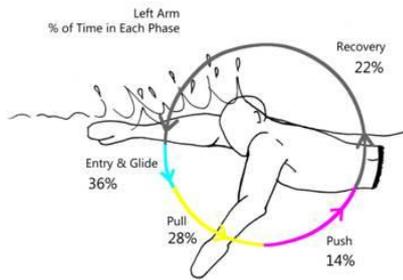
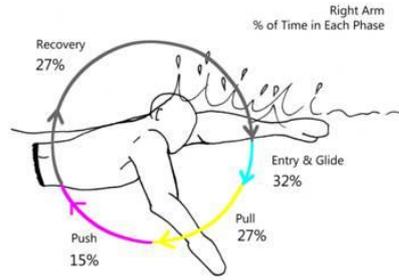
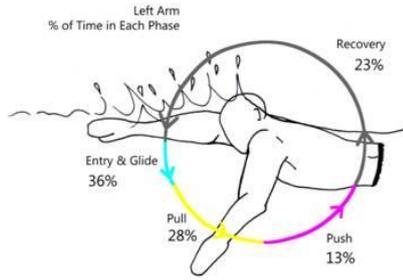
Average Stroke Phase Duration - Lengths 1 & 2



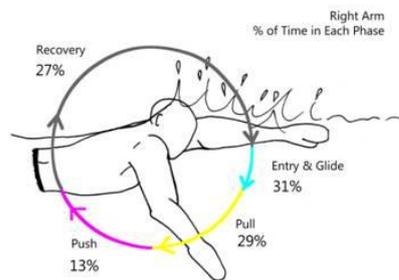
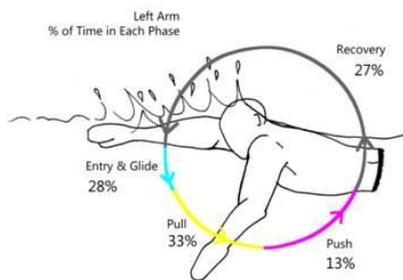
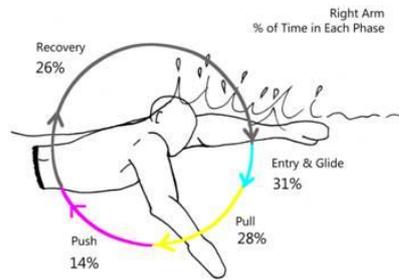
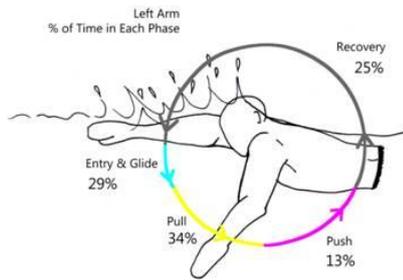
Average Stroke Phase Duration - Lengths 3 & 4



Average Stroke Phase Duration - Lengths 5 & 6



Average Stroke Phase Duration - Lengths 7 & 8



LEFT: Average Duration for Each Phase (Seconds)

Length	Stroke Duration	Entry	Pull	Push	Recovery
L 1	1.43	0.37	0.48	0.17	0.40
L 2	1.64	0.55	0.49	0.29	0.32
L 3	1.75	0.67	0.50	0.18	0.40
L 4	1.71	0.54	0.55	0.21	0.41
L 5	1.77	0.65	0.50	0.23	0.41
L 6	1.83	0.66	0.52	0.25	0.41
L 7	1.71	0.50	0.58	0.21	0.42
L 8	1.67	0.47	0.55	0.21	0.45

RIGHT: Average Duration for Each Phase (Seconds)

Length	Stroke Duration	Entry	Pull	Push	Recovery
L 1	1.42	0.27	0.48	0.22	0.44
L 2	1.69	0.51	0.49	0.24	0.45
L 3	1.76	0.52	0.52	0.26	0.46
L 4	1.72	0.58	0.46	0.22	0.46
L 5	1.79	0.57	0.48	0.26	0.48
L 6	1.83	0.54	0.55	0.29	0.45
L 7	1.72	0.54	0.48	0.25	0.45
L 8	1.68	0.52	0.48	0.22	0.46

Average Index of Coordination (IdC) Per Length

Length	Time	IdC Left	IdC Right
L 1	15.79	-2.06	-2.34
L 2	17.52	-4.45	-4.97
L 3	18.21	-7.41	-8.48
L 4	18.54	-8.07	-7.86
L 5	18.81	-7.66	-8.36
L 6	19.38	-5.28	-6.21
L 7	18.36	-6.84	-6.08
L 8	17.72	-6.61	-6.35

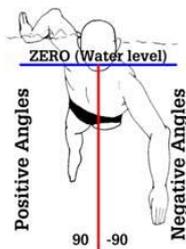
When there is a time lag between the propulsive phases (Push & Pull) of the two arms, the stroke coordination is called 'catch-up'(index of coordination < 0).

When the propulsive phase of one arm started when the other arm ends its propulsive phase, the coordination is called 'opposition' (index of coordination = 0). This shows symmetry in the stroke

When the propulsive phases of the two arms overlapped, the coordination was called 'superposition' (index of coordination > 0). This gives a small period of time where both arms produce propulsion.

Body Roll Angles and Consistency (%) (Upper, Lower)

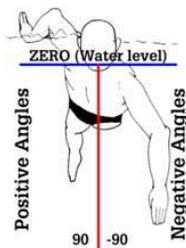
Length	Left Angle	Right Angle	Right Con(%)	Left Con(%)	Left Angle	Right Angle	Right Con(%)	Left Con(%)
L 1	60.64	73.22	96.90	97.15	55.13	49.69	97.45	96.35
L 2	67.51	74.69	94.02	97.34	55.21	50.67	94.31	94.07
L 3	67.46	74.88	95.61	95.69	57.44	53.08	95.24	94.95
L 4	65.74	71.11	90.51	93.32	55.53	53.52	93.20	90.84
L 5	69.46	74.42	96.35	95.19	56.50	54.00	96.34	94.11
L 6	65.06	71.95	96.69	94.30	57.27	52.20	95.49	93.84
L 7	67.98	73.81	96.20	92.94	56.86	52.61	95.74	94.27
L 8	67.58	73.46	95.98	96.06	58.99	53.71	94.42	93.23



Body Roll Angles Per Phase, Upper Body, Left and Right

Length	Entry	Pull	Push	Recovery	Entry	Pull	Push	Recovery
L 1	18.72	-58.65	20.01	63.74	25.03	73.08	-20.87	-59.25
L 2	21.45	-66.40	16.51	61.31	1.36	73.44	-9.58	-63.29
L 3	18.57	-65.86	29.25	66.27	-3.72	73.81	-13.24	-64.81
L 4	13.78	-65.43	18.36	64.54	-2.16	67.04	-16.05	-62.05
L 5	11.11	-62.37	30.71	56.60	-4.02	71.64	-10.12	-62.98
L 6	13.17	-51.91	29.02	70.83	-5.85	72.38	-9.340	-62.16
L 7	7.35	-64.67	24.36	68.61	-2.28	70.48	-12.67	-65.28
L 8	6.30	-64.90	25.03	69.46	-4.70	73.66	-13.56	-63.90

Body Roll



Body Roll Angles Per Phase, Upper Body, Left and Right

Length	Entry	Pull	Push	Recovery	Entry	Pull	Push	Recovery
L 1	1.58	48.45	-13.53	-51.90	-17.69	-52.36	28.07	47.60
L 2	-2.22	48.99	-19.76	-46.54	-8.48	-49.45	19.81	50.31
L 3	-1.40	48.94	-26.16	-53.11	-6.61	-53.36	22.55	51.52
L 4	6.00	52.00	-21.15	-51.27	-5.46	-46.78	24.62	51.93
L 5	2.41	45.70	-29.88	-39.82	-5.28	-49.88	22.56	54.57
L 6	-6.82	37.30	-32.48	-58.97	-4.85	-56.93	20.05	52.52
L 7	7.67	48.48	-24.70	-56.01	-3.55	-49.13	22.96	51.94
L 8	7.72	49.17	-27.50	-59.32	-3.39	-55.01	24.74	53.08

Body Roll

4 Swimmer A Profile

A

Swimming Profile 30/11/12

Training Notes:

4 x 25m (With devices on, Race Pace)
 Around 2 minutes to remove devices
 8 x 25m (Race Pace, no devices, to generate fatigue)
 Around 5 minutes to re-attached devices
 4 x 25m (With devices on, Race Pace)

Summary - Core Info

Time	Avg.Vel	Count	Rate	DistPerS(m)
Yes	Yes	No	Yes	No

Summary - Body Roll

Lower Angle (L)	Lower Angle (R)	Upper Angle (L)	Upper Angle (R)	Timing (L)	Timing (R)
Yes	Yes	Yes	Yes	No	Yes

Summary - Stroke Duration

Left	Right	Left IdC	Right IdC
Yes	Yes	Yes	Yes

Summary - Left Stroke Phase Duration

Entry	Push	Pull	Recovery
Yes	No	Yes	No

Summary - Right Stroke Phase Duration

Entry	Push	Pull	Recovery
Yes	No	Yes	No

Overview

These tables show if there is there a difference before and after fatigue.

If there is a differences in the core info, the tables below show where these changes occurred. If there is no difference in the core info, the tables show potential compensation strategies to ensure consistent lap times/rate etc.

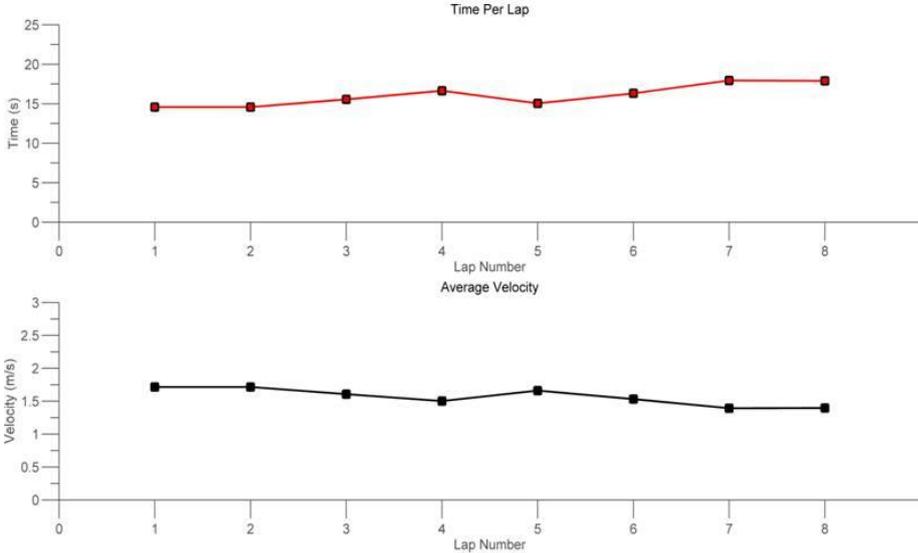
Overview



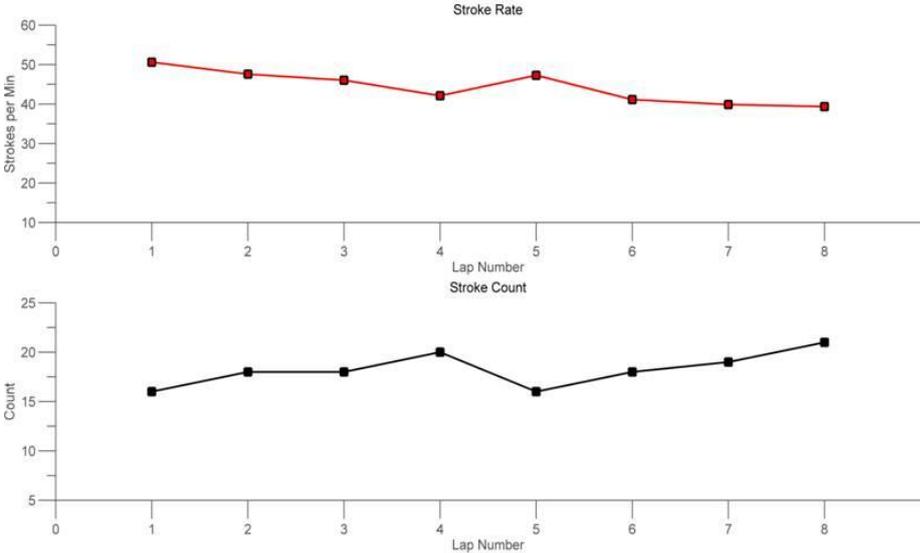
Core Info

Length	Time (S)	Stroke Count	Stroke Rate	Avg.Vel(m/s)	DistPerS(m)
L 1	14.57	16	50.60	1.72	2.03
L 2	14.57	18	47.55	1.72	2.16
L 3	15.55	18	46.04	1.61	2.10
L 4	16.64	20	42.10	1.50	2.14
L 5	15.04	16	47.28	1.66	2.11
L 6	16.32	18	41.12	1.53	2.24
L 7	17.94	19	39.87	1.39	2.10
L 8	17.90	21	39.36	1.40	2.13

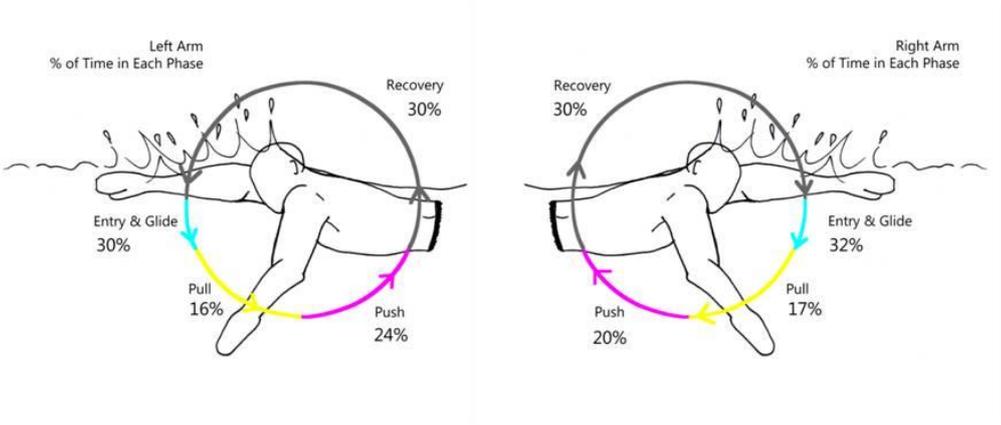
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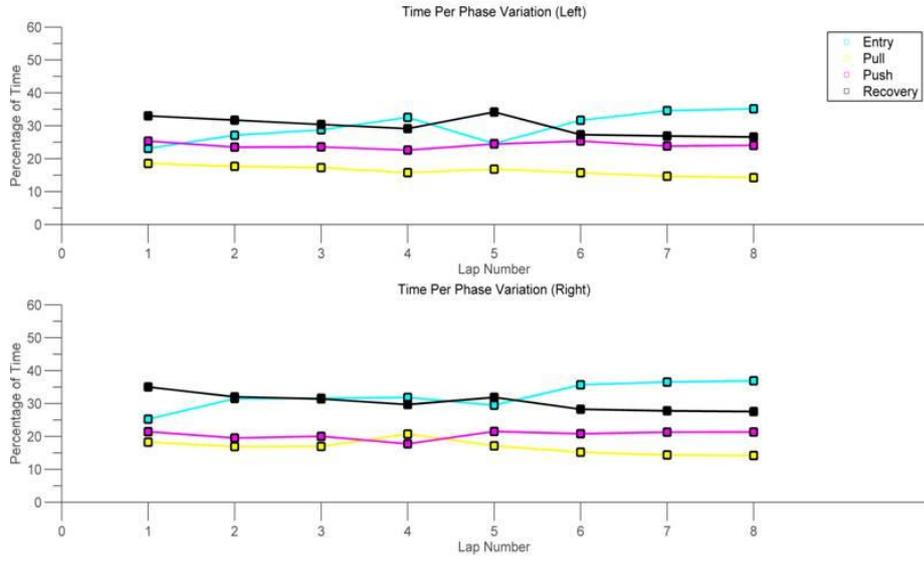
Overview



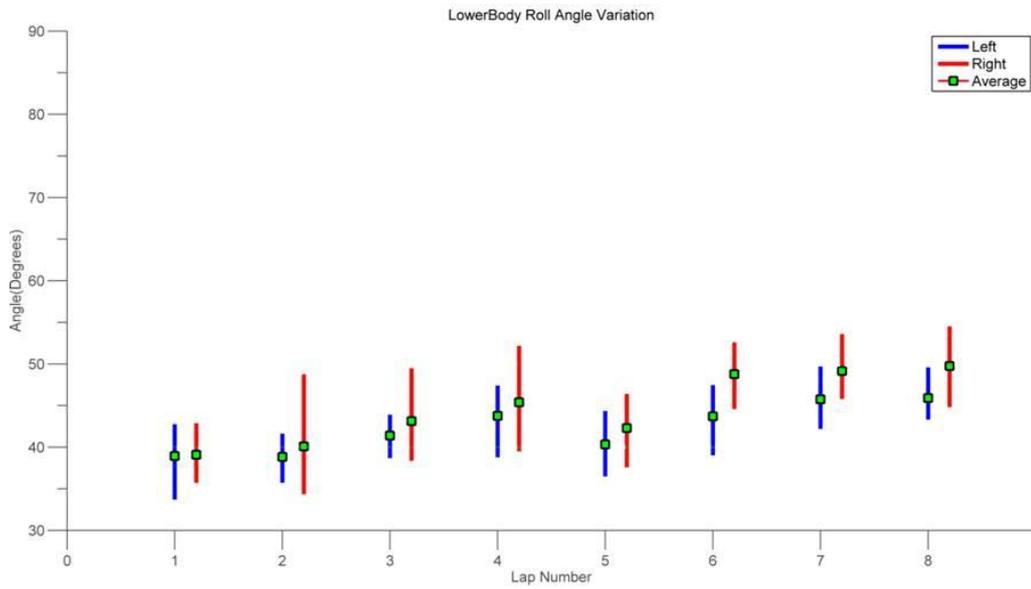
Average Stroke Phase Duration - Overall



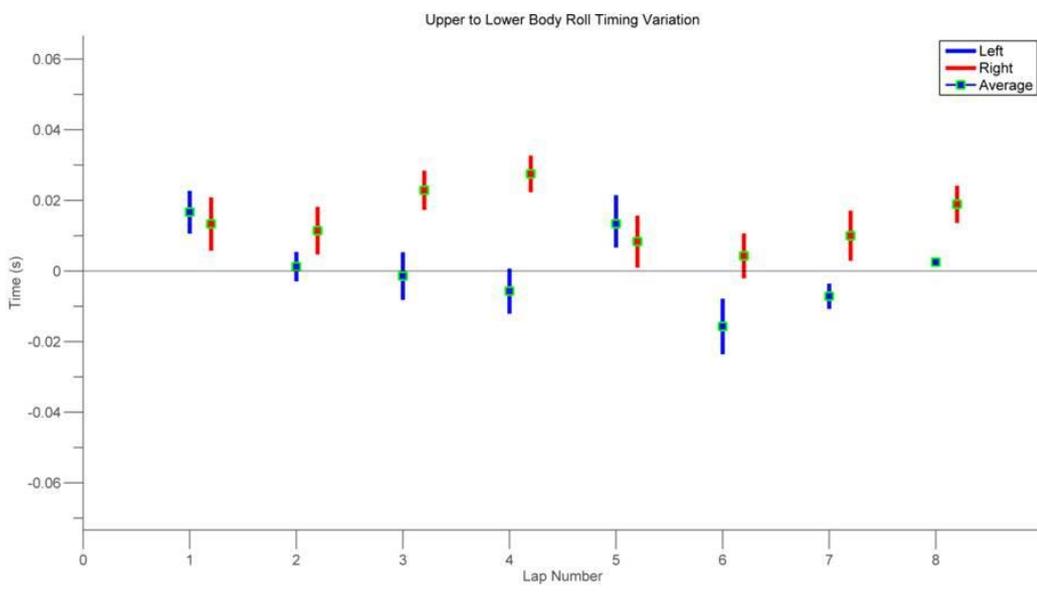
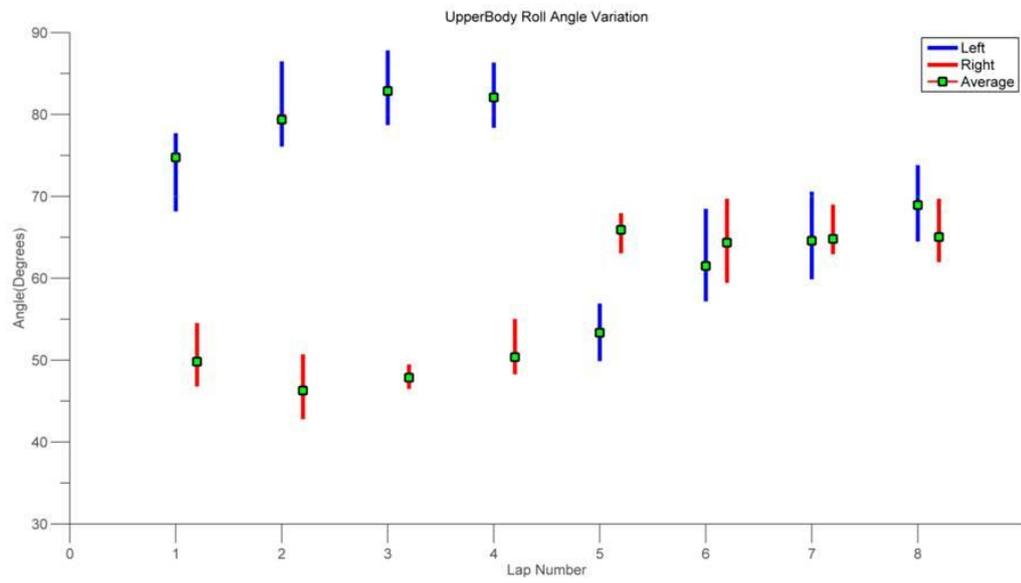
Stroke Phase Duration - Overview



Stroke Phases



Body Roll



Above Zero, Time from Upper body to Lower Body Peak (Upper body first, Lower body lags)

Below Zero, Time from Lower body to Upper Body Peak (Lower body first, Upper body lags)

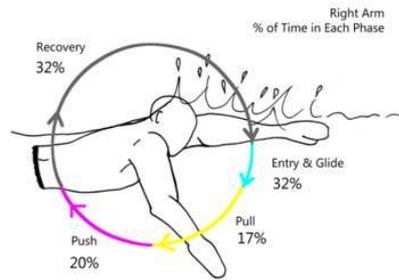
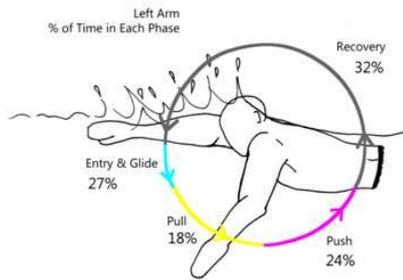
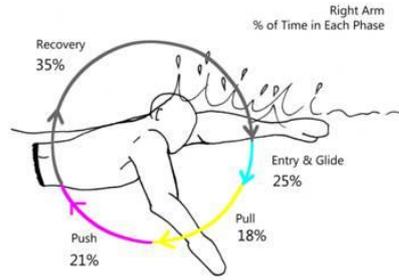
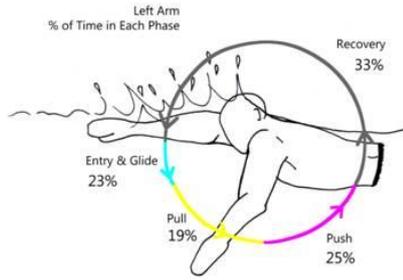
This table tells you which side is dominant showing potential asymmetry

Symmetry: Dominant Side

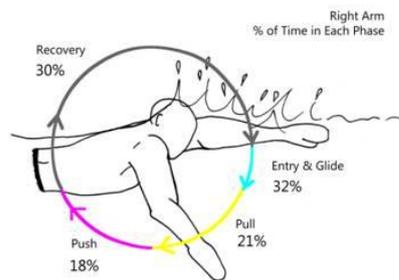
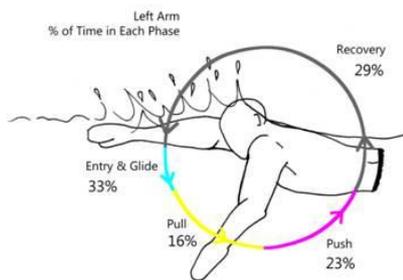
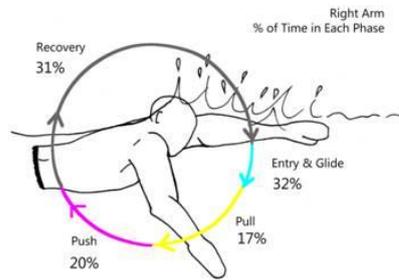
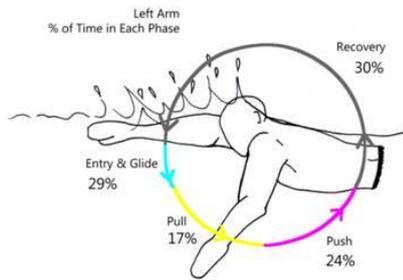
Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Equal	Left	Equal	Equal	Equal	Equal	Left	Equal
L 2	Equal	Left	Equal	Equal	Right	Equal	Left	Equal
L 3	Equal	Left	Equal	Equal	Equal	Equal	Left	Equal
L 4	Equal	Left	Equal	Equal	Equal	Right	Left	Equal
L 5	Equal	Right	Equal	Equal	Right	Equal	Left	Left
L 6	Right	Equal	Equal	Equal	Right	Equal	Left	Equal
L 7	Equal	Equal	Equal	Equal	Equal	Equal	Left	Equal
L 8	Equal	Equal	Equal	Equal	Equal	Equal	Left	Equal

Detailed View

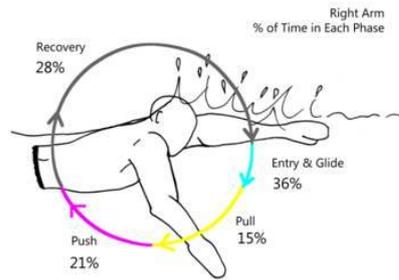
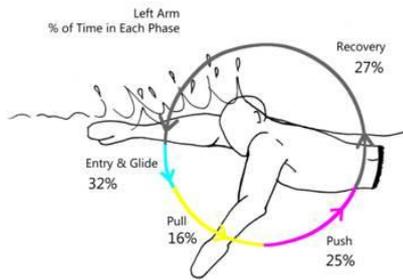
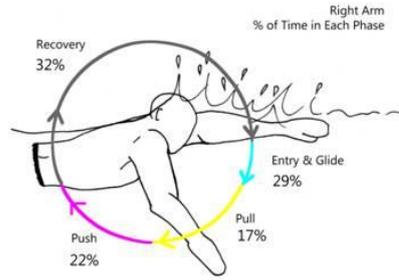
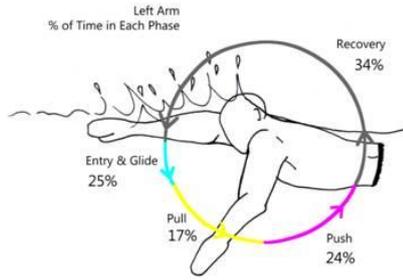
Average Stroke Phase Duration - Lengths 1 & 2



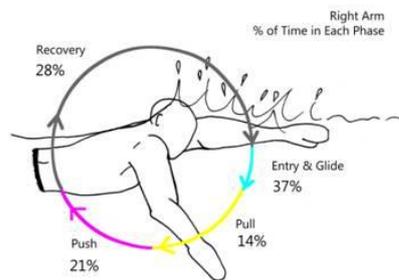
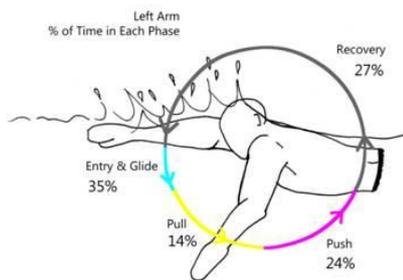
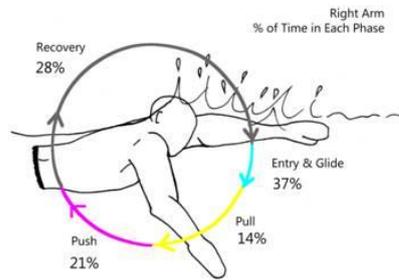
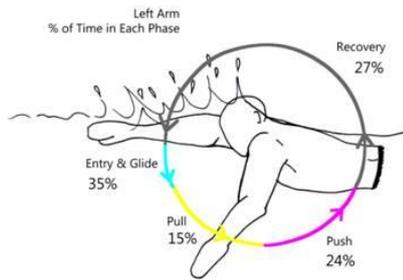
Average Stroke Phase Duration - Lengths 3 & 4



Average Stroke Phase Duration - Lengths 5 & 6



Average Stroke Phase Duration - Lengths 7 & 8



LEFT: Average Duration for Each Phase (Seconds)

Length	Stroke Duration	Entry	Pull	Push	Recovery
L 1	1.18	0.27	0.22	0.30	0.39
L 2	1.27	0.34	0.22	0.30	0.40
L 3	1.32	0.38	0.23	0.31	0.40
L 4	1.41	0.46	0.22	0.32	0.41
L 5	1.33	0.33	0.22	0.33	0.46
L 6	1.45	0.46	0.23	0.37	0.40
L 7	1.50	0.52	0.22	0.36	0.40
L 8	1.52	0.53	0.22	0.36	0.40

RIGHT: Average Duration for Each Phase (Seconds)

Length	Stroke Duration	Entry	Pull	Push	Recovery
L 1	1.18	0.30	0.21	0.25	0.41
L 2	1.28	0.40	0.22	0.25	0.41
L 3	1.30	0.41	0.22	0.26	0.41
L 4	1.41	0.45	0.29	0.25	0.42
L 5	1.26	0.37	0.22	0.27	0.40
L 6	1.46	0.52	0.22	0.30	0.41
L 7	1.50	0.55	0.22	0.32	0.42
L 8	1.52	0.56	0.22	0.33	0.42

Average Index of Coordination (IdC) Per Length

Length	Time	IdC Left	IdC Right
L 1	14.57	-8.32	-9.02
L 2	14.57	-11.13	-10.67
L 3	15.55	-11.39	-10.97
L 4	16.64	-11.19	-11.47
L 5	15.04	-9.04	-9.27
L 6	16.32	-11.63	-11.70
L 7	17.94	-12.99	-12.53
L 8	17.90	-13.12	-12.97

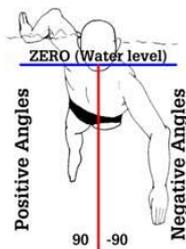
When there is a time lag between the propulsive phases (Push & Pull) of the two arms, the stroke coordination is called 'catch-up' (index of coordination < 0).

When the propulsive phase of one arm started when the other arm ends its propulsive phase, the coordination is called 'opposition' (index of coordination = 0). This shows symmetry in the stroke

When the propulsive phases of the two arms overlapped, the coordination was called 'superposition' (index of coordination > 0). This gives a small period of time where both arms produce propulsion.

Body Roll Angles and Consistency (%) (Upper, Lower)

Length	Left Angle	Right Angle	Right Con(%)	Left Con(%)	Left Angle	Right Angle	Right Con(%)	Left Con(%)
L 1	74.76	49.81	95.44	94.36	38.93	39.08	92.26	91.52
L 2	79.37	46.29	95.72	94.15	38.84	40.09	93.87	87.76
L 3	82.87	47.87	96.05	97.55	41.39	43.13	95.25	89.44
L 4	82.08	50.37	96.38	95.23	43.77	45.39	94.26	90.84
L 5	53.35	65.91	94.17	97.46	40.33	42.30	92.80	92.69
L 6	61.50	64.34	93.93	94.54	43.70	48.77	93.96	94.43
L 7	64.58	64.81	94.38	97.06	45.76	49.16	95.14	93.78
L 8	68.93	65.04	95.94	96.27	45.91	49.76	95.21	94.06



Positive Angles

ZERO (Water level)

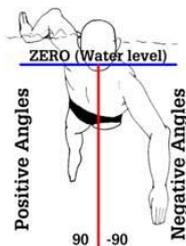
90 -90

Negative Angles

Body Roll Angles Per Phase, Upper Body, Left and Right

Length	Entry	Pull	Push	Recovery	Entry	Pull	Push	Recovery
L 1	-7.67	-74.34	-57.04	42.35	-9.68	47.76	2.62	-60.70
L 2	-12.18	-79.49	-41.78	37.70	-24.74	44.98	-2.82	-59.38
L 3	-12.95	-83.38	-34.42	40.21	-24.46	45.26	-7.23	-62.64
L 4	-11.43	-80.44	-25.62	41.06	-24.88	45.04	-9.99	-65.36
L 5	-5.43	-53.49	-21.90	59.70	-6.51	64.86	2.60	-41.42
L 6	6.54	-60.83	-17.05	57.98	-16.16	60.88	9.67	-42.61
L 7	5.08	-59.94	-10.68	57.79	-13.18	59.58	5.15	-46.28
L 8	4.90	-64.13	-12.55	58.54	-13.29	60.08	5.68	-49.53

Body Roll



Positive Angles

ZERO (Water level)

90 -90

Negative Angles

Body Roll Angles Per Phase, Upper Body, Left and Right

Length	Entry	Pull	Push	Recovery	Entry	Pull	Push	Recovery
L 1	-0.03	38.06	14.59	-34.41	-7.34	-38.18	-5.18	24.92
L 2	0.73	39.16	5.81	-33.46	-2.07	-36.84	-4.31	20.30
L 3	2.56	43.91	2.58	-38.66	-4.05	-37.30	-1.46	26.42
L 4	-1.11	44.59	1.34	-39.52	0.16	-39.01	-0.82	30.61
L 5	8.48	43.05	6.21	-37.52	-6.00	-39.84	1.71	31.70
L 6	0.15	48.44	6.77	-38.60	6.60	-40.90	-3.13	31.84
L 7	-1.18	46.42	1.25	-41.07	5.20	-41.59	-2.20	35.00
L 8	-2.39	46.45	1.62	-42.52	3.79	-41.09	-3.89	37.72

Body Roll

5 Swimmer Ka Profile

Ka

Swimming Profile 7/12/12

Training Notes:

4 x 25m (With devices on, Race Pace)
 Around 2 minutes to remove devices
 8 x 25m (Race Pace, no devices, to generate fatigue)
 Around 5 minutes to re-attached devices
 4 x 25m (With devices on, Race Pace)

Summary - Core Info

Time	Avg.Vel	Count	Rate	DistPerS(m)
No	No	No	No	Yes

Summary - Body Roll

Lower Angle (L)	Lower Angle (R)	Upper Angle (L)	Upper Angle (R)	Timing (L)	Timing (R)
Yes	Yes	Yes	Yes	Yes	Yes

Summary - Stroke Duration

Left	Right	Left IdC	Right IdC
No	Yes	Yes	No

Summary - Left Stroke Phase Duration

Entry	Push	Pull	Recovery
No	No	No	No

Summary - Right Stroke Phase Duration

Entry	Push	Pull	Recovery
No	No	No	Yes

Overview

These tables show if there is there a difference before and after fatigue.

If there is a differences in the core info, the tables below show where these changes occurred. If there is no difference in the core info, the tables show potential compensation strategies to ensure consistent lap times/rate etc.

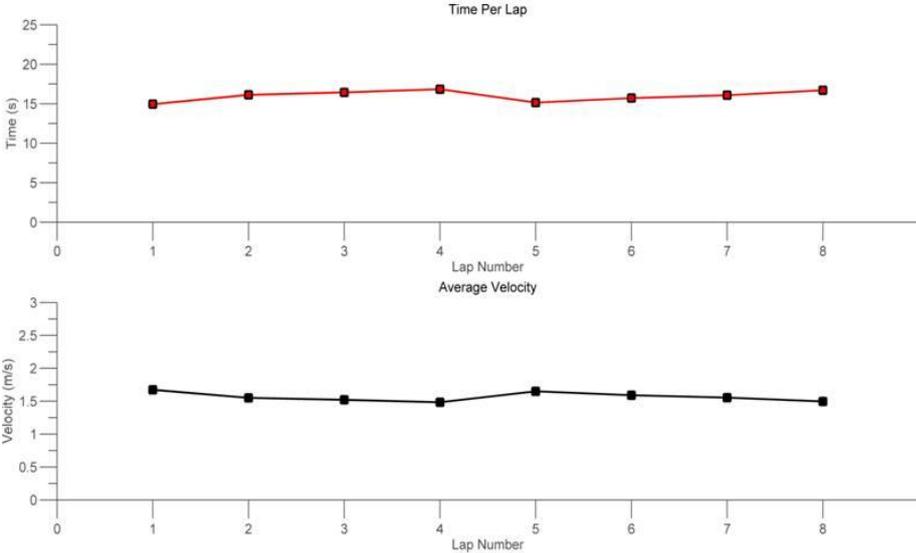
Overview



Core Info

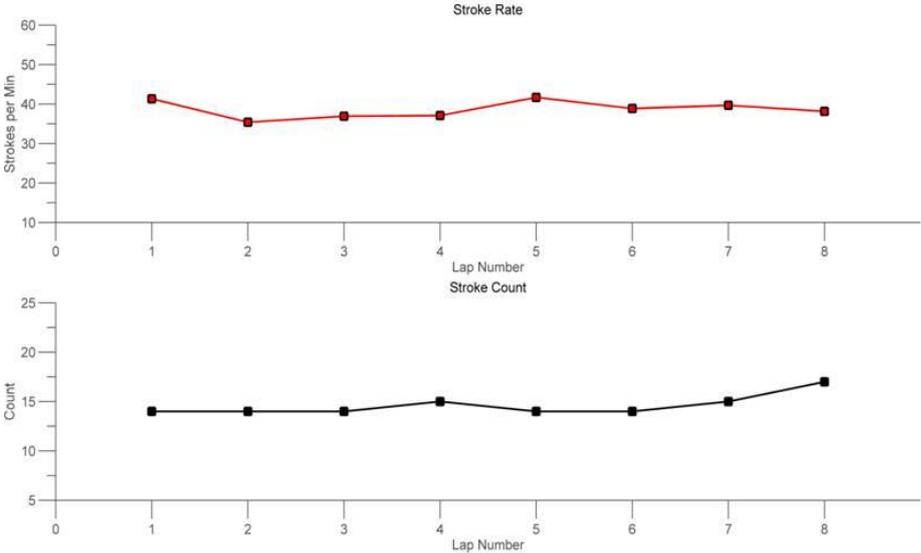
Length	Time (S)	Stroke Count	Stroke Rate	Avg.Vel(m/s)	DistPerS(m)
L 1	14.94	14	41.33	1.67	2.43
L 2	16.12	14	35.39	1.55	2.63
L 3	16.43	14	36.91	1.52	2.47
L 4	16.84	15	37.07	1.48	2.40
L 5	15.14	14	41.68	1.65	2.38
L 6	15.71	14	38.87	1.59	2.46
L 7	16.08	15	39.67	1.55	2.35
L 8	16.70	17	38.15	1.50	2.35

Overview

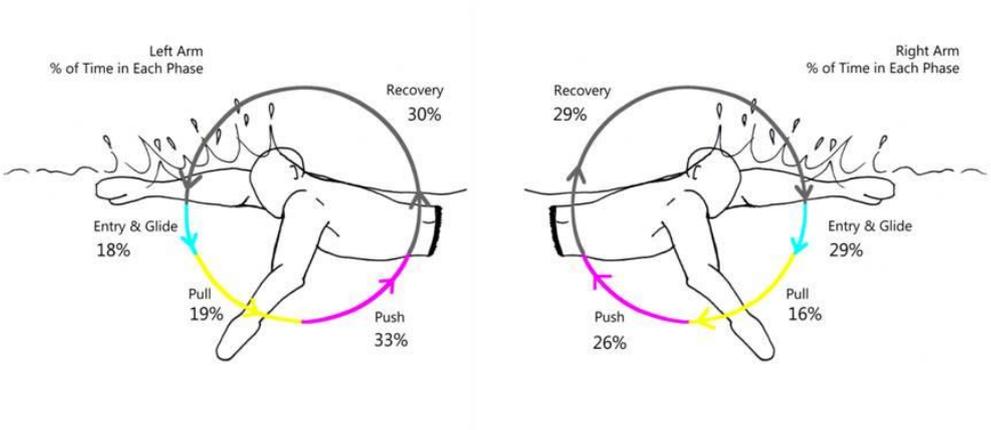


Overview

CORE

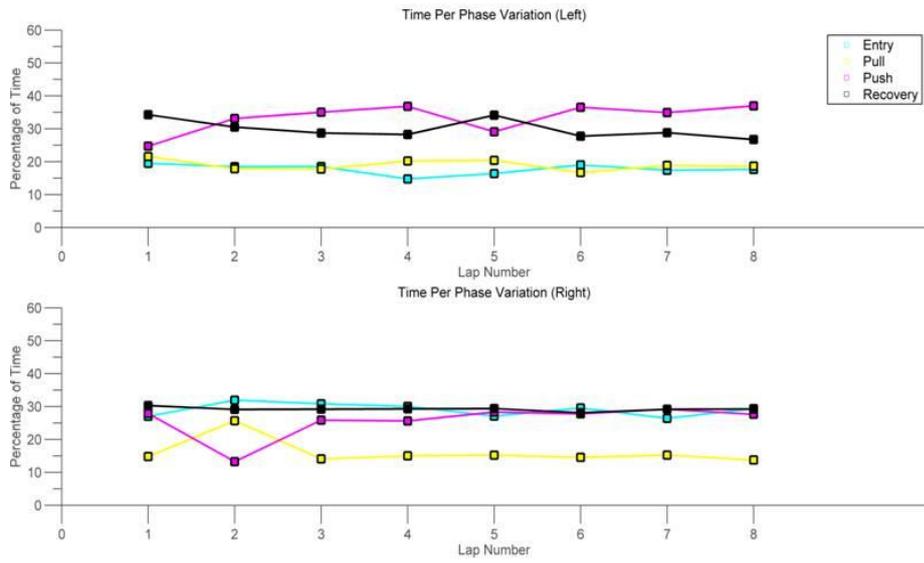


Average Stroke Phase Duration - Overall

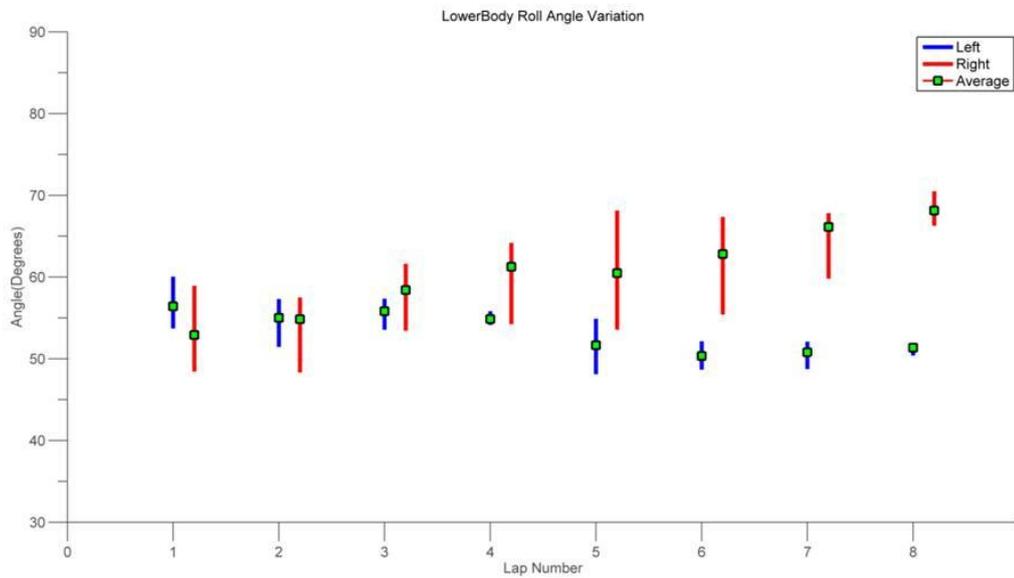


Stroke Phases

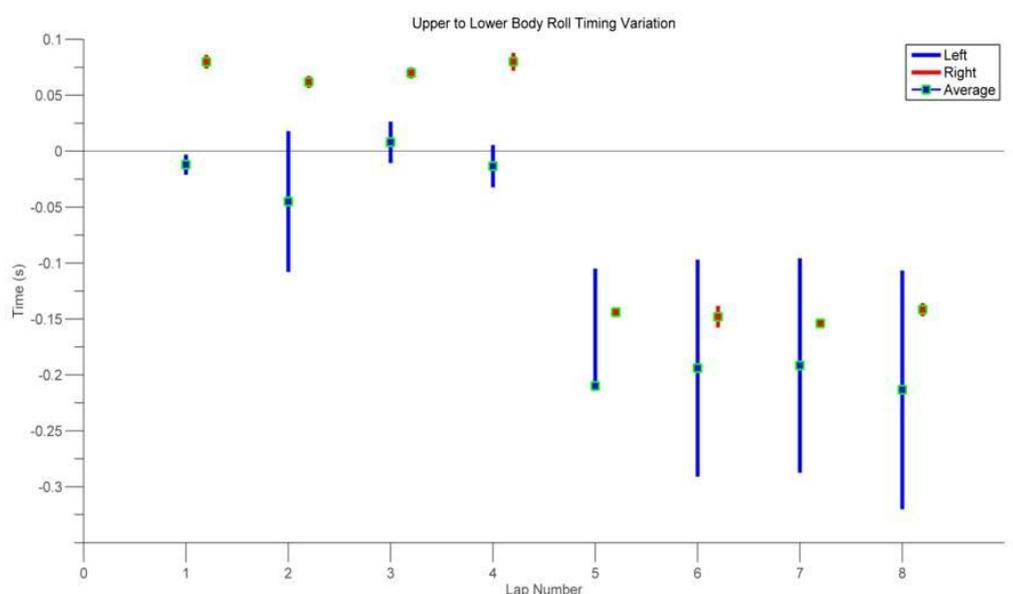
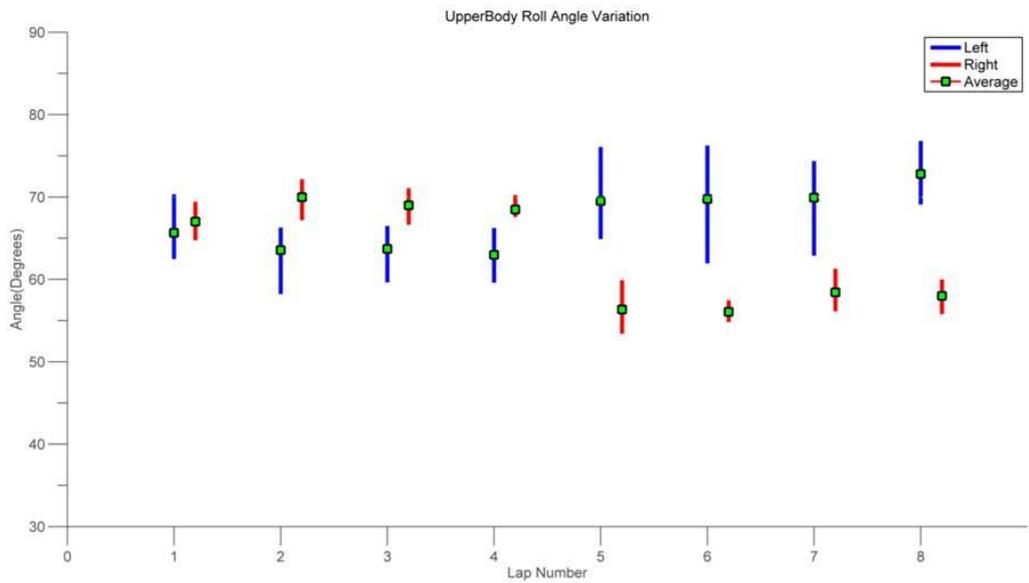
Stroke Phase Duration - Overview



Stroke Phases



Body Roll



Above Zero, Time from Upper body to Lower Body Peak (Upper body first, Lower body lags)
 Below Zero, Time from Lower body to Upper Body Peak (Lower body first, Upper body lags)

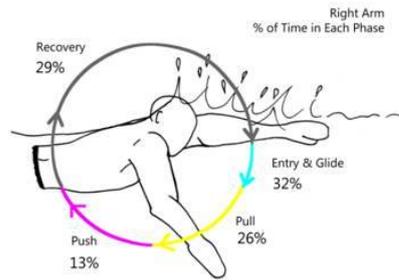
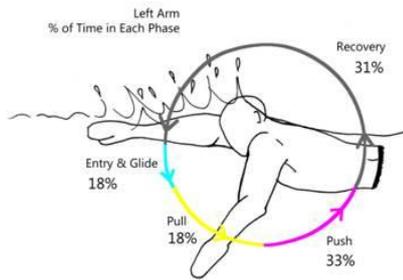
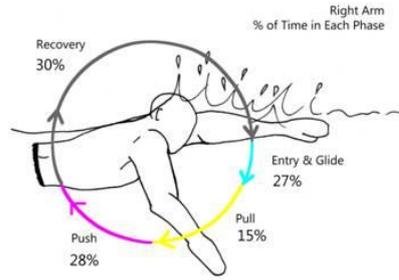
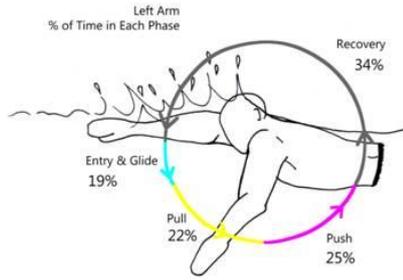
This table tells you which side is dominant showing potential asymmetry

Symmetry: Dominant Side

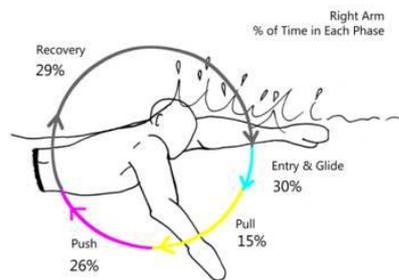
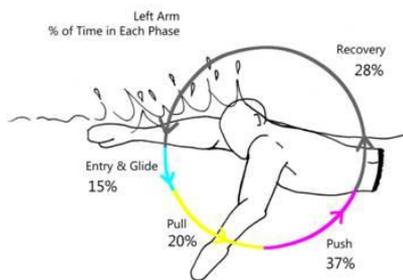
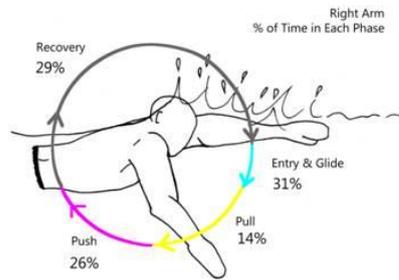
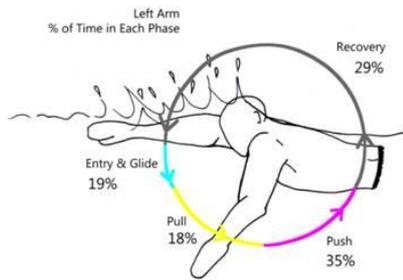
Length	L-Body Angle	U-Body Angle	IdC	Stroke Time	Entry Time	Pull Time	Push Time	Recovery Time
L 1	Equal	Equal	Right	Equal	Right	Left	Right	Left
L 2	Equal	Equal	Right	Equal	Right	Right	Left	Equal
L 3	Equal	Equal	Equal	Equal	Right	Left	Left	Equal
L 4	Right	Equal	Left	Equal	Right	Left	Left	Equal
L 5	Right	Left	Equal	Equal	Right	Left	Equal	Left
L 6	Right	Left	Equal	Equal	Right	Left	Left	Equal
L 7	Right	Left	Equal	Equal	Right	Left	Left	Equal
L 8	Right	Left	Right	Equal	Right	Left	Left	Equal

Detailed View

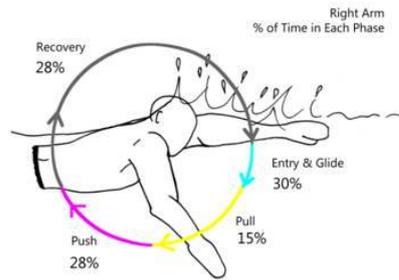
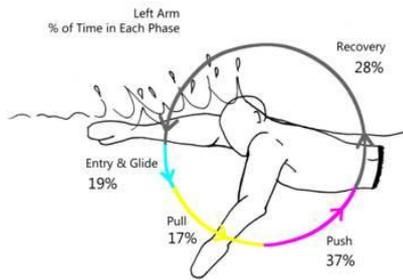
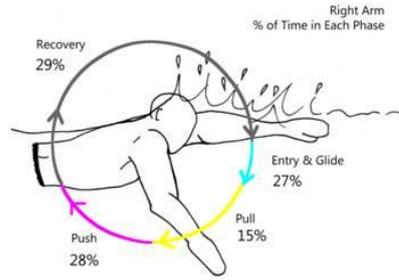
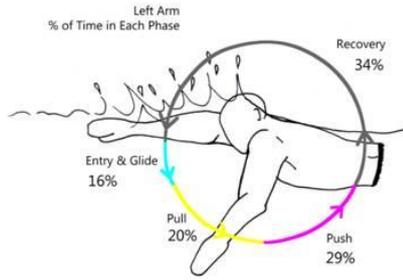
Average Stroke Phase Duration - Lengths 1 & 2



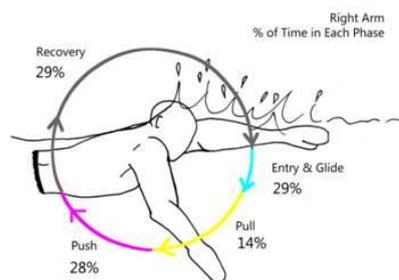
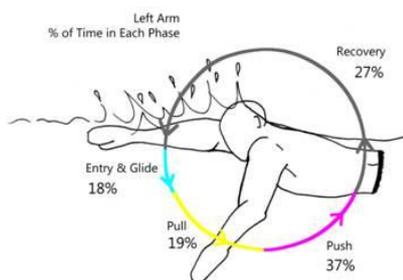
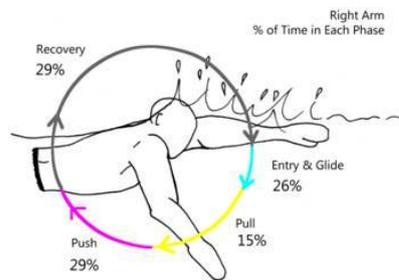
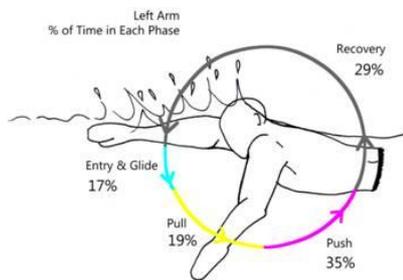
Average Stroke Phase Duration - Lengths 3 & 4



Average Stroke Phase Duration - Lengths 5 & 6



Average Stroke Phase Duration - Lengths 7 & 8



LEFT: Average Duration for Each Phase (Seconds)

Length	Stroke Duration	Entry-Catch	Push	Pull	Recovery
L 1	1.44	0.28	0.31	0.36	0.49
L 2	1.66	0.31	0.30	0.55	0.51
L 3	1.62	0.30	0.29	0.57	0.46
L 4	1.61	0.24	0.33	0.59	0.46
L 5	1.44	0.23	0.29	0.42	0.49
L 6	1.51	0.29	0.25	0.55	0.42
L 7	1.51	0.26	0.28	0.53	0.43
L 8	1.56	0.28	0.29	0.58	0.42

RIGHT: Average Duration for Each Phase (Seconds)

Length	Stroke Duration	Entry-Catch	Push	Pull	Recovery
L 1	1.45	0.39	0.22	0.40	0.44
L 2	1.66	0.53	0.43	0.22	0.48
L 3	1.61	0.50	0.23	0.42	0.47
L 4	1.62	0.49	0.24	0.42	0.48
L 5	1.43	0.39	0.22	0.41	0.42
L 6	1.53	0.45	0.22	0.42	0.43
L 7	1.52	0.40	0.23	0.44	0.44
L 8	1.56	0.46	0.21	0.43	0.46

Average Index of Coordination (IdC) Per Length

Length	Time	IdC Left	IdC Right
L 1	14.94	-5.20	-6.05
L 2	16.12	-5.30	-16.00
L 3	16.43	-4.25	-4.54
L 4	16.84	-1.52	-1.09
L 5	15.14	-3.59	-3.76
L 6	15.71	-2.44	-2.24
L 7	16.08	-1.02	-1.01
L 8	16.70	-0.69	-1.54

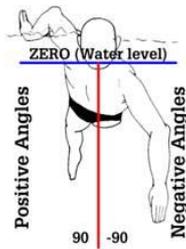
When there is a time lag between the propulsive phases (Push & Pull) of the two arms, the stroke coordination is called 'catch-up' (index of coordination < 0).

When the propulsive phase of one arm started when the other arm ends its propulsive phase, the coordination is called 'opposition' (index of coordination = 0). This shows symmetry in the stroke

When the propulsive phases of the two arms overlapped, the coordination was called 'superposition' (index of coordination > 0). This gives a small period of time where both arms produce propulsion.

Body Roll Angles and Consistency (%) (Upper, Lower)

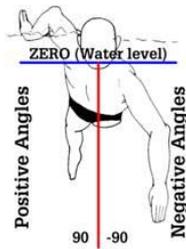
Length	Left Angle	Right Angle	Right Con(%)	Left Con(%)	Left Angle	Right Angle	Right Con(%)	Left Con(%)
L 1	65.65	67.01	93.97	96.79	56.42	52.91	95.51	91.40
L 2	63.56	69.97	94.30	97.44	55.01	54.84	95.82	92.05
L 3	63.70	68.99	95.47	97.70	55.82	58.41	97.19	94.75
L 4	62.98	68.47	95.79	98.46	54.86	61.26	98.71	94.11
L 5	69.51	56.35	92.12	94.97	51.65	60.48	94.55	89.61
L 6	69.76	56.06	89.97	97.96	50.33	62.82	97.37	91.07
L 7	69.92	58.43	93.90	96.75	50.78	66.13	97.17	95.30
L 8	72.80	57.99	95.35	96.84	51.35	68.13	98.58	97.60



Body Roll Angles Per Phase, Upper Body, Left and Right

	Length	Entry	Push	Pull	Recovery	Entry	Push	Pull	Recovery
L 1		0.95	-64.45	4.68	66.33	-29.08	67.32	53.98	-65.90
L 2		13.04	-61.47	-49.53	70.00	-27.09	69.05	22.38	-64.17
L 3		5.69	-61.88	-50.10	68.76	-27.00	68.27	56.05	-63.47
L 4		-5.23	-60.95	-47.85	67.68	-25.83	68.14	58.63	-62.26
L 5		-21.58	-66.94	-52.55	55.82	-39.25	54.58	38.02	-69.80
L 6		-12.31	-65.10	-52.07	49.57	-33.88	53.84	38.63	-71.11
L 7		-25.07	-66.25	-52.37	53.61	-20.49	56.95	43.29	-66.22
L 8		-28.52	-71.54	-53.31	52.21	-34.07	55.77	46.48	-72.17

Body Roll

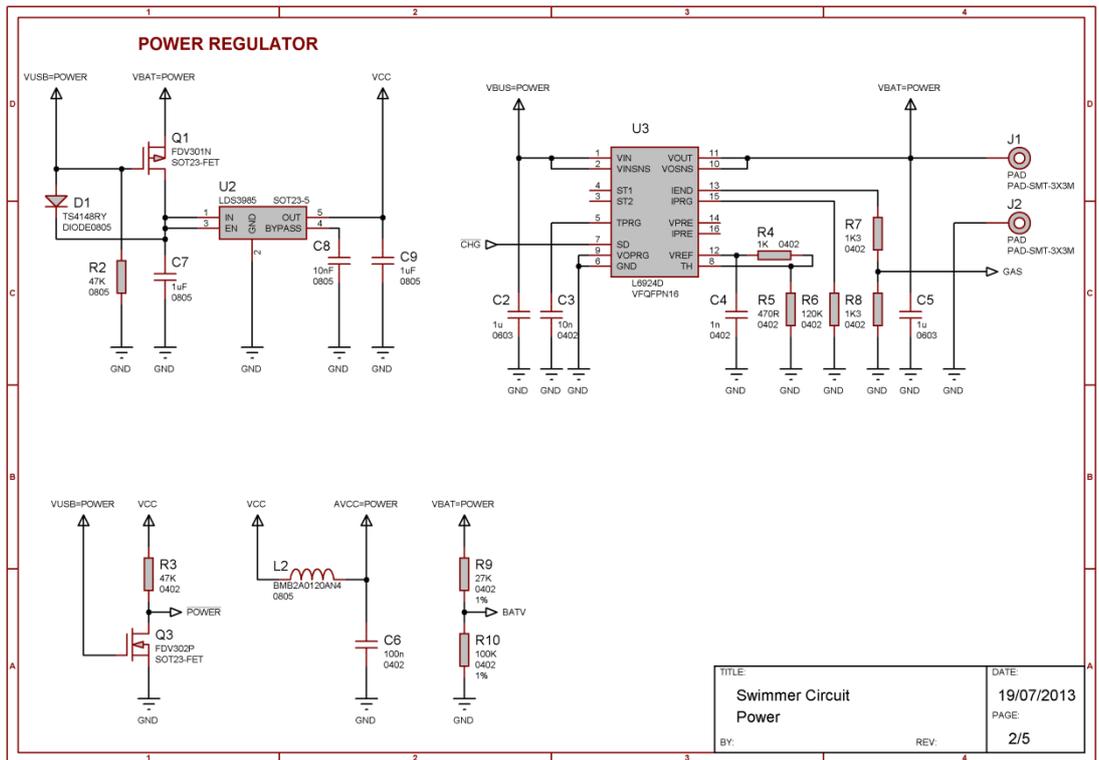
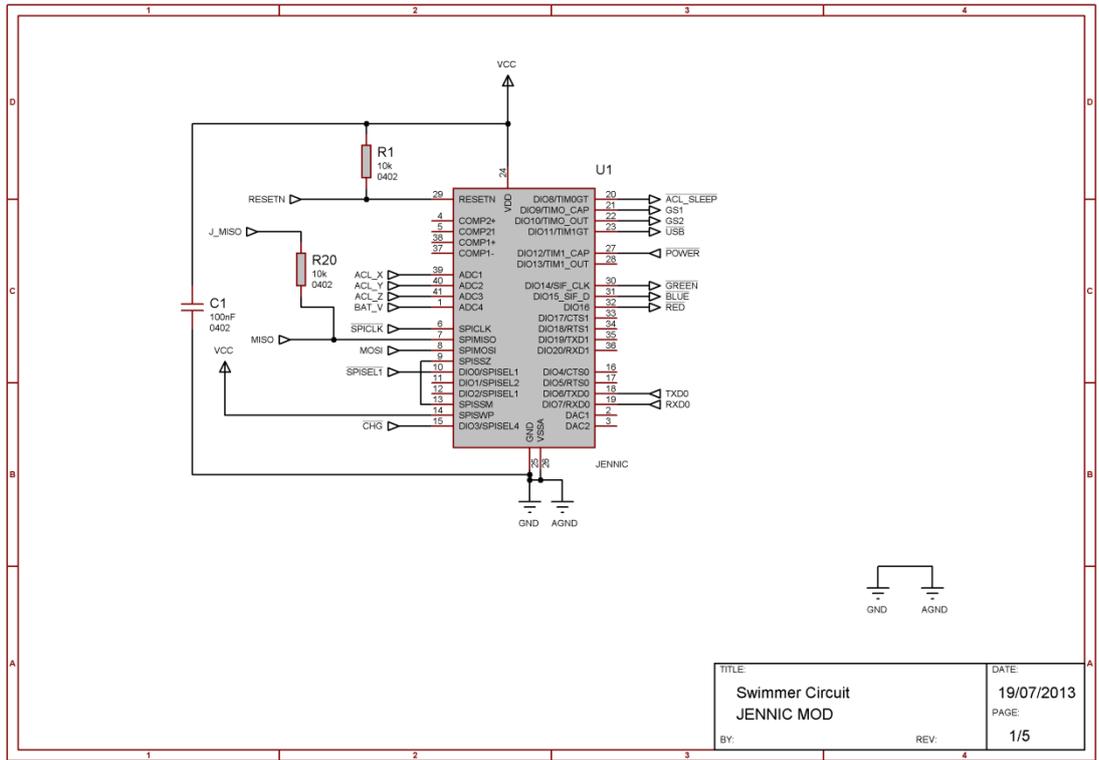


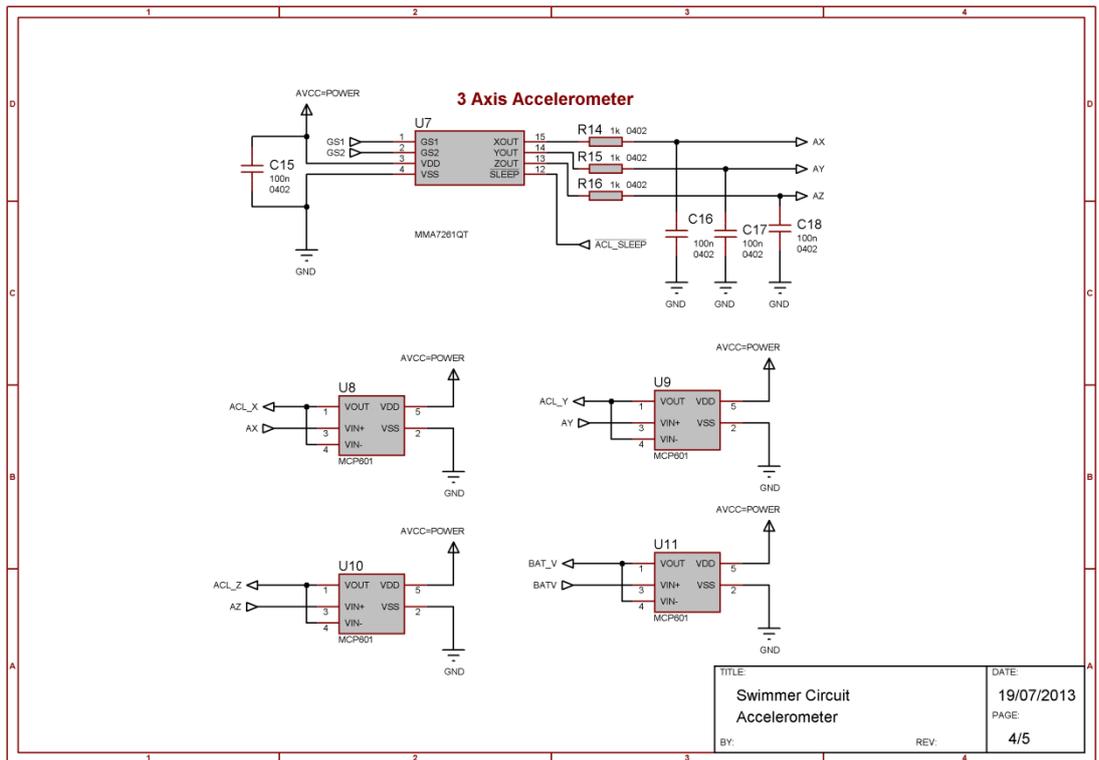
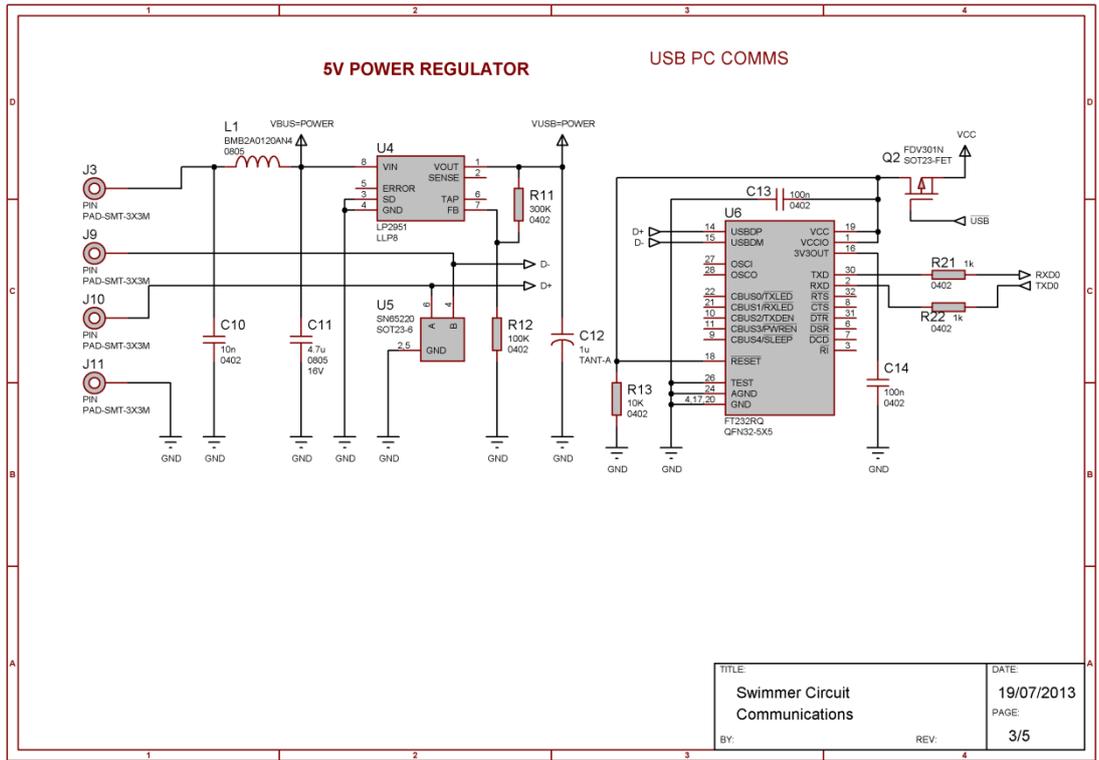
Body Roll Angles Per Phase, Lower Body, Left and Right

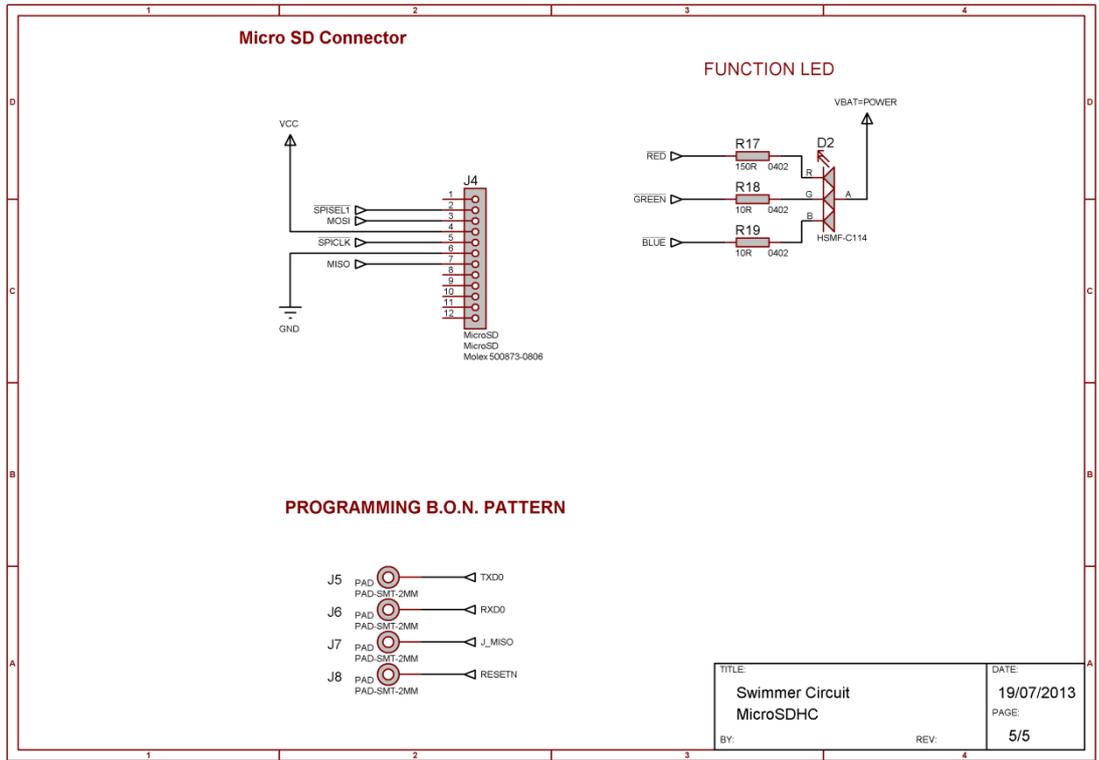
	Length	Entry	Push	Pull	Recovery	Entry	Push	Pull	Recovery
L 1		-4.39	51.81	-8.26	-51.22	20.41	-49.90	-21.97	52.43
L 2		-7.06	52.79	42.64	-52.34	20.56	-45.83	-5.58	55.86
L 3		-0.95	55.52	46.23	-48.92	23.56	-45.63	-23.14	59.22
L 4		5.54	59.13	47.49	-41.90	25.02	-46.85	-23.02	60.14
L 5		-21.50	43.55	55.00	-44.84	53.80	-48.28	-40.60	3.22
L 6		-18.89	58.04	56.09	-43.46	56.20	-47.89	-36.78	18.08
L 7		-18.81	58.13	59.99	-49.17	59.97	-47.93	-36.19	29.92
L 8		-20.53	55.18	64.41	-50.99	64.28	-48.52	-36.25	25.46

Body Roll

6 Swim Circuit







7 Published Work