Differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers

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By

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DECLARATION

Submitted in fulfilment of a degree in Master of Human Movement Science (Research), by dissertation, in the Faculty of Health Science at the Nelson Mandela University.

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Declaration: In accordance with Rule G4.6.3, I hereby declare that the above-mentioned dissertation is my own work and that it has not previously been submitted for assessment to another University or for another qualification.

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Signature:

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ABSTRACT

Context: Swimming is a highly competitive sport, with elite swimmers and coaches constantly looking for ways to improve and challenge themselves to meet new performance goals. The implementation of technology in swimming has proven to be a vital tool in athlete monitoring and in providing coaches with additional information on the swimmer's performance. Example of this technology is the use of inertial sensory devices such as tri-axial accelerometers. The accelerometers can be used to provide kinematic information with regards to the swimmer's stroke rate, stroke length and stroke mechanics. In a typical training session, coaches would have to manually time and count their swimmer's strokes to be able to gain the kinematic information they require. Hence, the use of inertial sensory technology, such as accelerometers, would provide the necessary information coaches require, allowing them to concentrate on other performance aspects such as their swimmer's technique.

Aim and objectives: The aim of this study was to determine the kinematic parameters and swimming stroke mechanics that could be derived from tri-axial accelerometers, during a 200-m individual medley (IM) event in South African national level swimmers. Three objectives were set to meet the aim of the study. The first was to identify and differentiate each of the stroking styles using tri-axial accelerometers. The second was to identify and differentiate the kinematic parameters and stroke mechanics for all four strokes using tri-axial accelerometers. The third objective was to implement machine learning to automate the identification and interpretation of the accelerometer data.

Method: A quantitative, non-experimental descriptive one group post-test only design was used, in which 15 national level swimmers, of which seven male and eight female (mean ±SD: age: 20.9 ± 2.90 years; height: 173.28 ± 10.61 cm; weight: 67.81 ± 8.09 kg; arm span: 178.21 ± 12.15 cm) were tested. Three anthropometric measures were taken (height, weight and arm span) prior to testing, with two tri-axial accelerometers and Polar V800 watch and heart rate belt attached to the swimmers left wrist, upper-back and chest, respectively. All swimmers were required to perform three main swimming sets: 50-m IM, 100-m variation and 200-m IM. Various descriptive statistics including mean, standard deviation and confidence intervals (95%) were used to describe the data. with further inferential statistics including paired t-test, intra-class correlation and Bland Altman analysis were used to describe the relationship between the accelerometer and the manually estimated parameters. Additionally, a repeated measures one-way ANOVA (with post-hoc Tukey HSD test) were also used in an inter-comparison of the stroke parameters between each of the stroking styles. A confusion matrix was used to measure the classification accuracy of the machine learning model implemented on the accelerometer data.

Results: The accelerometers proved successful in identifying and discerning the stroke mechanics for each of the four stroking styles, with the use of video footage to validate the findings. In the stroke kinematic differentiation, the Bland Altman analysis results showed an agreement between the manual method and accelerometer-derived estimates, although a discrepancy was evident for several of the kinematic parameters, with a significant difference found with the estimated lap time, average swimming velocity and stroke rate (paired t-test: $p < 0.001$ for all swim sets). The inter-comparison between the stroke parameters per stroking style showed a significant difference with average swimming velocity (repeated one-way ANOVA: $F = 1789.37$, $p < 0.001$), averages stroke rate (repeated one-way ANOVA: $F = 671.70$, $p < 0.001$) and average stroke length (repeated one-way ANOVA: $F = 346.46$, $p < 0.001$) for the population group tested. Further analysis with post-hoc Tukey HSD test showed no significant difference were evident for the average swimming velocity (Tukey: $p > 0.05$ for all strokes) and between freestyle and backstroke for the average stroke rate and stroke length (Tukey: $p = 0.0968$ and $p = 0.997$, respectively). Lastly, the machine learning model found a classification accuracy of 96.6% in identifying and labelling the stroking styles from the accelerometer data.

Conclusion: It was shown that the tri- axial accelerometers were successful in the identification and differentiation of all the stroking styles, stroke mechanics and kinematics, although a discrepancy was found with the average swimming velocity, stroke rate and lap time estimations. The machine learning model implemented proved the benefits of using artificial intelligence to ease the data process and interpretation by automatically labelling the accelerometer data. Therefore, the use of tri-axial accelerometers as a coaching aid has major potential in the swimming community. However, further research is required to eliminate the time-consuming data processing and to increase the accuracy of the accelerometer in the measurement of all the stroke kinematics.

<u>Keywords:</u> *Inertial sensors, tri-axial accelerometers, stroke kinematics, stroke mechanics, swimming*

Table of Contents

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

IM: Individual Medley

SC: Stroke count

$\overline{SR}$: Average stroke rate

$\overline{SL}$: Average stroke length

$\overline{v}$: Average swimming velocity

LT: Lap time

HR: heart rate

CSS: Critical swim speed

IdC: Index of Coordination

SD: Standard deviation

CHAPTER 1: PROBLEM IDENTIFICATION

1.1 Introduction

Swimming is a highly competitive sport, with elite swimmers constantly challenging themselves to meet new performance goals within specific swimming events (Mooney, Corley, Godfrey & Quinlan, 2015). These different events require the swimmer to perform specific strokes as optimally as possible (i.e. maximising overall locomotive efficiency) over a given distance. The specific swimming performance outcome measurement is then based on the "time to completion" of an event (Barbosa, Bragada, Reis, Marinho, Carvalho & Silva, 2010; Ribeiro, Figueiredo, Morais, Alves, Toussaint, Vilas-boas & Fernandes, 2016). Swimmers may choose to optimise either their technique (i.e. mechanics of specific strokes) or their ability (i.e. physiological capacity) to complete various distances adequately (Dormehl & Williams, 2016). Research has shown that swimmers favour specialising in a specific stroke, rather than in specific distances (Dormehl & Williams, 2016). Hence, in conjunction with the stroking style, the primary aim of the swimmer is to complete a given distance in the fastest time possible and that this is achieved by maintaining the highest average velocity over a given distance (Figueiredo, Pendergast, Vilas-Boas & Fernandes, 2013). Swimming is primarily performed in water, which is constantly changing due to the performance action required and other parameters acting on the swimmer within this fluid medium. These parameters include the surface, form and wave drag attributed to the swimmer's body position, their stroke length and stroke rate efficiency and additional factors attributed to their propulsion efficiency (Sanders, 2013). Therefore, a growing need exists whereby coaches and swimmers are continuously striving for alternative methods and strategies to measure and assess the swimming performance or technique (e.g. stroke length, stroke rate and stroke mechanics), which are attributed to optimising the performance efficiency of the swimmer (Mooney *et al.*, 2015).

Competitive swimming is extensively researched internationally, with specific interests in the fields of physiology and biomechanics (Anderson, 2006; Costa, Balasekaran, Vilas-Boas & Barbosa, 2015; Morais, Garrido, Marinho & Barbosa, 2013). Hence, elite swimming performance is determined by the optimisation of various biomechanical and physiological factors. The biomechanical factors include swimming speed, stroke mechanics, drag forces, propulsive efficiency, the starting and turning ability of the swimmer. Physiological factors, on the other hand, include components such as muscle power, flexibility, maximal aerobic capacity (i.e. $\dot{V}O_{2max}$) and anaerobic power (Anderson, 2006; Hay, 1993; Sanders, 2013). An example of how these factors play a role in the swimmer's performance is presented in

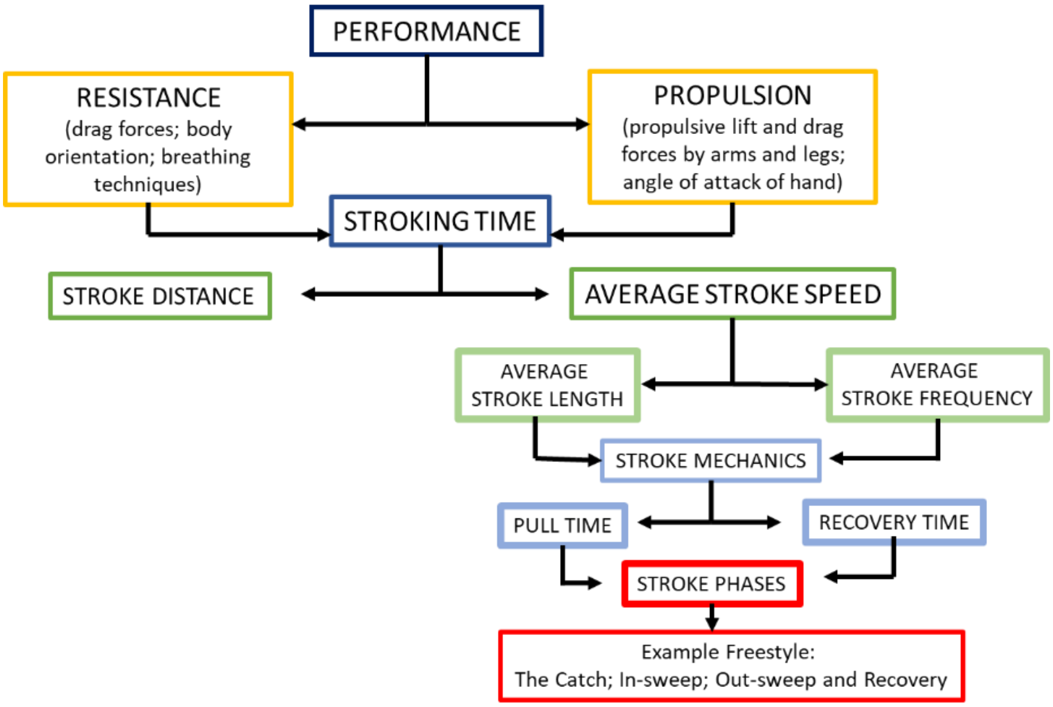


Figure 1: A model of the characteristics which affect swimming performance (adapted from Hay, 1993; Anderson, 2006; Sanders, 2013)

Swimmers should be diligent in their training to optimise their various biomechanical and physiological factors, which would subsequently increase their competitive success (Anderson, 2006). Coaches play a vital role in managing and monitoring the swimmers training regime, to ensure their training obligations are fulfilled. The most simple method of athlete monitoring, which most coaches use to oversee their swimmers, is through the use of monitoring tools such as stopwatches and wall-mounted pace clocks (Ganzevles, Vullings, Beek, Daanen & Truijens, 2017; Wright & Stager, 2013). These monitoring tools determine the time in which the swimmer completes a specified distance, from which the coach can predominantly derive the swimmer's *average lap time* (Ganzevles *et al.*, 2017). If the coach counts the number of strokes taken during a given length, coupled with the time over which the length was completed, the coach can determine the *average stroke length*, *stroke frequency*, and hence, *average swimming velocity* of the swimmer. This method is practically simple and efficient to use however, it is subjected to human error and oversimplification (Ganzevles *et al.*, 2017). A major problem in athlete performance monitoring for the swim coaches is that they would usually have to oversee multiple swimmers simultaneously during a typical training session. This poses a limitation on the feedback provided by the coaches to the swimmer, especially with regards to their specific stroke mechanics and any swimming inefficiencies observed during training (Wright & Stager, 2013).

Monitoring of a swimmer's performance both in training and during competition has been an on-going developing field in research, especially with regards to the limitation's researchers encountered when trying to collect data from swimmers while they were in the water (Justham, Slawson, West, Conway, Caine & Harrison, 2008). With the advancement in technology, alternative systems have been introduced into swimming to help enhance the monitoring of a swimmer's performance, as well as increase the amount of information available to coaches. Hence, various commercial and scientific sport monitoring systems have become available to support all athletes in their respective disciplines. These monitoring systems are divided into two categories, namely direct (i.e. equipment attached to the athlete, e.g. heart rate monitors) and remote (i.e. equipment set-up in the vicinity of the athlete, e.g. Vicon motion analysis) monitoring systems. Examples of remote monitoring systems include video and movement analysis technology such as Dartfish and Vicon. The Vicon is 3-dimensional (3-D) opto-electric motion analysis technology which can be used in swimming kinematic investigations with the aid of infrared cameras based above and below the water, during an assessment (Bartlett, 2007; Justham *et al.*, 2008; Sanders, Psycharakis, Naemi, Mccabe & Machtsiras, 2008). Therefore, this system enables coaches and researchers to gain valuable kinematic features of the swimmer, for their analysis and feedback. However, this method is not financially viable for most average coaches and requires additional skills to read the information, emphasising the need for other alternative technology which is commercially and financially accessible. An example of such a technology is represented by microelectromechanical systems (MEMS). MEMS are waterproofed and wearable inertial devices, such as gyroscopes, magnetometers or tri-axial accelerometers (Daukantas, Marozas, Lukosevicius & Marozas, 2008; Justham *et al.*, 2008). It is important to note that these MEMS devices would be considered a direct monitoring system, as it is attached to the swimmer.

Tri-axial accelerometers are the most popular of the MEMS devices, used in swimming monitoring and research (James, 2006; Justham *et al.*, 2008; Mooney *et al.*, 2015). These accelerometers enable the measurement of changes in accelerations of a moving object along specific reference axes, namely X-, Y- and Z-axis (referring to medio-lateral superior-inferior and antero-posterior accelerations, respectively). Dependent on the device orientation, each axis has characteristic peaks and troughs which are vital in the identification of various kinematic parameters in human movement; especially in swimming (Davey, Anderson & James, 2008; Mooney *et al.*, 2015). Research and development in the field of wearable devices have been long-standing and has shown that accelerometers proved to be more advantageous than other techniques, to quantitatively measure human movement (Yang & Hsu, 2010). The other techniques used in quantifying general physical activity or human movement, other than accelerometers, include goniometers, pedometers or gyroscopes (Yang & Hsu, 2010). Whereas in swimming, alternate performance analysis techniques other than accelerometers include commercial tethered velocity systems and pressure sensors on the starting blocks or swimmer's hand (Justham *et al.*, 2008; Le Sage, Bindel, Conway, Justham, Slawson & West, 2010; Stamm, James, Burkett, Hagem & Thiel, 2013). Henceforth, accelerometers are regarded as multi-faceted with its use in either the assessment of general physical activity or the monitoring and assessment of sporting activities. These inertial devices allow for researchers to assess *posture and movement, estimate energy expenditure* (Yang & Hsu, 2010) and investigate *kinematic (i.e. stroke phase recognition)* (Nakashima, Ohgi, Akiyama & Kazami, 2010; Ohgi, 2002; Ohgi, Ichikawa, Homma & Miyaji, 2003) and *kinetic (i.e. velocity profiling)* parameters (Stamm, James & Thiel, 2013; Zhao, Gerhard & Barden, 2015). A significant advantage of accelerometers is that it is body-fixed and relatively small. Therefore, it would be small enough to contribute minimally to the swimmer's surface drag and it does not interfere with their swimming technique (Zhao *et al.*, 2015). Overall, the most common use of accelerometers was found to be in the detection of biomechanical features within sporting activities as well as measuring general activity levels for health (Davey *et al.*, 2008).

Various studies have examined the use of either commercially available tri-axial accelerometer-based technology such as Finis Swimsense (FINIS USA, Livermore, CA, USA) and Garmin Swim (Garmin International Inc., Olathe, KS, USA) fitness watches or other MEMS in the measurement swimming kinematic parameters (Mooney *et al.*, 2015; Mooney, Quinlan, Corley, Godfrey & Osborough, 2017; Yang & Hsu, 2010). These parameters include average lap time, stroke length and stroke rate of the different stroking styles (Davey *et al.*, 2008; Mooney *et al.*, 2015, 2017). Furthermore, the accelerometers are also used to differentiate the stroke mechanics which is characterised by the stroke phases between the different stroking styles. The stroking styles, which include butterfly, freestyle, breaststroke and backstroke, have defined stroke phases which are the pull and recovery phases during a typical arm cycle associated with a given stroking style (Hay, 1993). The *pull phase* is defined by the point at which the hand enters the water, with the end of the phase determined when the hand leaves the water (Hay, 1993). The *recovery phase* is defined as the period after the completion of the pull phase as the swimmer lifts their hand from the water in preparation to re-enter the water after a given stroke (Hay, 1993).

One study conducted by Ohgi (2002), designed a custom device using multiple tri-axial accelerometers to determine the stroke sub-phases, which include "the catch, in-sweep, out-sweep and recovery", for the specific strokes of freestyle and breaststroke. Figure 2 represents an example of the possible the stroke phase extraction of freestyle determined by a GeneActiv tri-axial accelerometer (GeneActiv; Activinsights, England). The stroke phases and stroke mechanics can be clearly identified and labelled based on accelerometer data, which would have clear utility for swimmers and coaches alike, as it has shown to increase the amount of information available to coaches and swimmers (Callaway, 2015; Ganzevles *et al.*, 2017; Siirtola, Laurinen & Juha, 2011; Wright & Stager, 2013).

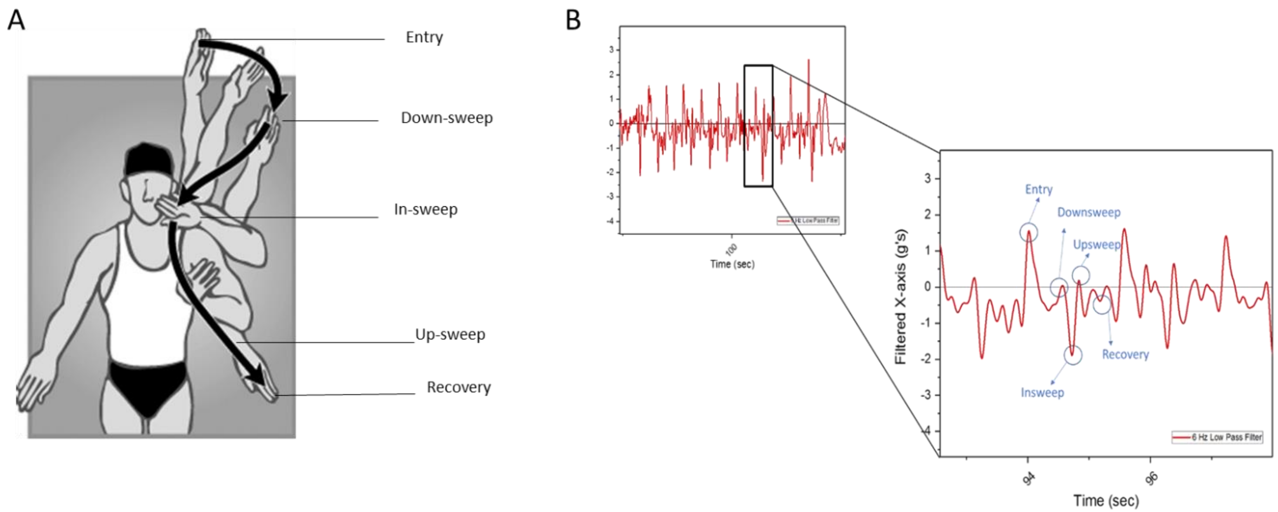


Figure 2: Stroke phases and mechanics; (a)- Stroke phases of freestyle. Pull phase is divided into four components: entry, down-sweep, in-sweep and up-sweep; with the recovery phase following thereafter. (b) Graphical representation of the tri-axial accelerometer data corresponding the relevant peaks and troughs to the stroke phases of freestyle.

In conjunction with the stroke phase differentiation (see Figure 2), accelerometers provide a sensor platform to extract the common kinematic parameters from the swimmer's training session, without the use of expensive equipment and are a useful measuring tool even in either the presence and absence of the coach during a given session (Davey *et al.*, 2008). These common kinematic parameters include average stroke length and stroke rate, swimming velocity, stroke type and swimming time (Mooney *et al.*, 2015). As previously mentioned, coaches typically would have to oversee multiple swimmers within a training session, which includes prescribed training bouts given with continuous instruction and feedback from the coach. However, coaches would have to entrust that the swimmer is performing the prescribed training efficiently, due to the constraints of overseeing multiple athletes simultaneously (Wright & Stager, 2013). Hence, the accelerometer would provide an additional measure to the coaching feedback, to allow coaches to concentrate on other technical aspects (e.g. swimming technique) in training. Alternatively, if the coach cannot attend the session, the accelerometer would provide all the information from the subsequent session and confirm if the swimmer performed the pre-requisite training bouts (Ganzevles *et al.*, 2017; Wright & Stager, 2013). One study by Ganzevles et. al. (2017), investigated the reliability and practical usefulness of tri-axial accelerometers in monitoring the swimmer's lap time, stroke count and stroke rate during their daily training. It was concluded that the tri-axial accelerometers were accurate and reliable in monitoring the swimmer's daily training. Henceforth, providing a more useful feedback tool for coaches than the typical hand-timed watches.

Furthermore, extensive research was conducted using specific databases, inclusive of EbscoHost, Science direct, Pubmed and Research gate, which in turn resulted in limited research to be found within a South African context with regards to the use of the accelerometers in swimming. Hence, a gap exists in the South African literature in the use of tri-axial accelerometers in the differentiation of kinematic parameters that influence the swimmer's performance efficiency.

Therefore, the purpose of the present study is to determine and differentiate between the kinematic parameters and the stroke mechanics amongst all four strokes in swimming, using tri-axial accelerometers and how this information can be used to aid coaches and swimmers' in enhancing their swimming performance.

In the section to follow, the research question, aim and objectives, as well as, the significance of the present study will be discussed.

1.2 Research question, aim and objectives

1.2.1 Research question

What kinematic parameters and swimming stroke mechanics can be derived from tri-axial accelerometers during a 200-m individual medley (IM) event in South African national level swimmers?

1.2.2 Research aim

The primary aim of this study was to determine the differences in the kinematic parameters and swimming stroke mechanics that could be derived from tri-axial accelerometers, during a 200-m individual medley (IM) event in South African national level swimmers.

1.2.3 Research objectives

To address the aim of the present study, the following objectives were adhered to:

1.2.3.1 To identify and differentiate between the stroking styles (i.e. freestyle, breaststroke, butterfly and backstroke) performed at different swimming speeds using two tri-axial accelerometers placed on the left wrist and upper-back, respectively.

1.2.3.2 To identify swimming kinematic parameters such as stroke length, stroke rate, swimming turns, swimming distance and stroke phases, as well as swimming velocity and swimming intensity for all four strokes, using the tri-axial accelerometers in conjunction with a Polar heart rate watch and heart rate belt located on the left wrist and upper-back.

1.2.3.3 To determine the effectiveness and accuracy of machine learning in identifying the stroking stylings, stroke kinematics parameters and stroke mechanics from the tri-axial accelerometers using a custom-designed computer algorithm implemented by the Nelson Mandela Computer Science department.

1.3 Significance of the study

The use of technology in swimming has proven to be a vital tool in athlete monitoring and in providing coaches with additional information on the swimmer's performance (Ganzevles *et al.*, 2017; Wright & Stager, 2013). Tri-axial accelerometers have been used extensively in general health and physical activity monitoring (Yang & Hsu, 2010) but are relatively under-utilised in a swimming context, especially within South Africa. Therefore, the novelty of this technology in South Africa emphasises the need to investigate certain kinematic parameters, which may influence the swimmer's performance (Davey *et al.*, 2008; Ganzevles *et al.*, 2017; Mooney *et al.*, 2015; Siirtola *et al.*, 2011) and how these inertial devices can be used as an additional coaching aid. Commercial swimming technology such as the Finis *Swimsense* (FINIS USA, Livermore, CA, USA) and Garmin *Swim* (Garmin International Inc, Olathe, KS, USA), which are inclusive of tri-axial accelerometers, only provide superficial kinematic parameter information to the coaches and swimmers (Mooney *et al.*, 2017). This kinematic information is inclusive of the swimmer's stroke length, stroke rate, swimming efficiency (also known as SWOLF), swim pace and stroke type detection (Finis, 2018; Garmin, 2018). However, a need still exists to analyse the swimmer's specific stroke mechanics such as in-sweep, out-sweep, recovery and turning, more efficiently and in a timely and cost-effective manner. One future goal of the present researcher is to implement a "live-streaming" or "real-time" feedback system to deliver the swim mechanics and other swim kinematics for each stroke, to the coach as an additional training tool and guide during a swim practice. Two studies performed by Le Sage et. al. (2010) and Le Sage, Bindel, Conway, Justham, Slawson and West (2011), implemented real-time sensor nodes with a network protocol integrated into the system, to transmit the kinematic and kinetic information from the swimmer to a computer in close proximity at the pool. However, at the present time, the theoretical development of the accelerometer data and the algorithms linked to the understanding and expansion of this inertial sensor's information will be addressed in this present study.

1.4 Terminology

The following table below serves as a concept clarification, aimed to eliminate any ambiguity related to the technical terminology associated with the general understanding of swimming and swimming biomechanics, as well as the understanding of the present study.

Table 1: Concept clarification of the common terminology used within the following dissertation

Concept	Definition
Kinematic	This is a branch of mechanics which investigates spatial and temporal components of movement without references to the forces causing the movement. With regards to sport and exercise, kinematic parameters may include linear and rotational position, displacement, velocity and acceleration (Bartlett, 2007). Kinematic parameters within swimming include stroke length, stroke rate, swim velocity and acceleration (Mooney et al., 2015).
Stroking styles	Swimming includes four stroking styles: freestyle, breaststroke, butterfly and backstroke. Each stroking style has characteristic stroke phases and biomechanical features to ensure optimal propulsion, whilst minimising resistive forces (drag forces) (Hay, 1993; Pan, Huang, Lu & Lin, 2016).
Stroke phases	The stroke phases form part of the pull and recovery phases of the stroke arm actions of the stroking styles. The pull phase starts as the hand enters the water and finishes as it leaves. The recovery phase is the period after the pull phase has ended, where the hand swings forward in preparation to re-enter the water, to start the next pull phase (Hay, 1993).
Stroke count	The number of completed arm cycles or strokes performed by the swimmer in a given length (Anderson, 2006).
Stroke rate or stroke frequency	Stroke rate is defined as the number of completed arm cycles performed in a given time-period (Hay, 1993).

Stroke length	Stroke length is defined as the horizontal distance covered in the water with each completed stroke cycle (Hay, 1993).
Accelerometer	This is an inertial sensor, which detects minute changes in inertia in both linear and radial directions. Hence, accelerometers measure the changes in an object's acceleration along reference axes (James, 2006). These devices contain microelectromechanical systems (MEMS), which enables the accelerometer to be reduced in size and weight to allow it to be used in physical activity. Accelerometers are used for numerous functions such as measuring posture and movement, estimation of energy expenditure and fall detection and balance control evaluation (Yang & Hsu, 2010).

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The purpose of this literature review is to indicate the past, current and novel research presented in the field of swimming, specifically focusing on the use of alternative technologies (i.e. inertial devices) in the assessment of swimming kinematics and kinetics. Research in the field of swimming has grown extensively over the last few decades, with new methods emerging with regards to identifying the swimmer's stroke mechanics and kinematic and kinetic parameters (see Figure 3). Additionally, more in-depth feedback platforms have also been researched and implemented for the coaches to enhance their scientific approach to their swimmer's training regime and monitoring.

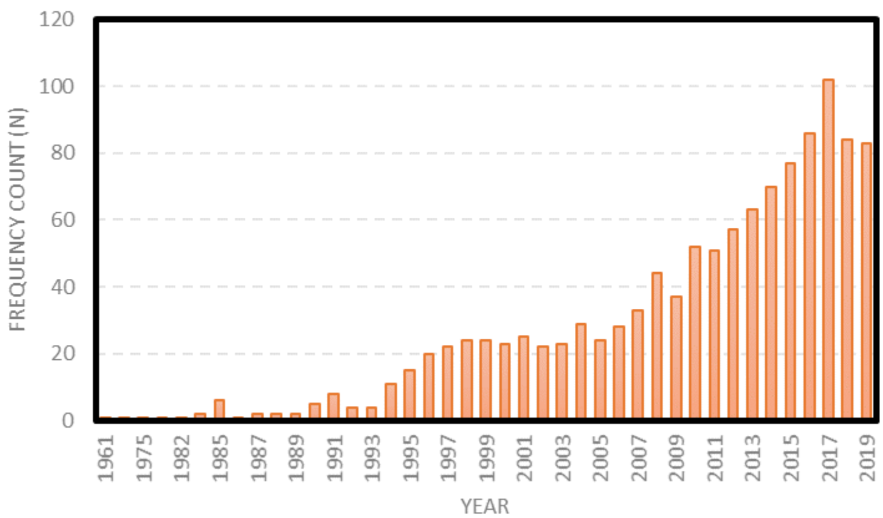


Figure 3: Literature search for publications related to swimming kinetics and kinematics. Results are based on a PubMed search using "swim*" AND "kine*" as keyword parameters

In the sections to follow the foundations of swimming as an aquatic sport and how this sport has evolved, in conjunction with the growth of technology, will be explained. Hence, specific emphasis will be placed on the use of technology, specifically accelerometers, as a performance enhancement, monitoring and coaching tool in a swimmer's daily training.

2.2 Swimming

Swimming is defined as a cyclical, bilateral overhead sport due to the repetitive body movements performed by the swimmer, to achieve the desired stroke action (Evershed, Burkett & Mellifont, 2014). Competitive swimming includes four main strokes; two symmetrical strokes (i) butterfly and (ii) breaststroke, and two asymmetrical strokes (iii) backstroke and (iv) freestyle (Reilly, Secher, Snell & Williams, 2005). For a typical swimming competition, a swimmer may choose to swim certain strokes over a specific race distance per the Federation Internationale de Natation (FINA) rules (FINA, 2017). The race distances for competitive swimming events include: short or sprint distance (50- and 100-m), middle distance (200- and 400-m) and long-distance (800- and 1500m) (Anderson, 2006; FINA, 2017). During regular swimming competition, the swimmer would partake in single events which are categorised by a specific stroke with a given distance (Dormehl & Williams, 2016). An example of this would be a 50-m freestyle event. Furthermore, swimming does not only include single stroke events but also a multi-disciplinary event known as an individual medley, which is inclusive of all four strokes (Anderson, 2006; FINA, 2017).

Swimming, like any sport, requires the swimmer to balance both their physiological and biomechanical demands, as well as coping with the psychological aspects which may affect their sporting performance (see Figure 4) (Anderson, 2006; Figueiredo, Silva, Sampaio, Vilas-Boas & Fernandes, 2016). In elite swimming performances, the swimmer and coach, strive to achieve the ideal stroke biomechanics and technique to optimise the swimmer's performance efficiency, whilst gaining a mechanical advantage (Evershed *et al.*, 2014). According to international literature, to achieve a high standard of performance in competitive swimming, the biomechanics and energetics of the swimmer must be enhanced (Barbosa *et al.*, 2010; Figueiredo *et al.*, 2016). Hence, a large aspect of the literature has focused more on the swimmer's biomechanical parameters, whilst discovering alternate technology to aid in further optimisation of these parameters (Barbosa *et al.*, 2010; Figueiredo, Pendergast, *et al.*, 2013; Mooney *et al.*, 2015; Ribeiro *et al.*, 2016; Seifert, Schnitzler, Bideault, Alberty, Chollet & Martin, 2015). However, the physiological parameters of the swimmer should not be disregarded as this plays an important part, if not an equally beneficial role, in the swimmer's adaptation to their biomechanical changes. These biomechanical parameters include swimming speed, stroke mechanics, drag forces, propulsive efficiency, starting and turning ability of the swimmer. Whereas the physiological parameters include muscle power, flexibility, maximal aerobic capacity (i.e. $\dot{V}O_2max$) and anaerobic power (Anderson, 2006; Hay, 1993; Sanders, 2013).

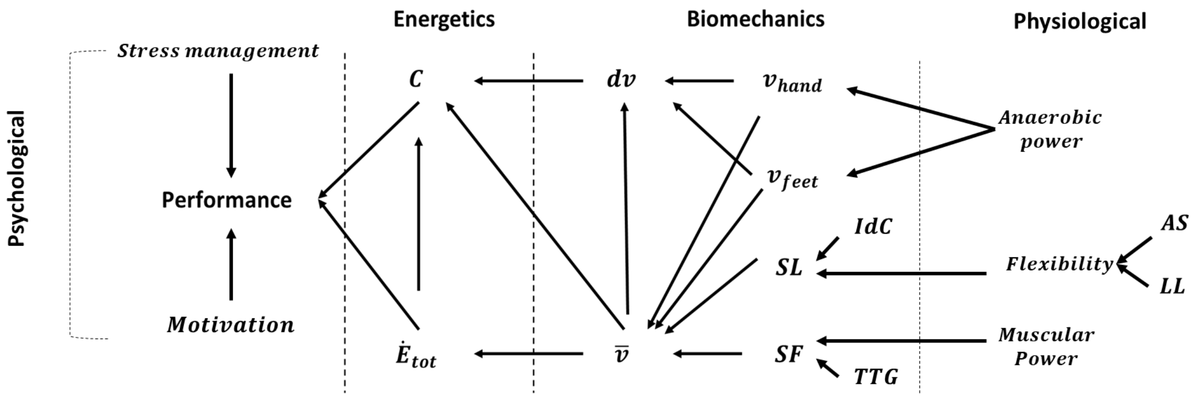


Figure 4: Overview of physiological, biomechanical and psychological parameters that may influence swimming. C: energy cost, $\dot{E}_{tot}$: energy expenditure, dV: intra-cyclic variation of the horizontal velocity of the centre of mass, IdC: index of coordination, TTG: total time gap, SL: stroke length, SR: stroke rate, $\bar{v}$: average swimming velocity, v_{hand}: hand's velocity, v_{feet}: feet velocity, AS: arm span, LL: leg length. performance (Adapted from Anderson (2006) and Barbosa et. al. (2010))

The common goal of every swimmer is to try and perform their chosen race distance in the fastest time possible. This is typically achieved by the swimmer obtaining their highest average swimming velocity for that respective race distance (Figueiredo, Pendergast, *et al.*, 2013). Therefore, the *average* swimming velocity ($\bar{v}$; m/s) is seen as the product of the *average* stroke rate ($\overline{SR}$; strokes/s) and *average* stroke length ($\overline{SL}$; m/stroke) of the swimmer (Barbosa *et al.*, 2010; Figueiredo, Pendergast, *et al.*, 2013)., which is expressed as:

$$\bar{v} = \overline{SR} \times \overline{SL}$$

Equation 1: Average swimming velocity formula (Hay, 1993)

The average SR ($\overline{SR}$) is determined by the average number of completed arm cycles performed in a given time period (as expressed in Equation 2) (Figueiredo, Pendergast, *et al.*, 2013; Hay, 1993). Whereas, the average SL ($\overline{SL}$) is determined by the average horizontal distance covered in the water with each completed stroke cycle (Figueiredo, Pendergast, *et al.*, 2013; Hay, 1993) (as expressed in Equation 3).

$$\overline{SR} = \frac{number\ of\ completed\ arm\ cycles}{time\ spent\ stroking}$$

Equation 2: Average stroke rate formula (Hay, 1993)

$$\overline{SL} = \frac{distance\ stroked}{number\ of\ completed\ arm\ cycles}$$

Equation 3: Average stroke length formula (Hay, 1993)

The relationship between SR, SL and $\bar{v}$ has proven to play a major role in the swimmer's performance, with the swimmer adapting to these stroke parameters to meet the demands of the swimming event (Barbosa *et al.*, 2010). If the swimmer were to maintain their highest $\bar{v}$ throughout the course of their race distance, propulsive and resistive forces would play an interactive role in the maintenance of this required speed (Figueiredo, Morais, Vilas-boas & Fernandes, 2013; Seifert *et al.*, 2015). The propulsive forces are achieved by a combination of lift forces (i.e. lift propulsion force), and drag forces (i.e. drag propulsion) (Bilinauskaite, Mantha, Rouboa, Ziliukas & Silva, 2013; Grimshaw, Burdan, Lees & Fowler, 2006). Particularly in swimming, the swimmer's hand would produce the lifting force. How the swimmer achieves this propulsive lifting force is dictated by the hand angle of attack in the water and the stroking pattern performed during their stroke cycle. The hand angle of attack is characterised by the direction to which the swimmer's hand is inclined in the water. Hence, with an increase in the angle of attack, would increase the lifting forces produced (Grimshaw *et al.*, 2006). However, this would also increase the drag (resistive forces) that the hand experiences (see Figure 5).

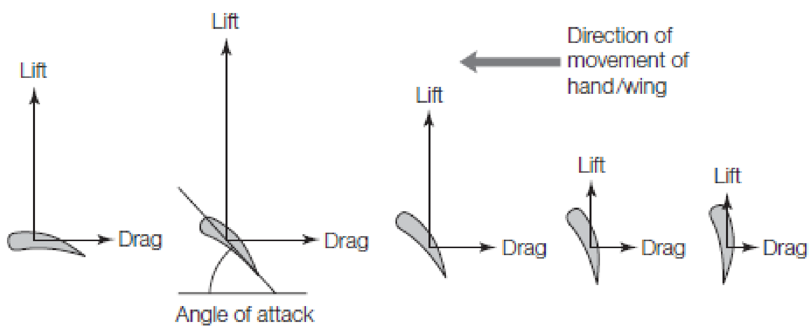


Figure 5: Ratio of propulsive lift forces experienced versus drag forces. As extracted from Grimshaw et. al. (2006)

Therefore, the optimal angle of attack is often determined by the trade-off between the swimmer’s hand angle and the drag forces which is determined by this angle. Based on this principle, Grimshaw et. al. (2006) found that the optimal angle of attack for freestyle swimming was between 30° and 50°. Additional to the hand angle of attack, the contribution of the swimmer’s arms and legs also dictate the effects of the propulsive force produced in the water. It was found that for freestyle and backstroke, the swimmer’s arms contributed more than their legs (Hay, 1993). In butterfly, the propulsive forces generated were approximately the same between the legs and arms of the swimmer. However, for breaststroke, the swimmer's legs contributed more to the propulsive force generated than their arms (Hay, 1993).

On the other hand, one of the most pre-dominant resistive forces the swimmer experiences in the water is known as drag. Drag is described as a resistive force that acts in opposition to the direction of the fluid flow, thereby resisting forward motion (Bartlett, 2007; Sanders *et al.*, 2008). Three types of resistive (drag) forces act upon the swimmer to decrease their stroking parameters and swimming velocity, namely form (pressure), surface and wave drag (Bartlett, 2007; Hay, 1993; Sanders *et al.*, 2008). *Form drag* is defined as the differential pressure between the front and rear of the swimmer’s body or individual limbs (Sanders *et al.*, 2008), therefore causing a boundary layer separation, resulting in an area of low pressure to form behind the swimmer (Bartlett, 2007). This drag force magnitude is dictated by the speed at which the swimmer travels through the water (Hay, 1993). Therefore, the form drag can be reduced by minimal disturbances to the fluid flow in a process known as “streamlining”. Swimmers can achieve a “streamlined” movement by manipulating their body position (Bartlett, 2007; Hay, 1993), to increase their chances for optimal propulsion in the water. *Surface drag* is defined as a resistive force between the fluid medium and the body surface area and smoothness of the swimmer, as well as the relative velocity of the oncoming fluid flow (Grimshaw *et al.*, 2006). Swimmers may reduce surface drag by wearing friction-reducing swimsuits designed by sports companies such as Speedo and Adidas. These suits create a surface that causes eddy currents to form around the swimmer thereby reducing the surface frictional drag (Bartlett, 2007; Grimshaw *et al.*, 2006). Lastly, *wave drag* is caused by the swimmer moving through both water and air medium, causing pressure differences at the boundary layer resulting in the water level to rise and fall, generating waves (Bartlett, 2007). Factors such as the swimmer’s speed, body shape and movement in the proximity of the water surface dictates the overall effect of this resistive force on the swimmer's performance in the water (Hay, 1993; Sanders *et al.*, 2008).

To fully understand the extent to which these abovementioned drag forces affect a swimmer's performance, Sanders et. al. (2008), described an equation to quantify the drag forces acting on the swimmer (see Equation 4).

$$F_D = \frac{1}{2}\rho v^2 C_D S$$

Equation 4: Formulae for drag. Adapted from Sanders et. al. (2008).

Where F_D is the drag force, which is determined by the density of the fluid (ρ), the velocity of the limb relative to the fluid (v), the surface area of the limb (S) and the coefficient for drag (C_D), which varies according to the shape of the limb and its orientation to the fluid flow (Sanders *et al.*, 2008).

Other than the drag forces, if one were to consider an increase in resistive forces with an increase in speed, the swimmer would not be able to maintain a consistent forward movement in the water due to the onset of fatigue. Ultimately, a decrease in their swimming speed would result, with the concomitant changes in stroke parameters to adapt to this change (e.g. decrease in SL with a compensatory increase in SR) (Barbosa *et al.*, 2010). In earlier literature, Hay (1993), described the SR and SL stroke parameters as an interdependent relationship. A reason for this description was due to the observation that, for a given swim velocity, when one of the parameters was increased, the other would typically decrease to compensate for this change. Therefore, the interdependent relationship was linked to the swimmer trying to maintain an advantageous swimming speed throughout their swimming event. The most common change research has found amongst these two parameters, was when the swimmer was required to maintain a relatively high $\bar{v}$. It was found that the swimmer would increase their SR, leading to a compensatory decrease in their SL (Barbosa *et al.*, 2010; Figueiredo, Pendergast, *et al.*, 2013). However, it must be noted that other factors such as fatigue and increases in propulsive and resistive forces, also contribute to the decrease in SL and not only the change in SR (Barbosa *et al.*, 2010; Figueiredo, Morais, *et al.*, 2013; Figueiredo, Pendergast, *et al.*, 2013; Hay, 1993; Seifert *et al.*, 2015).

The relationship between the stroke parameters (SR, SL and $\bar{v}$), is not only interdependent on each other but also on other modifications by the swimmer within their stroke cycle. A stroke cycle is divided into two common phases across all four stroking styles, namely a pull phase and a recovery phase. Hay (1993), described the pull phase as the point at which the hand enters the water, with the end of the phase determined when the hand leaves the water. The recovery phase is described as the period after the completion of the pull phase as the swimmer lifts their hand from the water in preparation to re-enter the water after a given stroke. The pull phase can then be sub-divided further into decisive stroking phases, which is characteristic to a specific stroking style. Figure 6, highlights the different sub-phases within the pull phase of each stroking style.

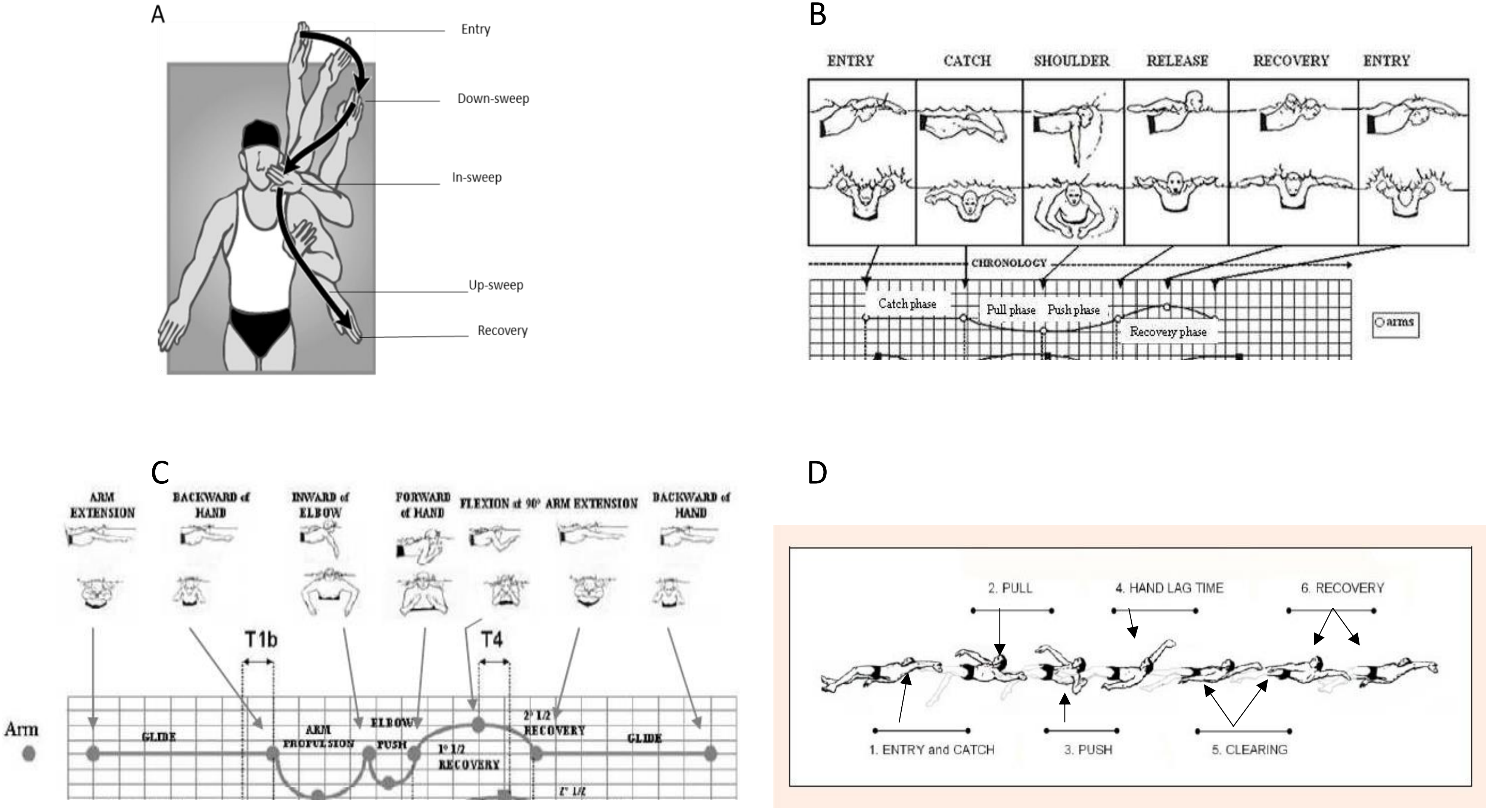


Figure 6: Diagrammatic representations of the stroke phases of the FINA regulated strokes. (a) freestyle (b) butterfly (c) breaststroke (d) backstroke (Cortesi, Fantozzi & Gatta, 2012; Didier & Seifert, 2011; Orgen, 2017)

As seen in Figure 6, each respective stroking style has several different or similar stroke phases. However, the description of the stroke sub-phases for each stroking style differs throughout various literature as the swimming technique (i.e. stroke mechanics) and how researchers could investigate it, has changed and adapted over time. An example of this is by Maglischo (1993), who defined the stroke phases for freestyle and breaststroke as follows: the entry, stretch, down-sweep, in-sweep, up-sweep and recovery (for freestyle) and out-sweep, in-sweep and recovery (for breaststroke). Although the stroke phases for freestyle have remained relatively consistent throughout the literature, the stroke phases for breaststroke have become more complex compared to that of Maglischo's (1993) definition. In a study by Didier and Seifert (2011), the arm stroke phases for breaststroke were divided into five distinct phases (see Figure 6c): (i) arm glide, (ii) arm propulsion, (iii) elbow push, (iv), part one of the recovery phase until the arm or forearm reached an angle of 90 degrees and (v) part two of the recovery phase till the start of the new arm cycle. Therefore, in comparison to Maglischo's (1993) three distinct phases for breaststroke, further research is required to determine which of the two definitions is more closely related to the actual stroking action.

Alternatively, throughout the literature researchers have also investigated and developed new concepts to quantify the stroke phases within a stroking style. One of these concepts is the swimmer's interarm coordination, which is classified as the time spent in the different phases of their stroke cycle (Figueiredo, Pendergast, *et al.*, 2013). Therefore, a swimmer's interarm coordination can be determined by measuring their index of coordination (IdC) during freestyle (Figueiredo, Pendergast, *et al.*, 2013). Chollet, Chalies and Chatard (2000), developed the concept of the IdC to quantify the arm movements of the swimmer during a freestyle performance. Links between IdC and stroke kinematics was investigated and observed within a study by Seifert, Chollet and Rouard (2007). It was found that each stroking parameter (SR, SL or swimming velocity) had a significant effect on the IdC of the swimmers tested, with the stroke rate showing the most influence (R^2 = 35.9%) on the IdC. This finding supports the foundation of IdC, as its base measurement is represented by the *time* between the pull and recovery phases. Therefore, changes in SR would result in equivalent changes in IdC of the swimmer (i.e. increase in SR, results in a high IdC) (Seifert *et al.*, 2007). The concept of IdC and the role it plays in swimming is an on-going developing area of research. Hence, scientists are still discerning its specific role related to swimming kinematics. However, at present IdC and its links to swimming kinematics falls outside the scope of the present study.

In the section to follow, alternative methods were sought out in quantifying the kinematic swimming parameters, to allow coaches to make scientific adaptations to help improve their swimmer's performance. Hence, common methods used in kinematic swimming performance analyses were investigated further.

2.3 Common methods of kinematic swimming performance analysis

Swimming kinematics includes a vast number of parameters such as stroke length, stroke rate, swimming velocity, joint kinematics within a range of motion, as well as the stroke index and index of coordination (Barbosa *et al.*, 2010; Evershed *et al.*, 2014). The research within each of these areas is extensive, with researchers constantly discovering innovative ways to quantify these parameters with the goal of optimising the swimmer's performance and efficiency. However, in swimming, constraints were evident in the measuring of the swimmer's performance when they were in the water (Justham *et al.*, 2008). Such limitations motivated for new quantifiable monitoring and performance analysis systems to be developed. Therefore, commercialised systems were made available to support of various sporting disciplines and could be sub-divided into three categories: *direct monitoring systems* (equipment attached directly to the athlete, e.g. heart rate monitors), *modelled monitoring systems* (theoretical modelling software/systems used in athlete analysis, e.g. ergometer use) and *remote monitoring systems* (equipment attached remotely from the athlete, e.g. Vicon motion analysis) (Justham *et al.*, 2008). In conjunction with these categories, swimming performance analysis techniques have grown substantially over the years, with Justham et. al. (2008), summarising all techniques which were available from 1996 to 2008 (see Figure 7). Each of these systems has a certain role in swimming kinematic and kinetic performance analysis, as well as in swimming monitoring.

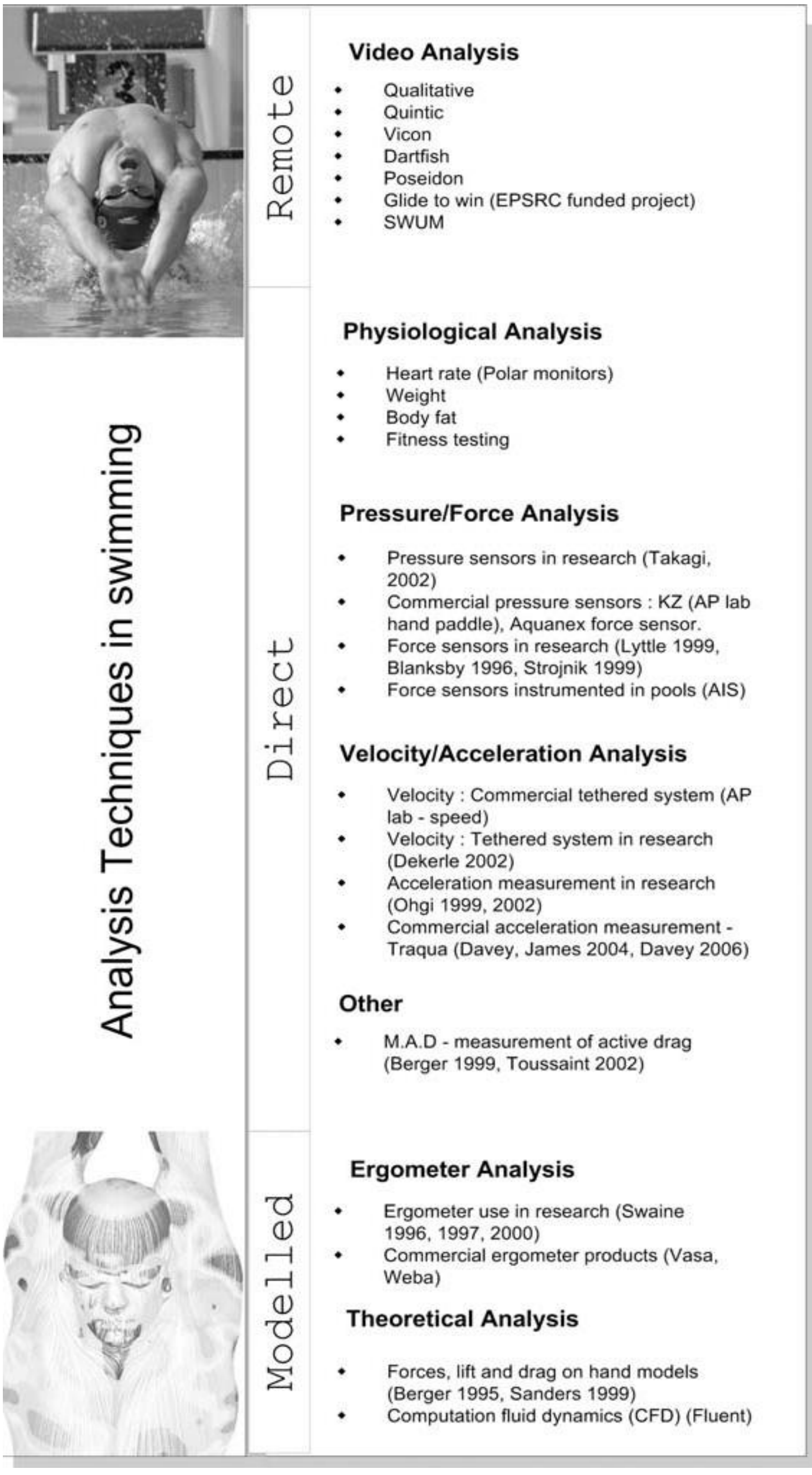


Figure 7: Monitoring techniques used in performance analysis from 1996- 2008, extracted from Justham et. al. (2008)

Therefore, in the sub-sections to follow, the mechanisms on how these performance analysis methods of swimming kinematics have grown rapidly with the increase of technology within the sport, will be discussed.

2.3.1 Lab-based analyses and testing

Swimming is classified as an aquatic sport as it is performed in water, with this aquatic environment posing unique challenges on the swimmer (Costa *et al.*, 2015). Therefore, methods in which to test these challenges on land are limited due to specific environmental constraints. One method used by researchers to overcome such constraints is the use of a swim bench apparatus or swimming ergometer, primarily used to measure swimming kinematics on land. According to Dalamitros, Manou and Pelarigo (2014), the biokinetics swim bench test is one of the most widely used land-based swimming tests with a high-reliability relationship (r= 0.93) with measuring swimming based parameters (i.e. swimming velocity), whilst simulating the arm stroke action of the swimmer. However, limitations in using this type of swim bench test were presented in various studies, to which researchers had to modify the equipment to more accurately represent the swimmers stroking style on land. For example, one of the earliest swim bench assessments required the swimmer to start in a prone position, with their hands placed in paddles attached to pull ropes. The swimmer then pulled back quickly to complete an arm cycle with their arms in unison or alternating, to mimic the stroking style of choice (Dalamitros *et al.*, 2014). Similarly, in a study by Zamparo and Swaine (2012), the swim bench was then modified into a whole-body swimming ergometer to monitor the swimmer's power output and to test additional physiological parameters. The whole-body swimming ergometer was designed to apply a resistance to the movement of each limb by using four air-dynes. These four air-dynes were mounted on rotating spindles attached to pulley ropes with paddles on the end for the swimmer’s hands and feet (see Figure 8).

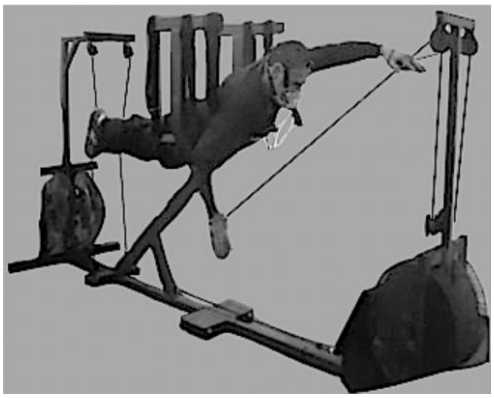


Figure 8: Photo illustration of the whole-body simulated swimming ergometer presented in Zamparo and Swaine (2012) research study

Zamparo and Swaine (2012), subsequently discovered various limitations with this method of analysis. Their first limitation was simulating the exact resistance the swimmer would experience in the water, during each swimming stroke. As the swim bench used a pulley system, the resistance was not applied to the swimmer's body movements but perpendicular to the fixed point on the swim bench. This posed additional problems, such as the inability to incorporate a 'sculling motion' during the freestyle action. A "sculling" motion contributes to the swimmer's overall forward propulsion; such a limitation would have meaningful implications. Therefore, due to the set-up of the ergometer, the action was predominantly performed in the frontal and sagittal plane, whereas this sculling action was more commonly performed in the transverse plane. This limitation was supported by an earlier study by Clarys (1985) who found the biokinetics swim bench to lack specificity in mimicking the stroking action of the swimmer observed in the water. The second limitation found by Zamparo and Swaine (2012), was the limitation of body roll when using a swimming ergometer. As seen in Figure 8, Zamparo and Swaine (2012) modified the ergometers to have a suspended cradle to support the swimmer's upper body. This allowed the swimmer's torso to flex laterally and more freely, adding to the simulation of the stroking action. However, research is yet to be developed to what extent this body roll within this land assessment differs from that experienced by the swimmer in the water when performing freestyle as the stroke of choice. Therefore, one can see that this method of analysis has various constraints on the swimmer, either related to their technique, or the environmental aspects (e.g. resistive forces produced in the water) which could play a considerable role in the swimmer's propulsive ability in the water. An additional question one may ask is if the use of the swim bench ergometer, as a method of analysis, would be more suited for testing protocols versus for training purposes. Although the swim bench ergometer has various constraints related specifically to the reproducibility of the swimmer's technique in the water, it provides a means of resistance training on-land to increase power control in the swimmer's arms. A study by Tanaka, Costill, Thomas, Fink and Widrick (1993), used the biokinetics swim bench as a monitoring tool, to observe strength training improvements based on a given resistance training programme. The study found that no significant improvements were observed in the swimmer's maximal power produced on the swim bench, but improvements were seen in the swimmer's swim performance. Therefore, emphasising a need for specificity in the type of resistance-training exercises the swimmer performs during dry-land training. Alternatively, one study designed an intervention with high velocity swim training and biokinetic swim bench training sessions. It was found that no improvements were observed in the swimmer's performance both in the control group and the biokinetic swim bench group. This lack of improvement may have been due to the increased stability provided by lying on a stable surface compared to the relative instability produced by the water and the lack of reproducibility of the drag propulsion relationship on land (Crowley, Harrison & Lyons, 2017). Taking these above-mentioned findings into account, the use of the biokinetic swim bench is limited in the accurate display or "mimicking" of the swimming specific characteristics observed within the water. Therefore, adding constraints to investigating swim-specific parameters such as stroke mechanics, on land.

Subsequently, alternative methods inclusive of wearable devices (i.e. inertial sensors) or methods in which the swim specific parameters could be investigated, without hindering the swimmer's stroking mechanics, were sourced. One of these alternate methods was found to be video analysis. Hence, in section 2.3.2 to follow, the benefits of video-based performance approaches and its contribution to swimming kinematic identification will be discussed.

2.3.2 Video-based data acquisition

Video analysis can allow for 3-dimensional (3-D) data acquisition to take place but this is usually dependent on two orthogonally set up cameras. However, if this is not done accurately, it may produce a low kinematic data acquisition of the movement analysed (Sanders *et al.*, 2008). The "gold standard" for 3-D data acquisition would be the use of a multi-camera opto-electric motion analysis system such as Vicon (Vicon, Oxford UK) (Sanders *et al.*, 2008; Schurr, Marshall, Resch & Saliba, 2017). Vicon uses reflective passive markers on the subject that allow multiple infrared cameras to detect and recognise the subject's movement automatically (Bartlett, 2007; Sanders *et al.*, 2008). However, limitations with this system are that it is usually very costly and that it requires subject-specific expertise which would be beyond the reach of most coaches, who wish to correct the technique or enhance the performance of their swimmers (Sanders *et al.*, 2008). Another limitation also found with the use of opto-electric motion analysis systems was in a study that investigated the reduction of swimming performance using 25 reflective markers on the swimmer in kinematic swimming analyses. The study found that when 25 of these markers were placed on the swimmer, additional drag force was induced, reducing the swimmer's performance with an increase in their final 50-m time by 1.08 seconds resultant from a decrease in swimming velocity by 0.06 m/s (Washino, Mayfield, Lichtwark, Mankyu & Yoshitake, 2019). Therefore, posing a limitation in wearing reflective markers on the swimmer, although it forms part of the "gold standard" 3-D analysis system. Considering these limitations of the 3-D opto-electric motion analysis systems, the use of alternative methods of analysis using 2-D systems which are more cost-effective were sought out by researchers for kinematic analyses.

The use of video-based technology in swimming kinematic analyses has grown substantially with the development of technology, which in turn has opened many avenues in international literature. According to Stamm, James and Thiel (2013), video analysis is one of the most common non-invasive technological strategies used to monitor swimmers. This is due to the video equipment being set-up out of range of the swimmer and subsequently, not hindering their stroking mechanics. This was supported by an earlier study by Justham et. al. (2008), who stated that video and image processing is one of the most favoured methods of performance analysis, within the three analysis technique categories (i.e. direct, remote and modelled systems) mentioned above.

Various swimming kinematic parameters such as stroke length, stroke rate, joint angle kinematics and the identification of the different stroking styles have been investigated using video analysis (Callaway, Cobb & Jones, 2009; Mooney *et al.*, 2015). Like any performance analysis assessment, this method of analysis has various advantages and disadvantages. The advantages of video analysis include (i) above and below the water video footage, thereby providing the coach and swimmer with additional technical support through a visual aid (Dubois, Thiel & James, 2012). Furthermore, (ii) the underwater footage allows an opportunity for the coach to conduct stroke correction and technique analysis, to help enhance the swimmer's performance, especially at an elite level (Dubois *et al.*, 2012). On the other hand, the disadvantages include (i) the extensive time required to digitise each frame of data captured, (ii) the swimmer may cause turbulence or "bubbles", which would lead to the inaccurate measurements of certain kinematics due to unrecognisable reference points on the swimmer and lastly (iii) the error of parallax caused by the incorrect set-up of the video cameras in the initial performance analysis (Stamm, James & Thiel, 2013). Regardless of the disadvantages associated with this method of analysis, video-based data acquisition is still favoured as a preferred method of kinematic analysis as it allows the link to modelled software such as Dartfish, to help enhance the analysis process. Hence, emphasising the advantages of using video-based data acquisition analyses.

Video analysis as a method of kinematic investigation has proven beneficial for researchers to observe swimming characteristics in greater detail. In this regard, it has allowed for adaptations of certain swimming concepts due to the additional information provided by this method of analysis. A study by Callaway et. al. (2009), compared the use of video analysis versus accelerometer-based approaches in performance monitoring of swimming. Within this study, it was determined that the use of video analysis allowed researchers to refine their statement of the natural movement pattern of freestyle, that would generate sufficient forward propulsion in the water. The most common description of the natural freestyle technique, which coaches use as a learning tool, is teaching the swimmer to make an “s-shaped” pattern in the water when performing the stroke (see Figure 6a) (Orgen, 2017). However, according to Orgen (2017), this movement is not necessarily the most efficient and economic stroking pattern or best technical action for the swimmer. Alternatively, a study by Counsilman (1977), found that a significant number of elite swimmers demonstrated an “inverted question mark” stroking action as part of their natural freestyle technique. Hence, showing that this type of movement pattern provided sufficient forward propulsion, compared to the “common s-shaped” pattern. This finding by Counsilman (1977) was further supported by studies by Toussaint and Beek (1992) and Callaway et. al*.* (2009). Therefore, the use of video-based data acquisition allowed for refinement of the swimmers stroking action, adding support to the coach’s technique correction. Furthermore, within the stroke action refinement, the support of the video analysis lead to the implementation of stroke phases to each stroking style, to eliminate any misconceptions associated with the performance efficiency and correctness of the stroke (Hay, 1993; Maglischo, 1993). However, the use of video analysis (either 2-D or 3-D) as a performance monitoring or training tool, poses several limitations on the coach and researcher. These limitations include the inability to record multiple swimmers in the water during a team practice, as extensive camera equipment would be required to record swimmers individually (Lecoutere & Puers, 2014). Subsequently, a restriction would also be prevalent in the use of video systems in a public pool, due to the privacy of other swimmers, who do not form part of the main swimming team (Lecoutere & Puers, 2014). To avoid these limitations, alternative solutions or methods were sought out by researchers. These methods were used either in place of video analysis or in conjunction with it, to reduce the restrictions associated with the use of video in swimming performance monitoring.

In section 2.4 to follow, alternate technology known as inertial sensors will be discussed with regards to its application in swimming kinematic investigation. The sub-sections will describe the use of these inertial sensors in the monitoring of the swimmer's daily training regime and the differentiation of the swimmer's stroke mechanics and kinematics (Ganzevles *et al.*, 2017; Mooney *et al.*, 2015; Wright & Stager, 2013).

2.4 Inertial Sensors

Traditional methods of performance analysis such as video analysis and laboratory-based assessments (see section 2.3 above) have allowed researchers to investigate general swimming kinematics through both dry-land simulation (Dalamitros *et al.*, 2014; Tanaka *et al.*, 1993) and in-water comparisons (Callaway *et al.*, 2009). However, inertial sensors have, in part, overcome some of the limitations imposed by video analysis by allowing for direct data acquisition during various strokes with specific emphasis on swimming kinematics (James, Leadbetter, Neeli, Burkett, Thiel & Lee, 2011; Lee, Burkett, Thiel & James, 2011). Inertial sensors, also known as microelectromechanical systems (MEMS), are described as waterproofed, wearable devices (James, Leadbetter, *et al.*, 2011; Mooney *et al.*, 2015). Inertial sensors, unlike video analysis, do not require a complex set-up in the pool and are considered swimmer-centric, since they are attached to the swimmer (Magalhaes, Vannozzi, Gatta & Fantozzi, 2014). MEMS have allowed for the development of new kinematic swim sensor technology which includes GPS, accelerometers, gyroscopes and magnetometers (Justham *et al.*, 2008; Magalhaes *et al.*, 2014; Mooney *et al.*, 2015). All these different types of swim sensor technology play a vital role in the enhancement of the analysis of the swimmer's stroke mechanics, race performance and the evaluation of exercise intensity within swimming, thereby allowing for more efficient, competitive and quantitative coaching to take place, especially at an elite level (Mooney *et al.*, 2015).

The fundamental characteristic of an inertial sensor is to use force sensors to measure linear accelerations in multiple directions or angular motion along different axes. Throughout the literature, the most common inertial sensors used in swimming performance monitoring include accelerometers and/or gyroscopes (Yang & Hsu, 2010). For the present study, accelerometers were used as the inertial sensor source. Therefore, in section 2.4.1, the specific characteristics and roles of the accelerometer in swimming performance monitoring and kinematics will be discussed.

2.4.1 Accelerometers

Accelerometers measure the change in accelerations of a moving object along specific reference axes (Yang & Hsu, 2010). Therefore, acceleration is measured by the change in velocity as a derivative of time ($a = dv/dt$) (Hay, 1993; James, 2006). The accelerometer unit can range from mono- to tri-axial, referring to the number of reference axes it contains to monitor human movement. The most common accelerometers used by most researchers to obtain kinematic data, are tri-axial accelerometers (James, 2006; Mooney *et al.*, 2015; Yang & Hsu, 2010). The tri-axial accelerometers contain three main reference axes, namely an X-, Y- and Z-axis (Mooney *et al.*, 2015; Yang & Hsu, 2010), with the axes orientation dependent on the device placed on the individual or object and the type of accelerometer used. Figure 9 represents, an example of the axis orientation of GeneActiv accelerometers placed on the swimmers left wrist and lower back (Zhao *et al.*, 2015). Hence, the axes orientation is typically as follows: X-axis (medio-lateral direction), Y-axis (superior-inferior direction) and Z-axis (anterior-posterior direction) for both the left wrist and lower back sensors, respectively.

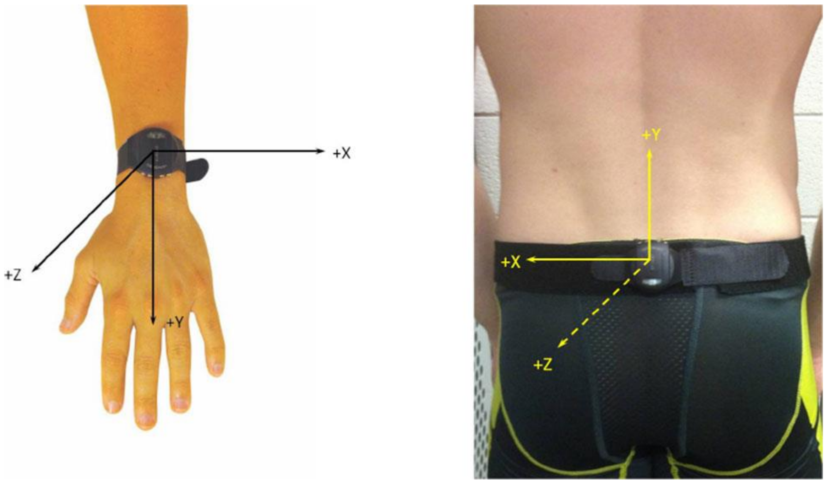


Figure 9: Image representation of the axes orientation with respect to the sensor location on the participant's wrist and lower back taken from Zhao et. al. (2015) research study.

The determination of the reference axis orientation is important for the differentiation of the information from the sensor itself, as this verifies how accurate the information corresponds with the intended course of the movement.

Since the implementation of these inertial sensors in research, an increase in the use of these devices has been observed in the measurement of biomechanical parameters in sporting activities, gait analysis and the measurement of general activity levels for health purposes (Callaway *et al.*, 2009; Davey *et al.*, 2008; Yang & Hsu, 2010). Furthermore, the use of these accelerometers in performance monitoring and analyses has become increasingly important in the development of athletes, not only at an elite level but all levels of sport (Justham *et al.*, 2008). In terms of swimming, visual-based performance techniques are more predominantly used, however, accelerometers have provided coaches and researchers with several advantages to obtain quantitative data with less complexity (James, 2006; Zhao *et al.*, 2015). These advantages include: (i) the small size of the accelerometer unit, which can be attached easily to the swimmer without it interfering with their stroke or increasing drag, and (ii) that 3D data may be continuously captured in a non-invasive manner. The data capturing by the accelerometer can be collected over an extended period of time (i.e. ranging from minutes to days), which would present a cyclic (or periodic) pattern that may be unique to a particular stroke and the swimmer's technique (Zhao *et al.*, 2015). Therefore, this would increase the amount of information given to the coach, further enhancing the performance analysis of the swimmer.

Although video-based analysis is favoured more in performance analysis of swimming, these inertial sensors have been used either as a substitute or as a complementary tool for video analysis. Hence, the use of video analysis with an inertial sensor has proven beneficial in the investigation of various swimming kinematics inclusive of *velocity profiling* (Stamm, James & Thiel, 2013), *stroke and turning analyses* (Ohgi, 2002), measuring *energy expenditure* (Nordsborg, Espinosa & Thiel, 2014), *automatic stroke phase recognition* (Ohgi *et al.*, 2003) and *performance feature extractions* (i.e. stroke length) (Le Sage *et al.*, 2010; Zhao *et al.*, 2015). To obtain swimming kinematic information from the accelerometer data precisely and reliably, several factors have to be taken into account such as the addition of *other inertial sensors*, (e.g. built-in GPS or gyroscope) (Beanland, Main, Aisbett, Gastin & Netto, 2014; Lecoutere & Puers, 2014), the *sensor placement* on the swimmer (Magalhaes *et al.*, 2014; Mooney *et al.*, 2015) and the *type of accelerometer used* (i.e. bi-axial versus tri-axial accelerometer) (Davey *et al.*, 2008; James, Leadbetter, *et al.*, 2011). The number of axes the accelerometer would have increases the kinematic data acquisition, with the addition of another plane of reference, therefore allowing for better data acquisition related to the swimmer's performance (James, 2006; Yang & Hsu, 2010). But of these factors, the sensor location plays an integral role in the differentiation of the kinematic information that can be retrieved from the inertial sensor. The importance of the sensor placement is related to the sensor's orientation and alignment with respect to the different planes of motion (Zhao *et al.*, 2015). Therefore, if the accelerometer only provided two reference axes (i.e. X- and Y-axis) the sensor placement would only provide limited kinematic characteristics based on the accelerometer type and the movement associated with the sensor region it is placed in. Hence, any change in orientation would affect the overall kinematic information extracted from the inertial sensor (see section 2.5.1 below for more detail).

In conjunction with the abovementioned factors, each reference axis of the accelerometer is governed by characteristic peaks and troughs, which are important in the identification of the specific kinematic parameters in human movement, especially with regards to swimming (Davey *et al.*, 2008; Mooney *et al.*, 2015). The peaks and troughs derived from the accelerometers allow researchers to gain valuable insights related to the stroke mechanics, swimming kinematics (i.e. stroke rate, stroke count) and other parameters such as the lap time and turning ability of the swimmer (Ganzevles *et al.*, 2017; Mooney *et al.*, 2015). However, these parameters cannot be derived directly from the raw accelerometer data, posing a limitation on the data interpretation process (see Figure 10). This limitation has then led researchers to investigate, design and implement various filtering algorithms, mathematical algorithms and zero-crossing methods (Davey *et al.*, 2008; James, 2006; Mooney *et al.*, 2015) (see section 2.5.2 below) to account for this limitation. Figure 10, represents a "typical profile pattern" of a 200-m IM raw accelerometer data (Justham *et al.*, 2008). It is evident by the graphical representation that the raw accelerometer data is relatively complex when viewed initially without any filtering adjustments. On the first observation of the data, one can identify each stroking style by its own unique combination of X-, Y- and Z- axis accelerations (Justham *et al.*, 2008). Therefore, as each stroke presents with a unique pattern, one could further link the different stroking pattern profiles to specific swimmers or for comparison of novice versus elite swimmers (Justham *et al.*, 2008). However, these stroking pattern profiles require further analysis to obtain the necessary kinematic parameters for the coach and swimmer.

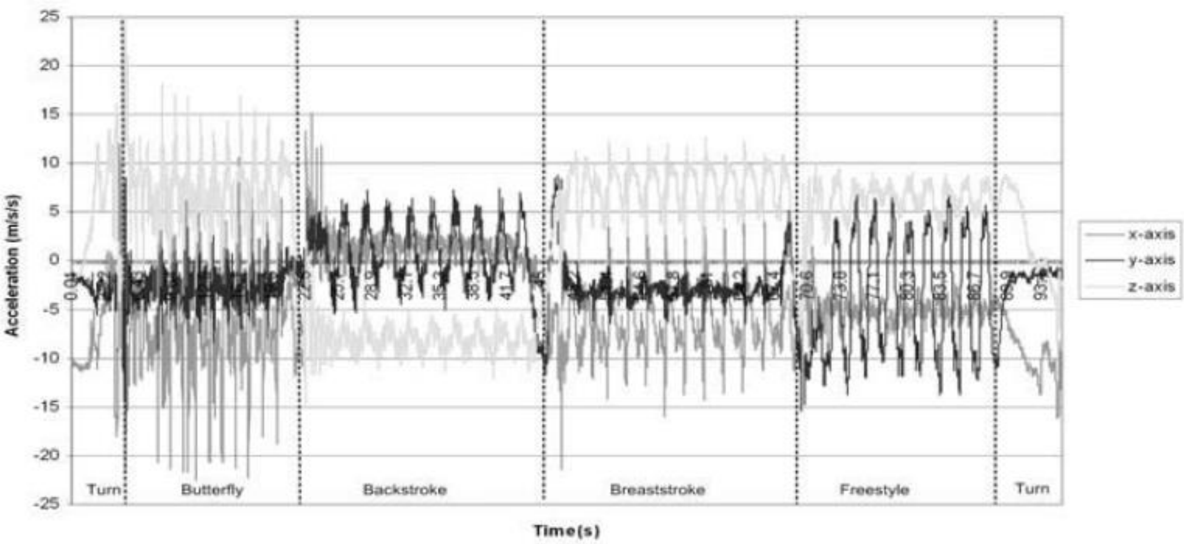


Figure 10: Graphical representation of the x-, y- and z-axis accelerometer data from a 200-m individual medley. Image adapted from Justham et. al. (2008).

Figure 11 represents an example of filtered lower-back accelerometer data for the stroking style of backstroke. Justham et. al. (2008), then discerned key areas from this accelerometer profile, related to the determination of certain kinematic parameters. These key areas include the magnitude of the acceleration (amplitude); duration of stroke (wavelength); the range of acceleration values; the standard deviation of accelerations and pattern profile of the accelerometer data.

As seen in Figure 11, the acceleration data presents a cyclical pattern, which allows for the stroke rate to be extracted easily from the respective data.

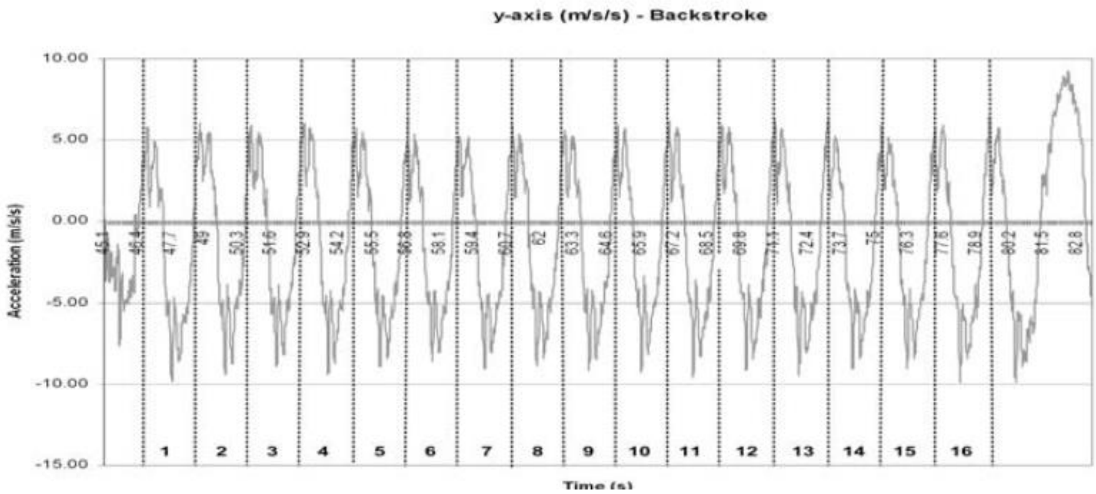


Figure 11: Graphical representation of y-axis backstroke acceleration pattern, as adapted from Justham et. al. (2008).

Visually, one can identify the kinematics related to the stroking style performed, stroke rate, lap time and tumble turns (James, 2006). However, to obtain information related to stroke mechanics or body roll dynamics, researchers had to develop and implement automated algorithms to extract these relevant stroke information and performance characteristics (James, 2006). Section 2.5.3 will further emphasise the development of these algorithms.

The use of accelerometers in the measurement of sporting activities and general physical activity is a continuously growing field, especially with the rapid growth of technology (Callaway *et al.*, 2009; Davey *et al.*, 2008; Yang & Hsu, 2010). As seen above, the accelerometer data can provide ample information to the coach and swimmer, once it is correctly interpreted. Therefore, accelerometers have not only been used in a research capacity but form part of commercialised technology as an additional tool in obtaining superficial kinematic information for the athlete. In section 2.4.2 to follow, the use of commercially produced accelerometer-based technology will be discussed, including the advantages and disadvantages of this technology.

2.4.2 Commercial technology/inertial sensors

The use of accelerometers in a commercial capacity has been an on-going developing field in the implementation of novel technology into the sporting world. This has allowed manufacturers to source alternative ways to lower costs in the purchases of singular inertial sensory devices, to ensure customers are provided with the same or more sensory devices for less (Yang & Hsu, 2010). This has brought about the development of commercial activity monitors, inclusive of accelerometers, which can be used in both a recreational and competitive manner. Examples include but not limited to the Fitbit Charge 3 (Fitbit Inc, San Francisco, California, USA) (Fitbit, 2018), Garmin Swim^{TM} 2 (Garmin International Inc., Olathe, KS, USA) (Garmin, 2019), Suunto 5 (Suunto Oy, Vantaa, Finland) (Suunto, 2019) or Polar V800 GPS (Polar Electro, Kempele, Finland) (Polar, 2018). All these commercial monitors include tri-axial accelerometers, heart rate monitoring systems, integrated GPS systems and additional sensory technology to monitor the individual's physical activity, sleeping patterns, calorie burn and so forth (Fitbit, 2018; Garmin, 2019; Polar, 2018). During physical activity, these devices are equipped with algorithms to detect which activity the individual is performing, swimming being but one example. However, these commercial devices provide superficial kinematic data to the individual, which is based on the popular demands of the athlete who use it. This kinematic data includes the stroking style performed, average stroke length, average stroke rate, swimming efficiency (also known as SWOLF) and swim pace. Additionally, heart rate telemetry data such as peak, minimum and average heart rate is also measured if the device includes heart rate systems (Polar, 2018). A study by Mooney et. al. (2017), investigated the use of two commercially available swimming monitoring devices in quantifying temporal and kinematic swimming parameters. These devices were the Finis Swimsense (FINIS USA, Livermore, CA, USA) and Garmin Swim activity monitors (Garmin International Inc., Olathe, KS, USA). Mooney et. al. (2017) found that both devices were accurate in the identification of each swimming stroking style. However, these devices could not always accurately time the beginning and end of each lap interval, which caused a significant difference in the stroke count measurement on two occasions within the study. This affected the overall accuracy in the determination of the swimmer's stroke rate, stroke length and average stroke speed. It was concluded that these devices were similar in their performance level measurement but were more suited for recreational use, rather than for swimmers of an elite level. Reasons for this conclusion was the level of accuracy required from devices with respect to elite swimmers versus recreational swimmers. For example, elite swimmers require their lap time to be within ±0.3 seconds of the stopwatch time (used as the reference time). Whereas, recreational swimmers would present with a ±2 second error in lap time, usually related to the swimming proficiency of the swimmer and the devices ability to detect accurate lap boundaries with the lower swimming proficiency (i.e. not touching the wall correctly), compared to the elite swimmers. The accuracy of the kinematic parameters is vital for elite swimmers to make decisions on their swimming performance; therefore, the level of accuracy of the commercialised device is vital. Mooney et. al. (2017) further highlighted system requirements by an elite swimmer versus a recreational swimmer in Table 4 within their study. Therefore, these commercial devices, such as the Finis Swimsense and Garmin Swim, offer recreational swimmers and triathletes with additional methods in quantifying and analysing their own training in the pool. Whereas, the utility of these devices for swimmers of a higher level may however be limited. This would be especially true with regards to the identification of stroking mechanics and the provision of consistent and accurate measurements of kinematic stroking parameters (Mooney *et al.*, 2017), throughout a given training session.

Due to the market demand and increasing growth of technology, commercial inertial sensors, in conjunction with manufacturers, tend to offer more services or applications in a singular unit in order to keep up with the growing demand by athletic individuals. However, this poses a limitation with regards to the accuracy of all these applications in a sporting or daily activity setting. In section 2.6.2, the use of commercialised fitness branded watches (i.e. Fitbit Surge) in the measurement of heart rate telemetry will be discussed and the problems found with these multi-disciplinary devices. As commercial devices still pose limitations on the athletic individual, researchers have often opted to use singular inertial sensors such as tri-axial accelerometers, to monitor elite performances in an isolated form for more specific and reliable kinematic data (Ganzevles *et al.*, 2017; Justham *et al.*, 2008; Mooney *et al.*, 2015). However, with the commercialisation of fitness watches and technology, coaches and swimmers often select the multi-disciplinary devices versus the singular sensory units largely due to convenience, although it provides superficial information. Therefore, researchers must determine all the information these singular inertial devices can provide, in order to compete with the commercial market and multi-disciplinary monitoring devices.

In section 2.5 to follow, the accelerometer data detection and extraction methods used in the swimming kinematic differentiation will be discussed.

2.5 Accelerometer data detection methods

Typically, accelerometer data is recorded digitally, with the sampling rate and resolution of the accelerometer specified according to the movement activity it is applied in. According to James (2006), most human movement activity occurs at a sampling frequency below 20 Hz, with higher sampling rates capturing more detailed information in relation to the movement in question. In conjunction, with the correct sampling rate, three important factors must be considered to ensure meaningful information is obtained from the accelerometer data. These factors include the *sensor placement* on the swimmer (Magalhaes *et al.*, 2014; Mooney *et al.*, 2015; Siirtola *et al.*, 2011; Yang & Hsu, 2010; Zhao *et al.*, 2015), the *filter techniques* applied to the data and the *data algorithms and zero-crossing criteria* used in the differentiation of the swimming kinematic parameters (Magalhaes *et al.*, 2014; Mooney *et al.*, 2015; Zhao *et al.*, 2015). Therefore, in the sub-sections to follow, these above-mentioned accelerometer data detection and extraction methods will be discussed.

2.5.1 Sensor placement

Sensor placement is defined as the location of where and how the sensors are attached to a specific location; in the context of the present study, this would refer to a specific body part (Yang & Hsu, 2010). The most common sensor placements in swimming monitoring are on the lower- and upper back, the head, wrist and ankle of the swimmer (Lecoutere & Puers, 2014; Magalhaes *et al.*, 2014). In *general movement* activity studies, the sensor would be commonly placed on the participant's waist, as this location is closest to the centre of mass of the person’s body and causes less constraint and discomfort when they have to perform a movement (Yang & Hsu, 2010). The placement of the accelerometer on the swimmer then dictates the kinematic information which can be extracted from this body region. Furthermore, the selected placement of the sensor should not increase the drag force applied on the swimmer (Bächlin

& Tröster, 2012; Callaway *et al.*, 2009; James, 2006), or interfere with their swimming action (James, 2006) and limit their free movement (Bächlin & Tröster, 2012; Magalhaes *et al.*, 2014). Zhao et. al. (2015), emphasised the importance of the location and placement of the accelerometer on the swimmer's body, as well as the orientation and alignment of the device with respect to the different planes of motion. Typically, accelerometers which are placed on the wrist or close to the hand, provide kinematic data associated with stroke frequency and the stroke-phase identification (Magalhaes *et al.*, 2014; Zhao *et al.*, 2015). Alternatively, if the accelerometer was placed on the swimmer's lower back, kinematic information associated with the swimmer's body roll angles and total body acceleration would be provided (Zhao *et al.*, 2015). If the accelerometers are attached incorrectly, potential errors may occur associated with unnecessary sensor movement relative to the swimmer's body. An example of this would be if the sensor was attached to the swimmer's lower back and they missed a turn, in which their foot slipped off the wall. This incorrect body movement would cause a spike in the acceleration data due to the sensor moving within its sensor region, resulting in irregular noise occurring in the data processing (Zhao *et al.*, 2015). An additional error would be the lack of correspondence between one or more of the reference axes of the accelerometer in relation to the swimmer's direction of motion (Zhao *et al.*, 2015).

The sensor placement of the accelerometer has proven that various regions on the swimmer's body can provide vital information related to the swimmer's movement kinematics. However, which of these regions provides the most accurate information, essential for both the coach, swimmer and researcher? A study by Siirtola et. al. (2011), investigated the use of tri-axial accelerometers in tracking swimming exercises using low sampling rates. Two accelerometers placed on the swimmer's upper back and wrist were used in the study. The original sampling rate of the accelerometers was recorded at 50 Hz, with the researchers extracting the sensor placement accuracy from the sample data, at frequencies of 5-, 10- and 25 Hz respectively, at the specified regions. The study found that the accelerometer placed on the swimmer's back was more accurate than that of the wrist accelerometer with an accuracy window of 95% versus 89%, respectively (see Table 2).

Table 2: Accelerometer recognition accuracy within different sensor locations and sampling frequencies. Extracted from Siirtola et. al. (2011) and Mooney et. al. (2015)

Comparison Measure	Recognition Accuracy	
	Wrist	Upper Back
Sampling Frequency		
5Hz	88.5%	95.1%
10Hz	88.9%	95.4%
25Hz	89.8%	95.3%
Swimming Style		
Freestyle	90.8%	96.1%
Backstroke	88.8%	97.1%
Breaststroke	92.6%	96.7%

A reason for this difference was that the sensor placed on the upper back was more stable and less susceptible to environmental or movement disturbances compared to that of the wrist sensor. Furthermore, Siirtola et. al. (2011) investigated the stroke identification (for three out of the four stroking styles) and the accuracy in the determination of these strokes. As seen in Table 2, both sensor locations were successful in the identification of all three of the stroking styles. What is also noteworthy is that the accuracy tends to increase at higher sampling frequencies irrespective of the body location.

Although the wrist sensor was found be less accurate compared to the back sensor (largely due to the instability of its anatomical region), according to Siirtola et. al. (2011) other factors can pre-determine the variability measured at this sensor location. These variabilities include the hand movement pattern generated by the swimmer's stroke which may be affected by factors pertaining to the swimmer's anthropometric and technique differences, the skill level of the swimmer, swimming speed and the onset of fatigue (Anthony & Chalfant, 2010; Mooney *et al.*, 2015). Therefore, according to Mooney et. al. (2015), these factors may be the underlying contributors to the accuracy obtained at this specific anatomical region. Regardless of these variabilities, the wrist or hand region allows for additional information to be investigated in relation to the swimmer's stroke mechanics, which is not easily obtained from other anatomical regions. Hence, from this sensor location, insight into the swimmer's stroke phases is achieved, which is important for the overall performance outcome of the swimmer (Mooney *et al.*, 2015).

Once the sensor location for accelerometer placement is selected, several analysis techniques and data extraction methods must be performed on the raw accelerometer data, to aid in the discrimination of the specific kinematic parameters acquired from this inertial sensor. Consequently, Zhao et. al. (2015), designed a general accelerometer-based parameter extraction approach (see Figure 12), to help distinguish which of these analysis techniques need to be performed to attain these kinematic parameters. Therefore in Figure 12 these analysis techniques and data extraction methods are inclusive of the filtering techniques used to remove unnecessary "noise" or contaminated data from the main data set (Magalhaes *et al.*, 2014; Zhao *et al.*, 2015). The use of different elimination or cross-over criteria within the data to correlate the respective local minimum and maximum accelerations related to the specific swimming kinematic parameters (Mooney *et al.*, 2015; Ohgi, Yasumura, Ichikawa & Miyaji, 2000; Yang & Hsu, 2010) or the use of algorithms in conjunction with the cross-over criteria to determine the different stroke events and kinematics (Callaway, 2015; Davey *et al.*, 2008).

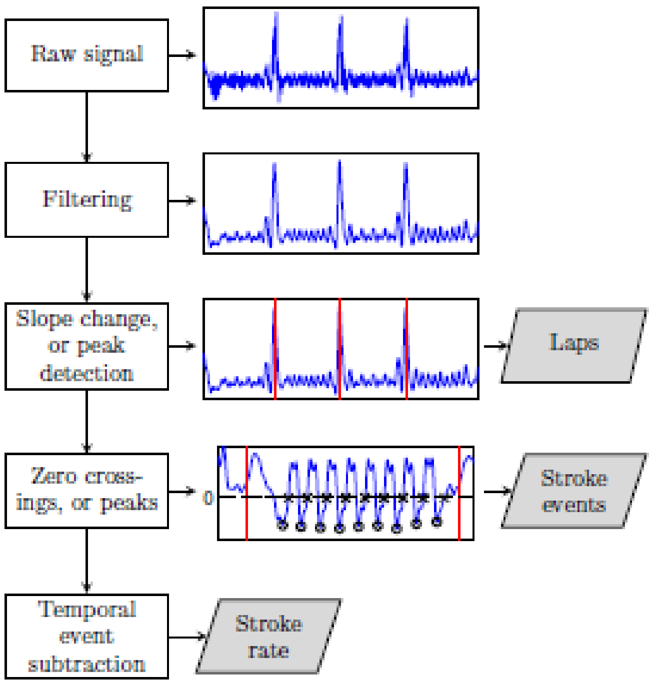


Figure 12: Flowchart depicting the common accelerometer-based lap and stroke analysis performed on the raw accelerometer data. Extracted from Zhao et. al. (2015).

Once these analysis techniques and methods have been completed, the information obtained from the accelerometer data would be reliable for both the researcher and the coach. Therefore, in section 2.5.2, these respective analysis techniques and data extraction methods required to decipher the raw accelerometer data will be discussed.

2.5.2 Filtering techniques

The filtering techniques are used for the removal of "noise" caused by additional vibrations of the accelerometer that obscure the actual movement-based signal associated with (i) the sensor placement and (Magalhaes *et al.*, 2014; Zhao *et al.*, 2015) as well as (ii) other rapid movements performed by the swimmer (Bächlin & Tröster, 2012; Davey *et al.*, 2008). The purpose of the filtering, therefore, is to enhance the signal-to-noise ratio. Several different filter techniques have been used throughout the literature by researchers, which include a high/low-pass Hamming windowed finite impulse response (FIR) filter (Davey *et al.*, 2008; Stamm, 2018; Stamm & Thiel, 2015), low-pass digital filter (Mooney *et al.*, 2015; Pan *et al.*, 2016; Stamm, Thiel, Burkett & James, 2011; Zhao *et al.*, 2015), high/low pass 2nd order Butterworth filter (Bächlin & Tröster, 2012; Ganzevles *et al.*, 2017; Ohgi *et al.*, 2003; Le Sage *et al.*, 2010), Savitsky-Golay smoothing filter (Siirtola *et al.*, 2011), Kalman filter (Dadashi & Millet, 2013) or a moving average filter (Siirtola *et al.*, 2011).

Although a vast number of filter techniques have been used by researchers to filter the accelerometer data, one should question which filter is more suitable for the data detection and extraction process and why? For example, researchers Stamm and Thiel (2015), used a high-pass Hamming windowed FIR filter (with a cut-off frequency of 0.5Hz) to remove the gravitational components from the accelerometer signal and to allow for a smoother data interpretation. Other researchers opted to use one filter over another based on its filtering ability. Le Sage et. al. (2010), for example, used a low-pass Butterworth filter (with a cut-off frequency of 2Hz) versus a Chebyshev filter, due to its ability to be implemented in real-time processing and thereby avoid ripples in the data passband. Therefore, the filter technique used is partly dependent on the researcher's objectives with the accelerometer data and the filter's ability to remove the contaminated data. One of the criteria within the filter technique used for the removal of the "noise" from the accelerometer data, is the type of cut-off frequency used. Hence, the importance in the selection of the correct or appropriate cut-off frequency was investigated by Le Sage et. al. (2011), who used different cut-off frequencies for different tasks and stroking styles. The accelerometer was placed on the swimmer's lower back, with the lap boundary identified at the point at which the largest trough occurred as the swimmer turned at the wall. From this threshold point, the lap time and lap count were determined by the filter and signal processing algorithms. The lap count criterion was set by a filter cut-off frequency of 1 Hz, with the differentiation of each stroking style and stroke count occurring at different cut-off filtering frequencies. The cut-off filter frequencies for the stroke count for freestyle and backstroke was set at 2Hz, with breaststroke and butterfly occurring at 6- and 8 Hz, respectively. From Le Sage et. al. (2011) study, simply using one cut-off frequency to obtain the kinematic information was not ideal, as each stroking style for the respective stroke parameter (i.e. stroke count differentiation) required a different cut-off frequency due to its stroke characteristics. These characteristics are related to the frequency threshold at which certain peaks and troughs occur at, for the respective stroking styles, to ensure the correct extraction of the stroke parameters can take place. Therefore, careful consideration must be given to the type of filter used and associated cut-off frequency, to maximise the elimination of the "noise" from the accelerometer data and the extraction of the kinematic features from the respective data.

Although this multi-filter approach by Le Sage et. al. (2011) offers a more exact stroke count identification (based on individual cut-off filter frequency criteria) for each individual stroking style, Zhao et. al. (2015) found several problems within this complex approach. Firstly, the prescribed cut-off filter frequencies did not work for all swimmers within Zhao et. al. (2015) study. This was prevalent with the 1Hz filtering criterion to obtain the lap count. The specific characteristic of this criterion stated that a single large trough differentiated the swimmer's turn (Le Sage *et al.*, 2011). However, this could not be diversified across all the swimmers within Zhao et. al. (2015) study. Secondly, the first and last lap (alternatively, the start or end of a lap), did not necessarily end in a peak or "large" trough. Hence, resulting in an inaccurate stroke count for these lengths due to the noise presented at the terminal strokes. Thirdly, the cut-off filter frequencies would change according to the axis orientation of the accelerometer on the swimmer, if placed in a different sensor location. Lastly, as the multi-filter approach method requires a different cut-off filter frequency for each stroking style, the user or coach would have to pre-set this prior to application. Therefore, inconveniencing the user in automating their data processing. One should then ask which approach (single cut-off filter vs multiple cut-off filters), is more appropriate in the kinematic parameter differentiation from the accelerometer data? Therefore, further research is required to determine the appropriate approach to the filtering of the accelerometer data.

In accordance with Figure 12, once the filter techniques have been applied to the raw accelerometer data, further steps must be taken to differentiate the kinematic parameters from the data. Hence, these steps include using either zero-crossing or peak algorithms to detect stroke parameters or alternatively, peak detection or slope change algorithms to detect other kinematic parameters such as lap count (Zhao *et al.*, 2015). Hence, in section 2.5.3 to follow, these data analysis algorithms and thresholds criteria will be discussed in further detail.

2.5.3 Algorithms and Zero-crossing criteria

The purpose of the accelerometers is to provide coaches with a means to monitor their swimmers, whilst gaining detailed feedback on how to improve the swimmer's performance (Anthony & Chalfant, 2010). This feedback allows for the coach and swimmer to reflect on the critical parameters within their performance during their practice (Le Sage *et al.*, 2010) or after training has finished (Wright & Stager, 2013). However, this feedback would not be meaningful without the aid of data analysis criteria, to discriminate the relevant parameters from the filtered accelerometer data. Subsequently, various data analysis techniques have been developed to interpret the accelerometer data for the researcher and coach. These analysis techniques include a *peak detection method* (Beanland *et al.*, 2014; Davey *et al.*, 2008; Siirtola *et al.*, 2011), *zero-crossing technique* (Callaway, 2015; James, Burkett & Thiel, 2011; Stamm & Thiel, 2015) and *stroke algorithms* (Callaway, 2015). Each of these techniques has a purpose with regards to the differentiation of swimming kinematics from the filtered accelerometer data. These parameters include the swimmer's stroke phases, stroking style utilised during their swim set, stroke rate, stroke count, swimming velocity, lap time and stroke duration.

In the sub-sections to follow, the methods in which these parameters are obtained (using the above-mentioned data analysis techniques) will be discussed.

2.5.3.1 *Stroke Identification (or stroking style)*

Each stroking style has definite stroke phases which stem from the movement characteristics, which are performed by the swimmer (Cortesi *et al.*, 2012; Didier & Seifert, 2011; Hay, 1993; Orgen, 2017). Hence, these stroking styles would present with unique accelerometer data characteristics. Throughout the literature, several different sensor locations have been used to detect and differentiate the stroking styles including the upper or lower back (Davey *et al.*, 2008; Siirtola *et al.*, 2011), wrist (Siirtola *et al.*, 2011), chest (Ohgi, Kaneda & Takakura, 2014) and head (Lecoutere & Puers, 2014; Michaels, Taunton, Forrester, Hudson, Phillips, Holliss & Turnock, 2016) of the swimmer. In a study by Davey, James and Anderson (2004), the identification of the different stroking styles was performed using a tri-axial accelerometer on the swimmers lower back. This was done by the development of algorithms by Davey et. al. (2004) using hand-timed data and underwater video footage as benchmarks to detect strokes and turns. These algorithms used a series of simple mathematical concepts, coupled with decisions made objectively on large quantities of collected data (Davey *et al.*, 2008). The device orientation was first determined by the Z-axis (i.e. anterior-posterior direction of acceleration) to distinguish backstroke from the other three stroking styles. Once this distinction was made, axes thresholds were set for each axis based on the magnitude of the filter signal. Freestyle and backstroke were identified by the large Y-axis (medio-lateral directional movement) amplitude. This was characteristic of the body roll by the swimmer during each stroke cycle. Alternatively, breaststroke and butterfly were identified by means of other axis characteristics as these strokes do not perform this body movement and were then classified as "short axis" strokes. Overall, Davey et. al. (2004) had a recognition accuracy of approximately 95% across all four strokes, in this sensor location (i.e. lower back) when compared against the prescribed swimming protocol in the study. One study by Siirtola et. al. (2011), compared the accuracy of a wrist and upper-back accelerometer in the identification of the three out of four stroking styles. As seen in Table 2 (section 2.5.1), the upper back sensor showed a more superior outcome in the identification of the stroking style compared to that of the wrist sensor, with a percentage accuracy of 96.6% versus 90.7%, respectively. Siirtola et. al. (2011) used simple classification methods, namely linear and quadratic classifiers, with a sliding window technique to identify the stroking style. Irrespective of the sensor accuracy, both sensor locations were adequate in the stroking style differentiation.

Various methodologies have been used in the differentiation of the stroking style from the accelerometer data. However, the preferred method in the stroke type differentiation from the accelerometer data is yet to be distinguished. Therefore, further investigation and analysis must be done to determine which method is more suited in the data processing of this kinematic parameter from the accelerometer data.

2.5.3.2 *Stroke phases*

The use of inertial sensors in stroke phase identification was first investigated by Ohgi et. al. (2000), who used the wrist accelerometer to differentiate the stroke phases of freestyle, with the aid of underwater footage. Similarly, in another study by Ohgi et. al. (2003), the wrist accelerometer was used to discriminate the stroke phases associated with breaststroke. In both these studies, the wrist-based accelerometer proved advantageous in the stroke phase identification, as well as providing additional information with regards to the swimmer's skill level (Ohgi *et al.*, 2000). However, in both these studies, a common definition of each of the corresponding stroke phases of the investigated strokes had to be considered. The common definition ensured that the data obtained correlated with the respective stroking style. The stroke phase definitions of the investigated stroking styles were then outlined in accordance with the hand pattern definitions developed by Maglischo (1993). Therefore, the described stroke phases of freestyle were "the entry and stretch, down-sweep, in-sweep, up-sweep and recovery" and for breaststroke were the "out-sweep, in-sweep and recovery" phases.

From these outlined phase definitions, the stroke phases were identified by the corresponding the associated peaks and troughs (local minimum and maximums) to the defined stroke movements (Mooney *et al.*, 2015; Ohgi, 2002; Ohgi *et al.*, 2000). However, these stroke phase associations with the relative peaks and troughs had to be validated using underwater footage.

As seen in Figure 13, Ohgi (2002) determined the points in the acceleration data that correlated with Maglischo (1993) described stroke phases. Phase I (entry and stretch) was determined by a sharp negative peak in the X-axis, which corresponded with the entry of the swimmer's hand. Thereafter, the Y-axis acceleration decreased to 0m/s^2 corresponding to the end of the stretch phase. Phase II (down-sweep) was determined by the steep increase in the X-axis to reach a local maximum, as the swimmer's hand moved outward and downward in the water. At this local maximum, the swimmer's hand was at the deepest position in their stroke pattern. Phase III (in-sweep) was determined as the point at which the swimmer's hand moved inward, marked between the X-axis local maximum and the X- and Y-axis local minimums. Lastly, Phase IV (up-sweep and recovery) was determined at the point at which the Y-axis increased steeply.

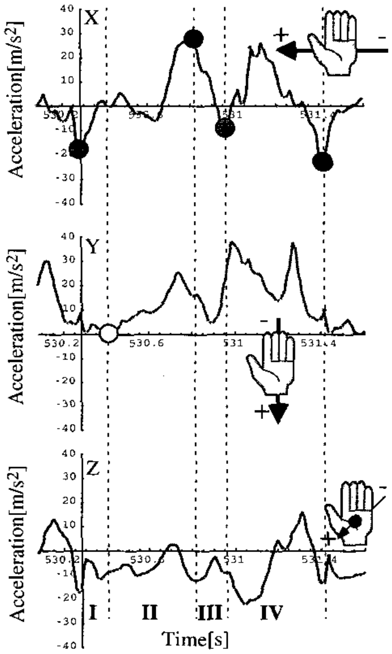


Figure 13: Acceleration profile of freestyle, with stroke phases identification. I- Entry and Stretch phase; II – Downsweep; III- Insweep and IV- Upsweep and Recovery phases. Extracted from Ohgi (2002)

Hence, within Ohgi's (2002) study, it can be seen that both the X- and Y-axes provided substantial and important information related to the differentiation of the stroke phases of freestyle. However, Ohgi et. al. (2000), hypothesized that the Z-axis acceleration value and sign at the hand entry indicated the angle of attack of the swimmer's palm at the water surface. Subsequently, further research must be done to support this hypothesis due to the complexity of the accelerometer data and the analysis of the kinematic data obtained from it.

Throughout the stroke phase identification process, Ohgi et. al. (2000) and Ohgi (2002) used video footage to validate the points at which the swimmer's hand performed each phase. Similarly, researcher Callaway (2015) used video footage in conjunction with algorithms they developed, to automate the stroke phase identification process within their study. However alternative to these studies, researchers Anthony and Chalfant (2010) designed and implemented algorithms in software, which automatically searched and isolated the stroke phases throughout the given stroke cycle without the use of video footage. As stated in section 2.3.2, limitations were found with the use of video in practice. Therefore, alternatively one would seek ways to extract the relevant kinematic information from the accelerometers without video validation. Emphasising the importance of Anthony and Chalfant (2010) approach in the kinematic data extraction from the accelerometer data. Within the present study, video validation was required for the stroke phases, however, for the stroke kinematics extraction, this was completed without the use of video footage.

Figure 14, graphically illustrates an isolated section of the stroke phases presented within the stroke freestyle, extracted from Anthony and Chalfant (2010) study. As stated above, Anthony and Chalfant (2010) developed algorithms to automatically search and determine the number of stroke cycles within a given length or before a "turn" event was identified. How this was determined, was by the algorithm searching for the pull phase boundaries identified by the greatest negative acceleration on the X-axis, which was parallel or in the direction of the swimmer's arm in the water (see points 15691 and 16702 in Figure 14). Therefore, once these boundaries were identified, the total time that elapsed between each pull phase boundary point represented the total time for one stroke cycle. Furthermore, Anthony and Chalfant (2010), also investigated algorithms to isolate an event phase from a series of events. How this was performed was identifying the X-axis greatest negative acceleration points as seen in Figure 14, as well as the Z-axis nearest greatest negative acceleration point (see point 4506 in

Figure 14). This Z-axis point represented the start of the recovery phase. From this point, the algorithm searched for the next point on the Z-axis that was near or equivalent to the previous Z-axis point, marking the end of the recovery phase and transitioning into the reach phase.

Therefore, the total time that elapsed between these two axis points represented the time taken from the start to the end of the recovery phase.

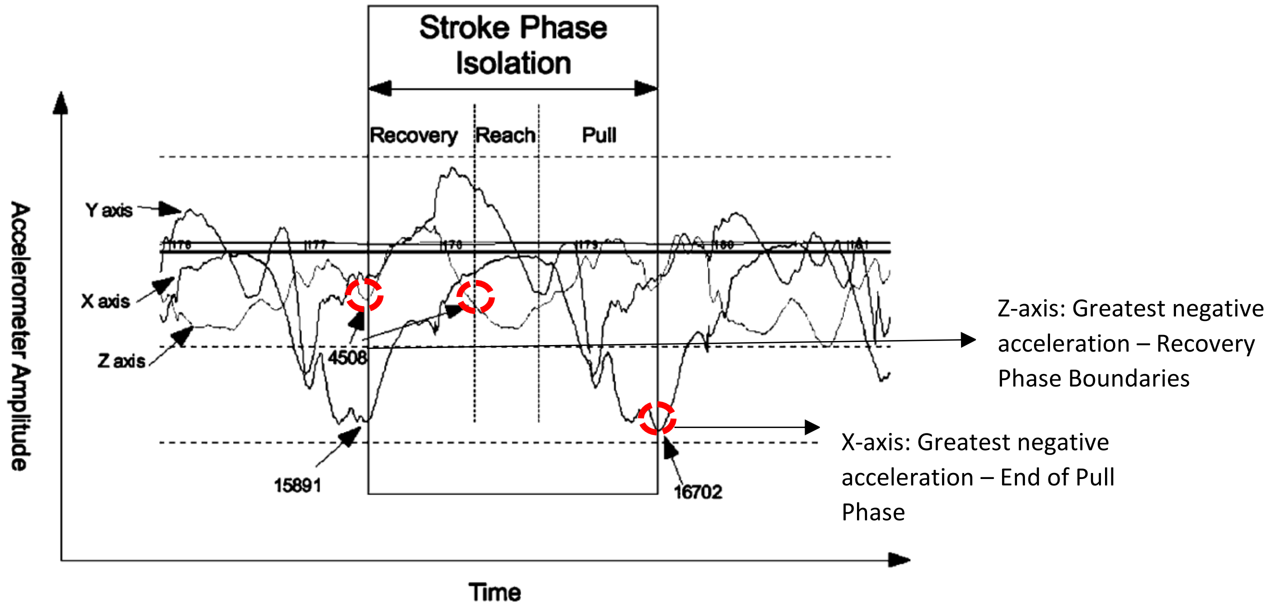


Figure 14: Stroke phase isolation graphical representation as presented by Anthony and Chalfant (2010)

Ultimately, these event phases that were extracted by Anthony and Chalfant (2010) algorithms, would prove to be beneficial for coaches to do a cross-analysis of their elite versus novice swimmers, by determining the timing differences of each phase event, for the respective swimmers. Subsequently, if the phase event timings of the novice swimmer were determined and compared against the elite swimmer's phase event times, this would allow coaches to identify the section within the novice's stroke phases that requires improvement. Hence, these phase event timings provide the coaches with an "elite swimmer standard" to which they can compare the novice swimmer too (Anthony & Chalfant, 2010). For future developments in this regard, these timing events of the phases could be used to set benchmarks for different types of swimmers based either on their age, skill level, body type, gender or flexibility, to allow coaches to have a normative characteristic model to which the swimmers bases their stroking action. Additionally, one could also look at the timing changes between the stroke phases; for example, a negative change in the timing may be due to the onset of fatigue or alternatively the swimmer may show improvements in their fitness and technique. Hence, becoming more efficient in their stroking mechanics (Anthony & Chalfant, 2010). However, further research needs to be performed to support this hypothesis.

2.5.3.3 *Stroke count and rate*

As previously mentioned, swimming includes a vast number of stroke or swimming kinematic parameters such as stroke length, stroke rate, swimming velocity, index of coordination and so forth (Barbosa *et al.*, 2010; Evershed *et al.*, 2014). The most popular parameters investigated using inertial devices are the stroke rate and stroke count of the swimmer. Stroke rate is a key element for both the coach and researcher, to track and assess the swimmer's performance throughout their events and training (Davey *et al.*, 2008). Two methods can be used to obtain the stroke rate of a swimmer; this can be done manually (i.e. counting the number strokes per lap and dividing it by the time it takes to complete the strokes) or using an algorithm coupled with the accelerometer and video validation to obtain the stroke rate and stroke count of the swimmer (Mooney *et al.*, 2015). One study by Davey et. al. (2008), investigated the error rate between the stroke rate obtained manually (i.e. counting the strokes) versus using an accelerometer. Davey et. al. (2008), used a peak detection method of the medio-lateral acceleration signal (accelerometer placed on the swimmers upper-back), to automate and extract the stroke rate information from the accelerometer data. The study found that the stroke rate measured through the manual method was prone to a higher level of error compared to that of the stroke rate obtained through the automation of the accelerometer data (with a 90% accuracy of ± 1 stroke difference from the manually obtained stroke rate). Similar, to Davey et. al. (2008) stroke rate determination method, Siirtola et. al. (2011) used a different threshold criterion for each swimming stroke and different axes in conjunction with the peak detection acceleration method to determine the stroke count. It was found that this method resulted in a >99% accuracy for the detection of the swimmer's stroke count for all the strokes. Ideally, researchers would want to extract the stroke rate from the accelerometer without the need for the manual calculation. However, further steps must be made to ensure that the accuracy of the stroke count and further derivation of the stroke rate remains consistent. Therefore, the best kinematic extraction technique used with accelerometer data is yet to be determined, emphasising the need for further research to be done.

2.5.3.4 *Other kinematic parameters*

Additional kinematic parameters investigated using the inertial sensors include stroke length, lap time and swimming turns. As previously mentioned, the stroke length, stroke rate and swimming velocity of the swimmer are all inter-related. Therefore, the calculation to obtain the stroke length of the swimmer, with the use of the inertial sensor is the simplest of all the kinematic parameters. In most literature, researchers obtained the stroke length by calculating the swimming velocity and dividing this by the calculated stroke rate (SL = v/SR) (Ganzevles *et al.*, 2017; Stamm, 2018). Therefore, a complex method of analysis of the accelerometer data would not be required to obtain the stroke length, as it would be sufficiently obtained using the above equation.

The remaining two kinematic parameters that can be obtained from the accelerometer data, is the lap time and swimming tumble turn junction points, which enables the calculation of the swimmer's lap count and swimming distance. Both the lap time and tumble turn parameters occur at the same points in the accelerometer. Therefore, the method to obtain these parameters is similar. The lap time is important in allowing for the intensity of effort by the swimmer to be monitored throughout their training (Mooney *et al.*, 2015). The detection of the lap time is defined by events or point of contact that the swimmer makes with the wall during their swimming event (Mooney *et al.*, 2015). The method used to differentiate the lap time from the accelerometer data requires researchers to observe a sudden change in the accelerometer data to mark this specific event. An example of this was found in a study by Callaway (2015). It was concluded that the lap time boundary was marked by a wall push off event detected by the lower back sensor observing a large trough in the accelerometer data in the Y-axis (Callaway, 2015). Alternatively, Bächlin and Tröster (2012) used both the wall push-off and wall strike events as the determinants for the lap times, using a wrist sensor. The wall-strike event was described as the point at which a large impact peak and an increasing slope was identified in the Y-axis accelerometer data, with the wall push-off event marked at the point at which the first falling slope was observed in the same axis. Furthermore, Bächlin and Tröster (2012) used the wall push-off and strike events to determine the average swimming velocity of the swimmer. Therefore, the average swimming velocity for one lane was determined by measuring the time ($t_{lane} = t_{wallstrike} - t_{wallpushoff}$) for a given pool length (d_{lane}), with the average velocity per lane determined by $\bar{v} = \frac{d_{lane}}{t_{lane}}$. The use of the lap time information, contributed overall to the determination of the swimming velocity of the swimmer, which allowed for the determination of the other parameters including: the swimmers stroke count, stroke length and stroke rate (Mooney *et al.*, 2015) to take place.

As previously mentioned, the detection of the swimmers turns overlaps at the same junction point as the lap time events. Therefore, the assumption of the criterion of a "large increasing slope caused by the wall-strike events" in the accelerometer data was used as a point of reference for the identification of the swimmer turns. However, this criterion was not supported by Siirtola et. al. (2011), who found that the shape magnitude of the accelerometer data at the point that the swimmer performed their turn, could be greater than the shape magnitude of the data caused by the swimmer's stroke or alternatively, smaller. This was caused by the swimmer performing a "turn" in one or more ways (see Figure 15 for example).

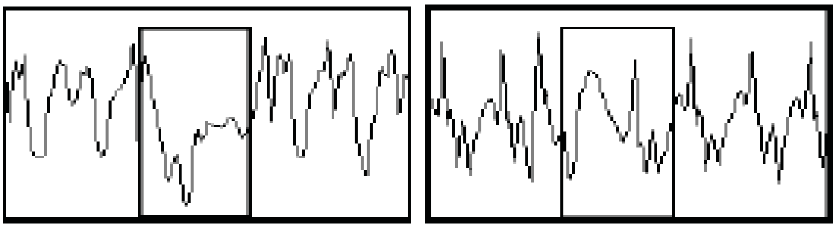


Figure 15: Graphical illustration of different turning styles found in accelerometer data. Extracted from Siirtola et. al. (2011)

As seen in Figure 15, two different "turn" events were identified within the accelerometer data, with noticeable shape magnitude changes in both turns. Therefore, the use of the increasing slope criterion was not favoured for this parameter. Hence, Siirtola et. al. (2011) used classification algorithms such as linear and quadratic classifiers to determine the swimmer's turns, by selecting the "turn" as a separate class in the classification process. Alternative, to Siirtola et. al. (2011), researchers Davey et. al. (2008), identified the turns of the swimmer by using zero-crossing transitions or algorithms on the Z-axis (axis perpendicular to the body, with the sensor placed on the lower back) as the swimmer's body underwent a rotation. Therefore, the definite method in which the swimmer's turns could be identified was largely dependent on the classification method the researchers chose to use within their study.

2.5.4 Video-based support

With the implementation of several different algorithms and criteria to determine the kinematic parameters from the accelerometer data, validation support was required to assess the accuracy of these methods (Ganzevles *et al.*, 2017). Therefore, the use of video analysis was sought out by various researchers to support their kinematic findings from their accelerometer-based research (Beanland *et al.*, 2014; Callaway, 2015; Ganzevles *et al.*, 2017; Mooney *et al.*, 2015). However, some researchers aimed to eliminate the use of video analysis in the future, due to the cumbersome set-up and ethical restrictions associated with public pool usage in daily training (Bächlin & Tröster, 2012; Lecoutere & Puers, 2014).

In a study by Davey et. al. (2008), a comparison was made between the data that was collected manually (i.e. stopwatch) versus with ADXL202 accelerometers (Analog Devices, Massachusetts, USA). Video data were recorded in parallel with both methods to ensure that the accelerometer data was both reliable and accurate in measuring the kinematic parameters in question. Furthermore, Davey et. al. (2008) developed data processing algorithms to extract the relevant data from the accelerometers, which included the push-off point, stroking style and stroke count parameters. The study concluded that the accelerometer-derived parameters were more acceptable than the manually determined data parameters, with a 95% and 90% accuracy in the identification of the stroking style and stroke count, respectively, using the accelerometer. Therefore, emphasising the benefits of using accelerometers over manual methods to measure kinematics, with the additive benefits of the video analysis to validate the results.

The use of video-based support has further aided research, in enabling real-time processing or real-time feedback to be developed. The implementation of real-time feedback is an area within accelerometer-based research with the most potential, as the use of video is a time-consuming process (Stamm, James & Thiel, 2013). The importance of a real-time feedback system, allows the swimmer to make real-time corrections to their swimming technique and measure the success of this improvement in the stroke, without the tedious post-data analysis (Justham *et al.*, 2008). Hence, Le Sage et. al. (2010), developed a real-time monitoring system to measure a swimmer's performance. The study aimed to provide "real-time transmission, processing and presentation" of the swimming data to the coaches and their swimmers during their training sessions. Within this real-time monitoring system, an accelerometer and high-speed camera, among other equipment, were used. The accelerometer data was filtered through a real-time Butterworth filter and signal processing equations and validated by the high-speed camera footage to allow for the real-time feedback to occur on the side of the pool. The filter process used to carry out the live feedback is seen in Figure 16. Through this process, Le Sage et. al. (2010) were able to provide feedback on the swimmer's stroke duration, lap count and stroke rate to the coaches on the side of the pool. Additionally, this system was able to differentiate between the different stroking styles, using the different filter techniques.

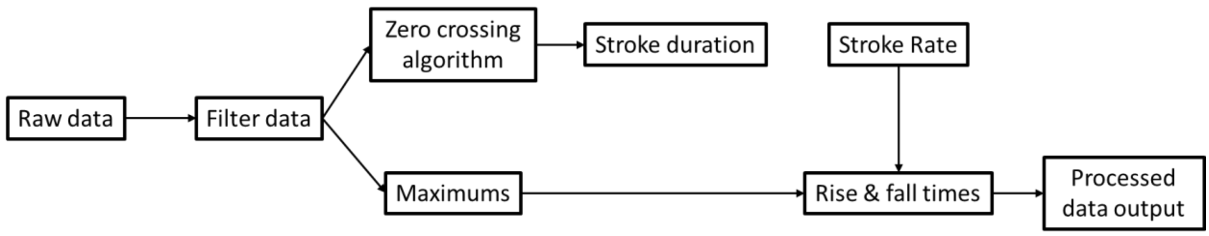


Figure 16: Filter process as extracted from Le Sage et. al. (2010)

Le Sage et. al. (2010) found this method of feedback advantageous over the current analysis techniques, which include manual processing of the accelerometer data which does not allow for live feedback to occur. Future research proposed by Le Sage et. al. (2010), was to investigate signal processing algorithms representative of different swimmers and the stroking styles, while also integrate other systems (i.e. pressure measurement technology) to analyse other kinematic parameters such as the turns of the swimmer.

Therefore, the potential to apply real-time feedback systems in swimming is a relatively novel area within research, especially with the use of inertial sensors as the main feedback system. Hence, further research into these feedback systems is required, with or without the use of video-based support to help validate the accelerometer data collected.

2.6 Physiological parameters

Swimming performance is based on the interplay between the physiological and biomechanical parameters, as well as the psychological factors of the swimmer (Anderson, 2006) (see Figure 4). As mentioned previously, the physiological parameters are inclusive of swimming muscular power, flexibility, maximal aerobic capacity and anaerobic power (Anderson, 2006; Hay, 1993; Sanders, 2013). Within the present study, two physiological parameters of the swimmers were investigated, namely the heart rate response and the critical swim speed. Therefore, in the sub-sections to follow the role of these two parameters in swimming performance and stroke kinematics will be discussed.

2.6.1 Critical swim speed

Critical swimming speed (CSS) is the measure of the swimming speed corresponding to the maximal lactate steady state (Takahashi, Wakayoshi, Hayashi, Sakaguchi & Kitagawa, 2009). The concept of CSS stems from the earlier work of Monod and Scherrer (1965) related to critical power. Therefore, CSS is described as the swimming speed that can be held for a long period of time without exhaustion, which is expressed as the slope of a regression line between swimming distances and the average times from the completion of these distances (Takahashi *et al.*, 2009; Wakayoshi, Ikuta, Yoshida, Udo, Moritani, Mutoh & Miyashita, 1992). The most common distances used to calculate CSS are 50-m, 400-m, 1500m and 2000m freestyle (Chatterjee, Nandy, Chakraborty & Bandyopadhyay, 2016; Takahashi *et al.*, 2009; Wakayoshi *et al.*, 1992). These distances are swum at maximum intensity with the swim times recorded (Wakayoshi *et al.*, 1992). Once these times are obtained, researchers may use the slope of the regression line (see Figure 17), to determine CSS or alternatively Equation 5 below. As seen in Equation 5, CSS is expressed as the difference between the longest distance (D_2) and the shortest distance (D_1), divided by difference between the corresponding swimming times (T_2 = D_2; T_1 = D_1) (Wakayoshi *et al.*, 1992).

Equation 5: Critical swimming speed calculation (Wakayoshi et al., 1992)

$$\frac{D_2 - D_1}{T_2 - T_1}$$

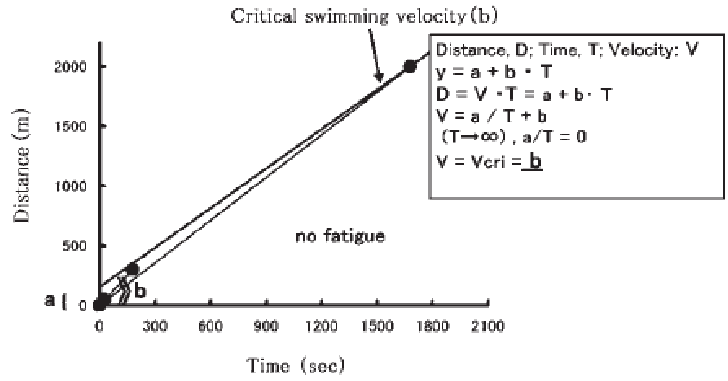


Figure 17: Relationship of critical swimming from the slope of the regression line from pre-determined swimming times and distances as extracted from Takahashi et. al. (2009)

CSS is typically used as a swimming performance determinant amongst competitive swimmers, to determine their training speed and evaluate their endurance capacity (Akşit, Zeki Özkol, Vural, Pekünlü, Aydinoğlu & Varol, 2017; Takahashi *et al.*, 2009). Therefore, CSS is used to assess both the aerobic and anaerobic capacity of the swimmer as the CSS value demarcates the boundary between sustainable and non-sustainable swim speeds (Neiva, Fernandes & Vilas-Boas, 2011; Wakayoshi *et al.*, 1992). A study by Marinho, Amorim, Costa, Marques, Pérez-Turpin and Neiva (2011) investigated the use of shorter distances to assess CSS by using anaerobic critical velocity (AnCV) as a tool to monitor and prescribe anaerobic training and predict swimming performance for short race distance (i.e. 50-m or 200-m) events in young swimmers (age: 12 ± 0.72 years). The AnCV was investigated for all four stroking styles for the distances of 50-, 100- and 200-m. The study found a strong relationship between AnCV and swimming performance velocity in the 50- and 100-m for backstroke (r_{50m}= 0.85; r_{100m}= 0.86), breaststroke (r_{50m}= 0.92; r_{100m}= 0.90) and freestyle (r_{50m}= 0.85; r_{100m}= 0.91), as well as in the 200-m for breaststroke (r_{200m}= 0.88) and freestyle (r_{200m}= 0.90). Marinho et. al. (2011) concluded that use of AnCV as a monitoring and prescription tool for anaerobic training was important in young swimmers. However, further research was needed to support Marinho et. al. (2011) findings in more detail. Presently no data exists in a South African context related to the CSS of high-level swimmers.

The link between the CSS and stroke kinematic parameters to swimming performance is an on-going area of research. An example of this is by Dekerle, Nesi, Lefevre, Depretz, Sidney, Marchand and Pelayo (2005), who investigated changes in stroke rate to maintain swimming speed at intensities close to CSS during interval training. Hence, this led to the proposal of a new concept known as the critical stroke rate (CSR) method, which is defined as the highest stroke rate that can be maintained indefinitely. It is calculated by the slope of the relationship between the number of stroke cycles and time using the same test trials to obtain CSS (Dekerle, 2006; Dekerle, Sidney, Hespel & Pelayo, 2002). In support of this concept, a study by Franken, Diefenthaeler, Moré, Silveira and De Souza Castro (2013) compared the CSR to the stroke rate observed at different intensities of CSS. The study found that the stroke rate was equivalent to the CSR at swimming intensities corresponding to 95, 100 and 103% of the swimmer's CSS. Therefore, Franken et. al. (2013) proposed the use of CSR as an additional method for coaches to use to control the intensity of effort and swim technique of their swimmers during their training session. Furthermore, the combination of CSS and CSR may prove beneficial in improving a swimmer's aerobic capacity and technique, with more focus on manipulating the stroke parameters to benefit the swimmer's performance (i.e. decrease in SR and increase in SL, when swimming at CSS). Therefore, the use of CSS in swimming performance monitoring and as a training tool shows potential in the swimming literature, with further research required in this area.

2.6.2 Heart rate

Heart rate (HR) is an important physiological tool used in elite sports to monitor performance during competition or as a training tool. This physiological tool provides valuable insight into an athletes daily training status, through "reliable, easy to use, fast and non-invasive" methods (Ganzevles, de Haan, Beek, Daanen & Truijens, 2014). Hence, heart rate is used to monitor responses to training load, by measuring the athletes resting HR, HR variability and HR recovery (Daanen, Lamberts, Kallen, Jin & Meeteren, 2012; Ganzevles *et al.*, 2014). The monitoring of HR variability, especially for swimmers, is important for coaches to avoid overtraining the swimmer if there is an imbalance between their training and adequate rest periods (Atlaoui, Pichot, Lacoste, Barale, Lacour & Chatard, 2007). Therefore, emphasising the importance of heart rate monitoring during training.

A study by Magel, McArdle and Glaser (1969) investigated heart rate response before, during and after selected competitive events. The study reported on the heart rate responses during selected distances for all four stroking styles. Therefore, the following maximum heart rate responses were found amongst the swimmers tested (n= 7; age= 20.1 ±1.1; level= varsity) by Magel et.al. (1969) (see Table 3). For the shorter freestyle distance events (50-, 100- and 200-m), the swimmers reached approximately 82- 92% of their heart rate maximum during the initial stages of the swim events, with a slightly lower heart rate response recorded in the longer distances (500- and 1000-m). Disregarding the stroking style, it was found that the swimmers reached approximately 81 – 94% of their heart rate maximum in the initial stages of each of the swim events swum. A trend was also found between all the stroking styles and the swimming distances, which saw a decrease in the swimming speed throughout the duration of each of the swim tests performed.

Table 3*:* Summary of maximum heart rate responses extracted from Magel et.al. (1969)

	Strokes			
Distances (m)	Freestyle	Backstroke	Breaststroke	Butterfly
50	172 ± 4.8 (n=6)			
100	174 ± 5.9 (n= 5)	176 ± 7.3 (n= 4)	168 ± 3.0 (n= 4)	173 ± 6.5 (n= 4)
200	180 ± 5.2 (n= 3)	178 ± 11.3 (n= 4)	165 ± 1.6 (n= 3)	173 ± 4.2 (n = 2)
500	181 ± 9.9 (n= 2)			
1000	180 ± 12.6 (n= 2)			

Further research is still required in the investigation of why one stroke records a higher heart rate response compared to another stroke during a competitive swim event. This difference in heart rate response may be due to the physiological and biomechanical demands related to the stroke, such as the stroke mechanic demands of the stroking style which may link to the energy output by the swimmer.

Limited research has been found within the swimming literature related to heart rate responses, with regards to either resting HR, HR variability or HR recovery role in swimming performance monitoring (Daanen *et al.*, 2012). Therefore, presenting a gap within the literature to research this aspect of swimming and the association of HR response with key performance areas related to the swimmer's training or stroke kinematics (Ganzevles *et al.*, 2014).

The use of HR monitoring in training has become increasingly important in performance monitoring, as well as daily monitoring of the general population. Therefore, with the commercialisation of technology, most fitness watch units incorporate a heart rate monitoring function. However, one would question how accurate these multi-disciplinary devices are, in the monitoring of heart rate responses of the athlete. One article by Profis (2014), questioned the ability of commercial monitoring devices in measuring one's heart rate, through a wrist input system. Profis (2014) tested five different commercial devices, with all the devices measuring the heart rate changes at the wrist, except for one which used a chest strap. The study found that all devices had an error percentage of approximately 3.1 to 10.7% in measuring the participant's heart rate between 80 and 90 bpm, with two monitors not successfully reading the participants heart rates between 160 and 170 bpm due to an error percentage of approximately 57.5% over the testing trials. Similarly, in 2016, a comprehensive study by Jo and Dolezal (2016) revealed that the PurePulse™ heart rate monitors in the Fitbit Surge (commercial fitness watch), showed an "extremely weak correlation" with the actual heart rates of the users, especially during elevated physical activity. Therefore, these inconsistencies question the reliability of such commercial devices in delivering valid and accurate heart rate results to the athlete. As of recent Polar released a new heart rate monitoring strap known as Polar OH1 Optical heart rate sensor, which attaches like an armband on either the athletes lower or upper arm (Polar, 2019). This innovative design allowed for a better heart rate telemetry detection to take place, especially during swimming as the chest strap (typically used) provided disrupted heart rate telemetry data (Mclarty, 2019; Polar, 2019). Therefore, technology is continuously changing and adapting to suit the needs of both the recreational and elite athlete, to ensure accurate information is given to help enhance their performance.

2.7 Conclusion

The research evolving around swimming kinematic differentiation with the aid of inertial sensors has grown exponentially over the years. However, various areas within this research remain unclear, specifically with regards to the methods in the differentiation of the kinematic information from the accelerometers. It was evident that limited research was focused on the differentiation of the kinematic parameters associated with the strokes backstroke, breaststroke and butterfly (Mooney *et al.*, 2015). Therefore, the present study was limited in the sources of information that could be used as a reference to substantiate any findings presented within this study, thereby emphasising the novelty of this present research with regards to three out of the four stroking styles. However, substantial research was found with the use of accelerometers in freestyle kinematics differentiation, providing a research base for the understanding of the accelerometer data. Similarly, research associated with the CSS and HR response to the different swimming intensities and stroking styles was also limited. Emphasising an additional gap in research, especially related to swimming performance enhancement.

In the sections to follow, the present researcher will discuss the methods and procedures implemented to differentiate the kinematic parameters from the accelerometers, to meet the objectives outlined.

CHAPTER 3: RESEARCH METHODS AND PROCEDURES

3.1 Introduction

The following research methods and procedures were used by the researcher to determine the kinematic parameters and stroking mechanics of each swimming stroke. These parameters were obtained using tri-axial accelerometers as the primary investigating tool. Therefore, in the sub-sections to follow, the data and analysis processes used to meet the objectives of the present study will be elaborated.

3.2 Research Design

The present study used a quantitative approach, specifically a non-experimental, descriptive one group post-test-only design (Kumar, 2011; de Vos, Strydom, Fouche & Delport, 2005). A non-experimental design includes a group of participants that are not randomly selected and non-manipulated independent parameters. Hence, the research stemmed from this type of design is exploratory in nature, as it is implemented to answer the researcher's questions and whether experimental differences exist (Salkind, 2012; de Vos *et al.*, 2005). Bearing this in mind, the present study design was used to assess the kinematic parameters and stroke mechanics (i.e. non-manipulated independent parameter) of the swimming population that was non-randomly sampled. The lack of randomisation (i.e. only swimmers from Nelson Mandela Bay region were selected) posed a limitation on the generalisability of the results, as some level of bias was present in the selection process. Hence, such an approach differentiates non-experimental designs from true experimental and randomised control trials (de Vos, et al., 2005).

3.3 Participants

A maximum of 15 national-level swimming athletes volunteered for the present study, with all swimmers sampled from the Nelson Mandela University swimming club and local swimming clubs. Each of the swimmers was given equal opportunity to be selected within the sample group, per the selection criteria specified in section 3.4. Hence, the sample group consisted of seven males (mean ±SD: age: 21.29 ± 3.50 years; height: 179.87 ± 9.84 cm; weight: 74.31 ±

4.44 kg; arm span: 186.57 ± 10.44 cm) and eight females (age: 20.50 ± 2.45 years; height: 167.51 ± 7.79 cm; weight: 62.11 ± 5.87 kg; arm span: 170.89 ± 8.40 cm). For inclusion purposes, all swimmers were required to be South African citizens and injury-free.

3.4 Sampling Methods

Non-probability sampling methods were required to select the swimmers following the research design implemented. Non-probability sampling is defined as "a technique which uses non-randomisation methods to select participants for the study" (de Vos *et al.*, 2005). With regards to the present study, the more specific sampling method of purposive sampling was used to select the swimmers (Kumar, 2011), under the guidance of the following inclusion criteria:

<u>National level:</u>

The swimmers must have represented their club or province at either South African Junior nationals (level 3), youth nationals, youth-elite nationals or senior nationals.

<u>Injury-free:</u>

All swimmers should have been injury-free, at least six months before the testing was commenced.

<u>No stroke specialisation:</u>

Swimmers were selected under a *non-specific* stroke criterion to eliminate stroke bias and preferences (i.e. the swimmers were non-specialists in any of the stroking styles). Taking this criterion into account, helped to extend the sampling pool for the availability of national-level swimming athletes in the Nelson Mandela Bay region.

The final sample group consisted of swimmers of approximately the same age range, with a majority of the swimmers residing from the university-based swimming club. The reason for this purposive selection was to maintain a relatively equal level of expertise amongst the swimmers. However, due to the limited number of university-based swimmers, swimmers younger than the age of 18 years old were selected from the local swimming clubs, to meet the remainder of the testing quota.

3.5 Measuring Instruments

The following measuring instruments were used to assess the kinematic parameters, heart telemetry and stroke mechanics of the swimmers within this present study.

- Two tri-axial accelerometers (GeneActiv, Activinsights, Cambridgeshire, England)
- Polar V800 watch (Polar Electro Oy, Kempele, Finland)
- Polar H7 heart rate monitor (Polar Electro Oy, Kempele, Finland)
- Sony Cyber-shot DSC-RX10 MK III (WW411000- Sony Electronics Inc., New York, United States)
- Go Pro 4 (GoPro Inc., San Mateo, California, United States)
- Anthropometric equipment:
    - Stadiometer (SECA GmBH, Hamburg, Germany)
    - Weighing scale (JW1546, South Africa)
    - Tape measure (Muratec-KDS corp., F10-02DM, Chicago, United States)
- Custom designed camera trolley system (eNtsa, Port Elizabeth, South Africa)
- Duct tape (SelloTape Duct tape, Builders warehouse, Port Elizabeth, South Africa)
- Stopwatch

In the sub-sections to follow, all the relevant information regarding the equipment manufacturer, accuracy (if provided), measuring precision and validity of the measuring instruments and the testing protocols that were adhered too, will be provided.

3.5.1 Anthropometric equipment:

3.5.1.1 Height

A SECA stadiometer (SECA GmBH, Hamburg Germany), was used to measure the swimmer's height. The measurements were recorded in centimetres (cm) to the nearest 0.1 cm.

The swimmer was required to have their upper back, buttocks and ankles pressed against the stadiometer, with their head position in the Frankfurt plane. The Frankfurt plane position was achieved by aligning the lower part of the swimmer's orbitale (lower bony margin of the eye-socket) in the same horizontal plane as the tragion (notch superior to the tragus). The headpiece of the stadiometer was then lowered onto the vertex of the swimmer's head and measurement was taken after the end of maximal inspiration (Norton & Olds, 2009).

3.5.1.2 Weight

A Scalemaster weighing scale (JW1546, South Africa), was used to measure the swimmer's weight. The measurements were recorded in kilograms (kg) to the nearest 0.01kg.

The swimmer was required to remove their shoes and any clothing and items that may contribute to the weight reading. The swimmer was then instructed to stand on the scale with their weight equally distributed over both feet and their head up and looking forward (Norton & Olds, 2009).

3.5.1.3 Arm span

A non-extensible, flexible tape measure (Muratec-KDS corp., F10-02DM, Chicago, United States) was used to measure the swimmer's arm span. The tape was required to be no wider than 7 mm, with a 3 cm stub before the zero line (Norton & Olds, 2009). The measurements were recorded in centimetres (cm) to the nearest 0.1 cm.

The swimmer was required to stand with their back against a wall, with their arms placed in a horizontal position. The measurement was the distance between the dactylia (tip of the middle finger) of the left and right hands, in this position. A tape measure was used to take this measurement. An alternate method to measuring arm span was to instruct the swimmer to stand in the corner of a room and a mark was made on one end of the wall. This distance was then measured to obtain the subject's arm span (Norton & Olds, 2009).

3.5.2 Hardware:

3.5.2.1 Accelerometers

Two portable GeneActiv (Activinsights, Cambridgeshire, England) tri-axial accelerometers were used to determine the kinematic parameters and stroke mechanics of the swimmer during the swim tests. The specifications of the accelerometers were as follows:

- Dimensions: 43 x 40 x 13-mm
- Weight: 16g
- Sampling rate: 100 Hz

- Acceleration range: ± 16g
- Resolution: 7.8mg
- Waterproof up to 10-m (GeneActiv, 2017).

The two accelerometers were attached to the swimmer's left wrist and upper-back and set to record at a frame rate of 100 Hz. This recording frequency was consistent with camera one and two's recording frame rate, which were set at the same frame rate. The data obtained by the accelerometers was then extracted using GeneActiv software (see section 3.7 below for further detail on the extraction process).

3.5.2.2 Polar watch and heart rate monitor

A Polar V800 watch and heart rate monitor (Polar Electro Oy, Kempele, Finland) were used to obtain heart rate telemetry information from the swimmer, throughout the testing procedure. In addition to the heart rate information, superficial kinematic parameters were recorded during the swim sets. These kinematic parameters included, swim distance, swim pace, average and maximum swimming speed, estimated lap time, minimum, average and maximum heart rate and body temperature (Polar, 2018). This additional information then allowed the present researcher to compare the accuracy of the data retrieved from the tri-axial accelerometers versus the data produced by this commercial watch.

3.5.2.3 Camera one

Sony Cyber-shot DSC-RX10 MK III (WW411000- Sony Electronics Inc., New York, United States) camera was used as one of two validation instruments for the accelerometer data gathered during the 50-m IM swim tests (see set one in section 3.6.3). The camera was placed on a custom-designed camera trolley system (see Figure 18 for more detail), perpendicular with the lane in which the swimmer was performing the swimming assessment. The primary purpose of this camera was to determine the point at which the hand of the swimmer entered and exited the water. These points allowed for the synchronization of the accelerometer data with the video footage to occur in real-time. The camera was set to record at 100Hz, consistent with the sampling frame rate of camera two and the tri-axial accelerometers recording frequencies.

3.5.2.4 Camera two

A GoPro Hero 4 (GoPro Inc., San Mateo, California, United States) camera, was used as the second validation instrument of the tri-axial accelerometer data. The GoPro Hero4 provided underwater footage, to determine the exact inflection points at which each of the stroke phases within the different stroking styles would occur in the accelerometer output data. The GoPro was attached to the camera trolley system, to allow it to be positioned underneath the swimmer and to be moved simultaneously as the swimmer completed the required 50-m IM set. The GoPro Hero 4 specifications allowed for the camera to be placed at a depth of approximately 40-metres and with recordings taking place either between 15fps to 240fps at a 480 to 1080 resolution (CNET, 2016). Hence, for the present study, the GoPro Hero 4 was set at a sampling frame rate of 100 Hz, consistent with camera one and the tri-axial accelerometers sampling frequencies. Additionally, the GoPro was set at a 720 resolution, to ensure the “wide superview” mode could be used by the researcher to obtain a greater field of analysis of the swimmers stroking style, underwater.

3.5.2.5 Camera trolley system

A custom-made camera trolley system was manufactured by the engineering company eNsta in Port Elizabeth at the Nelson Mandela University. The camera trolley was designed to meet the objectives of the present study, to obtain simultaneous footage of the swimmer performing the required swim set. The camera trolley was designed to move alongside the pool, whilst the swimmer performed the 50-m IM set.

The camera trolley specifications included attachment sites for two video cameras, which allowed for speed-matched video analysis of each swimmer to be done. Camera one was attached perpendicular to the surface of the pool and camera two was positioned directly beneath the swimmer at a depth of 1.1-m on a steel arm as seen in Figure 18. The depth of the camera was pre-determined based on the dimensions of the pool as seen in Figure 20 and Figure 21. Two fixed wheels and one swivel wheel allowed for the movement of the trolley alongside the pool, with weights attached on both sides to counter the torque forces produced by the steel arm’s drag in the water. This drag force was enhanced by the increase in the speed at which the trolley was pushed alongside the pool and the weight of the arm in the pool. Additional, to the weights on the trolley, the researcher or research assistant applied a counter torque force on the handle of the trolley to maintain a straight-line pathway alongside the pool.

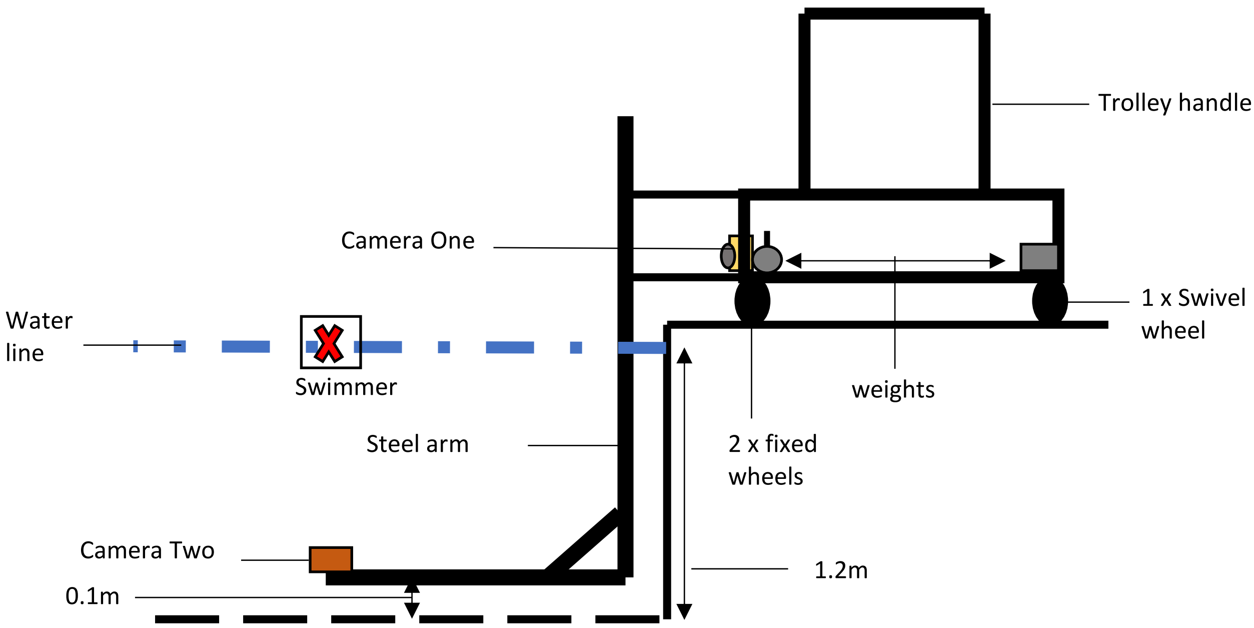


Figure 18: Custom designed camera trolley (eNsta, Port Elizabeth, South Africa) specifications. Illustration not drawn to scale.

The video data obtained was then time-synchronized with the accelerometer data to allow for unprecedented spatio-temporal analyses, as both systems captured at 100 Hz. Further information on the synchronization method is seen below in section 3.6.2.

3.6 Data collection and testing protocol

All the selected swimmers, swimming coaches and parents of the swimmers (if younger than 18 years old) were informed prior to testing of all the information regarding the present study, which included: the equipment that was used, the testing procedure and what was required of the swimmer prior to testing (see Appendix A and B, respectively). The swimmers were evaluated within a six-week period to accommodate their training and academic schedules. All swimmers were evaluated during their off-season and all efforts were made to keep testing consistent (i.e. within 45 to 60 minutes) to minimise diurnal variations. The data collection and the testing procedures were carried out in the following manner as seen in Figure 19.

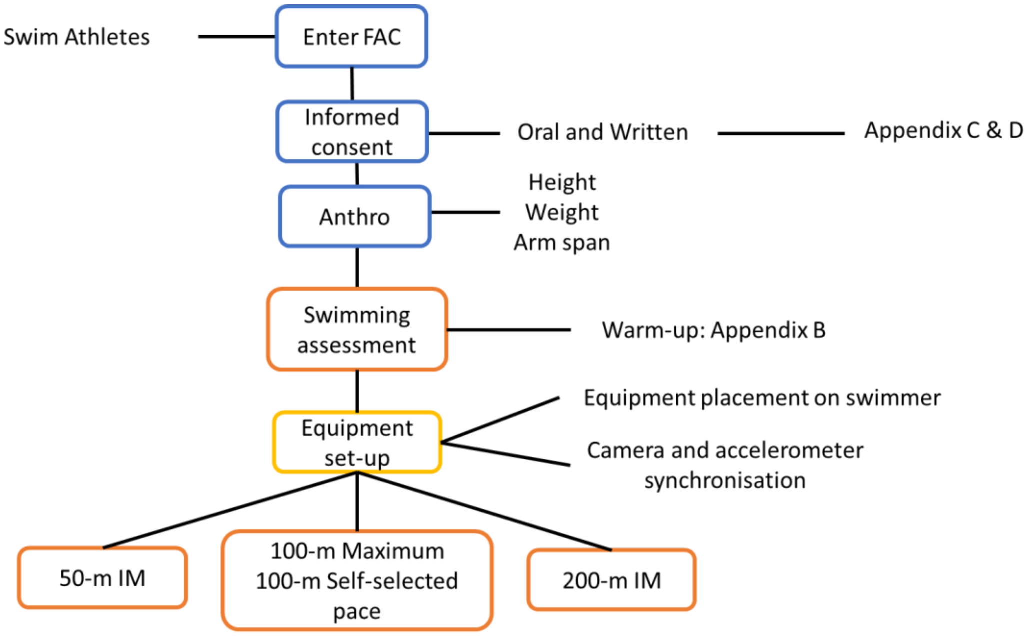


Figure 19: Summary diagram of the testing procedure

The anthropometric measurements taken were used to pre-program the tri-axial accelerometers to the specifications of the swimmer. After the warm-up, the tri-axial accelerometers were placed on the swimmers left wrist and upper-back, respectively. Additionally, the Polar watch was placed on the swimmers left wrist and the heart rate strap on their chest. The video cameras and the accelerometers were synchronised following the method described in section 3.6.2.3 below. After the swimming protocol was completed, the swimmer was debriefed and thanked for their participation in the present study, with the results of the study to be relayed via their coach once the master's study was completed.

3.6.1 Swimming pool dimensions and set-up

The overview of the pool dimensions, specifications of the testing facility and the specific equipment set-up used in the present study are shown in Figure 20 and Figure 21. Each of the specified distances was determined according to the pool size and dimensions measured out at the Fitness and Aquatics Centre at the Nelson Mandela University by the present researcher. The depth at which camera two was located was estimated according to the minimum depth at which the camera could be placed in the shallow end of the pool.

Hence, the pool dimensions were as follows:

- Pool length: 25-m
- Minimum and maximum depth: 1.2-m and 3-m respectively

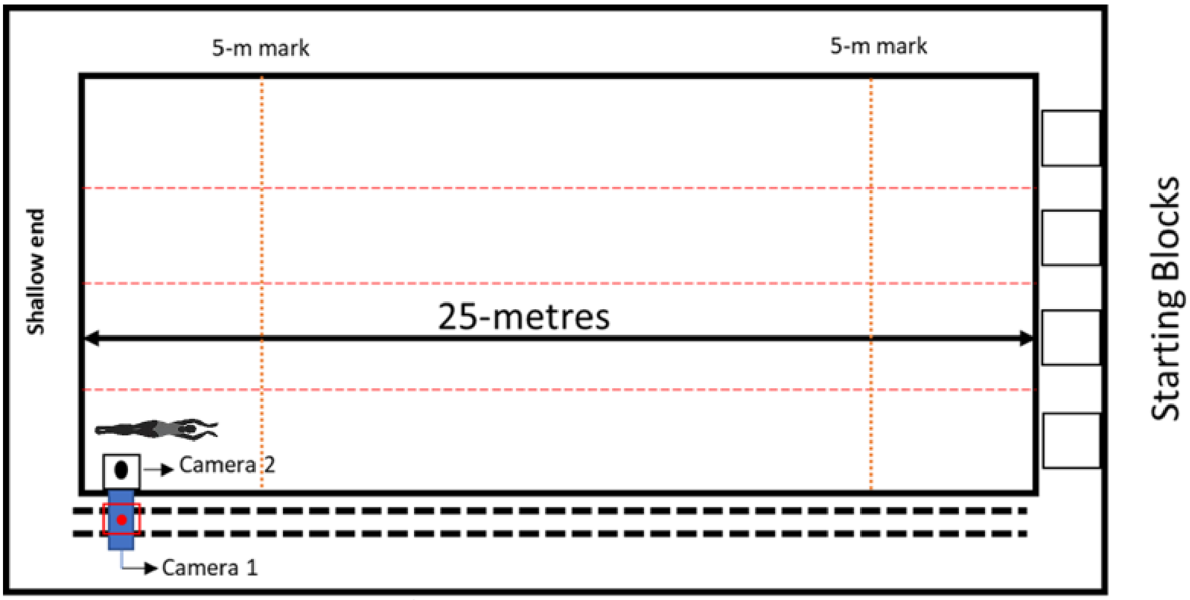


Figure 20: Illustrative overview of the pool dimensions and layout at the Fitness and Aquatics Centre at Nelson Mandela University. Note this illustration is not drawn to scale

The minimum depth of camera two was approximately 10-cm above the shallow end floor. The maximum depth of the shallow end was 1.2-m, which was pre-determined by the water level of the pool when filled to the maximum threshold (i.e. pool edge). Figure 21 represents the camera one and two placement, perpendicular to the last lane in the pool, with the depth markings.

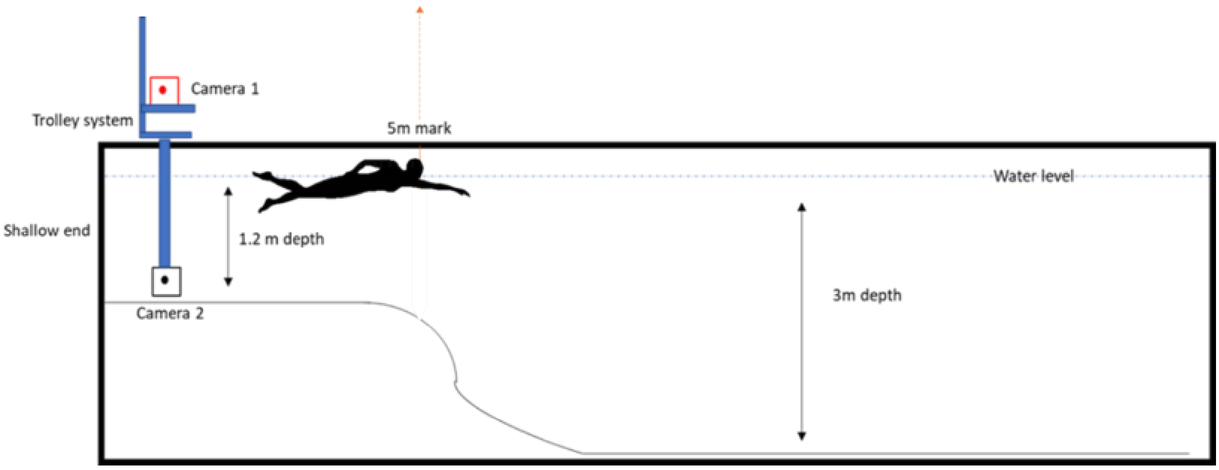


Figure 21: Side view of the pool underwater dimensions. Camera two was placed approximately a depth of 1.1-m and attached to the moving camera trolley system. Note this illustration is not drawn to scale.

3.6.2 Accelerometer specifications:

The following accelerometer specifications including the sensor placement, axis orientation and synchronisation methods used by the present researcher will be discussed below. Each specification highlighted, allowed for reproducibility and consistent testing data to be obtained throughout the data collection period.

3.6.2.1 Sensor placement

One tri-axial accelerometer was placed on the swimmer's left wrist and a second was placed on the swimmer's upper back (GeneActiv, Activinsights, Cambridgeshire, England). The swimmer was also fitted with a Polar heart monitor strapped to the swimmer's chest, with the Polar watch attached to their left wrist (Polar Electro Oy, Kempele, Finland). See Figure 22a and b, for sensor placement. To ensure the tri-axial accelerometer and heart rate belt did not move, adhesive duct tape was used to strap the equipment onto the swimmer. Reason for this was to minimise the "noise" caused by the swimmers stroking action.

A **B**

Figure 22: Sensor placement (a) front view: one tri-axial accelerometer and Polar watch placed on the swimmer's left wrist, with heart rate belt secured on the chest (b) back view: one tri-axial accelerometer placed on the swimmer's upper-back

3.6.2.2 *Axis orientation*

Due to the sensor placements, the axis orientations differed according to the anatomical position it was placed in. Figure 23 represents an illustrative diagram of the axis orientations of the GeneActiv tri-axial accelerometers placed in the respective sensor regions.

The axis orientations were validated according to the GeneActiv instruction manual provided (GeneActiv, 2017). As seen in Figure 23, the axes represented the following movement orientation: X-axis (medial-lateral movement), Y-axis (superior-inferior movement) and Z-axis (proximal-distal movement).

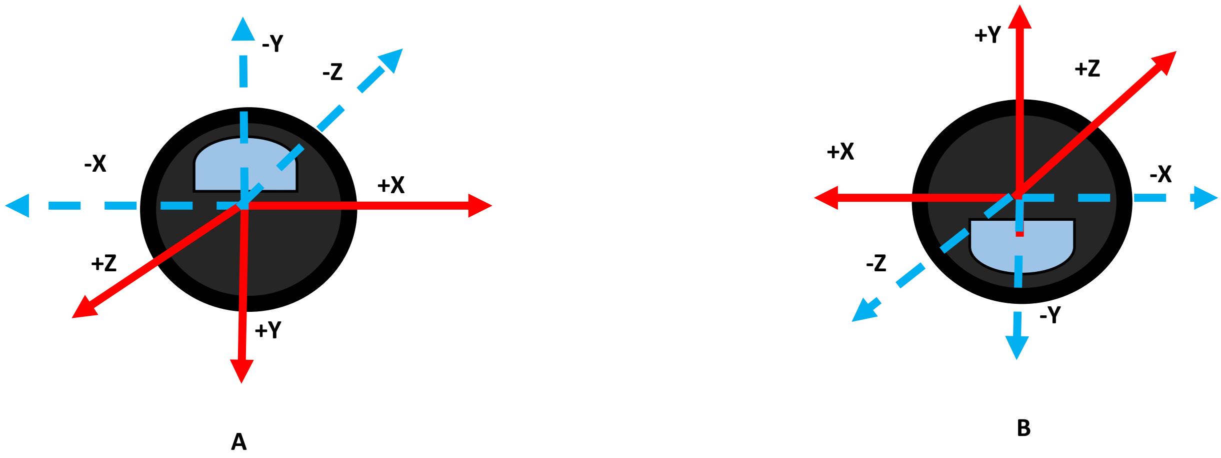


Figure 23: Axis orientation illustration of GeneActiv tri-axial accelerometers. (a) primary orientation for upper-back sensor (b) primary orientation for left wrist sensor

3.6.2.3 *Video and accelerometer synchronization*

The synchronization process of the two video cameras and the accelerometers were as follows: both camera one and two recordings were activated by the researcher. The cameras were then synchronized with the accelerometers by recording the exact time at which the accelerometer's (in their respective positions) were turned on, this was marked by a green light (see Figure 24). Thereafter, camera one and two were positioned on the camera trolley and set-up for swim set one. The green light marker seen in Figure 24, was used as the central synchronization point in the post-test analysis in Dartfish TeamPro Data (further detail is seen below in section 3.7).

Figure 24: Photo illustration of the green light activation of the GeneActiv tri-axial accelerometer, during the video and accelerometer synchronization method within the present study.

3.6.3 Swimming protocol:

The following swimming protocol was designed to test and differentiate between each of the kinematic swimming parameters, as well as investigate the swimmer's stroke mechanics, derived from the tri-axial accelerometers.

The data collection was performed by the researcher and a research assistant. The assistant was familiarised with the testing procedures prior to the data collection in the pilot testing.

3.6.3.1 50-m Individual Medley

The swimmers were required to perform a 4 x 50-m of each stroke (individual medley), between a slow to medium pace. The swimmers were required to start in the water and use a wall-push off start for each of the swimming sets performed. The test was selected specifically to differentiate between each stroking style, as well as to isolate the stroke mechanics of each stroke, with the aid of video footage. The swimming pace was dictated by the speed at which the camera trolley could be pushed alongside the pool. The steel arm produced an excessive amount of drag, resulting in the trolley not being able to be pushed at a high speed. Hence, the researcher instructed the swimmer to remain positioned above camera two, with their head directly above it, throughout each 50-m. If the swimmer moved past this point, for example, the camera was in-line with their lower abdomen, a drop-in swimming pace was required. The swimmers rested as needed between each 50-m (heart rate values were usually ~100 bpm before starting the next bout). As each 50-m did not require a high load of exertion to perform, the typical rest period ranged from 30-seconds to 1-minute.

The video validation for the accelerometer data was obtained only from set one's information. Hence, no video footage was taken of set two and three.

3.6.3.2 100-m Freestyle pace variation

The swimmers were required to perform two 100-m freestyle sets at different swim paces. The first 100-m was swum at maximum pace, with the second 100-m swum at a self- selected pace. Similar to the 50-m IM, the swimmers were required to start in the water and use a wall-push of start for each 100-m swim set performed. The test was selected specifically to obtain a variation in swimming pace. The self-selected pace was chosen, due to the age variation within the selected sample group. Although the swimmers were all of a national standard, swimmers of a younger age may not have been able to pace efficiently on a pre-determined speed compared to their older counterparts. Hence, the self-selected pace was swum at a speed less than the maximum intensity 100-m set. The swimmers rested as needed between each 100-m, with the heart rate values usually ranging between 100- 118 bpm before starting the next bout. Throughout each 100-m, the researcher manually noted each swimmers stroke count and lap time.

3.6.3.3 200-m Individual Medley

The swimmers were required to perform a standard 200-IM at maximum intensity. A wall-push off start was used by the swimmers, similar to that of the 50-m IM set. The test was selected to differentiate between the individual medley turning styles and to obtain a continuous set of accelerometer data with multiple variations in it. Each stroking style has its own specific turning style, which does not account for personal preferences. The researcher also manually noted the stroke count for each 50-m of each stroke and the lap time for the 200-m IM.

The swimmers were given 5- to 10-minutes rest between each main swim set, to allow the researcher to save the heart rate data into separate data files for the respective swimming sets. Additionally, after 50-m individual medley was completed, camera one and two recordings were stopped, with the left wrist accelerometer data extracted using the GeneActiv software and then re-programmed for remaining swim sets.

3.6.3.4 Critical swim speed

To obtain additional information, with regards to the swimmer’s performance efficiency, their critical swim speed was determined. This swim set required the swimmer’s maximum (freestyle) 50-m, and 400-m times. Therefore, the present researcher used the current season results (June 2018 – May 2019) of the swimmers, for these respective distances, to determine their critical swim speed. However, swimmers that did not have the required times and were then required to perform these distances to obtain the times. Thereafter, their critical swim speed was calculated according to the equation seen in section 3.7.1 below. The current season results were supplied by Nelson Mandela Bay Aquatics federation.

3.7 Data Extraction and Interpretation

The automation of the key swimming mechanics and kinematic parameters identified with the tri-axial accelerometer is critical in the use of the data for coaches and swimmers. Therefore, in the sub-sections to the follow, the data extraction, processing and analysis steps used will be discussed.

3.7.1 Kinematics extraction (Equations)

One of the main objectives of the present study, was to identify the kinematic parameters associated with swimming performance, using tri-axial accelerometers. Hence, the kinematic parameters in question were as follows:

- Lap time
- Stroke count
- Average swim velocity
- Average stroke rate
- Average stroke length
- Stroke phases

In order to validate the kinematic parameters that were differentiated from the tri-axial accelerometers, manual information such as counting the number of strokes per lap and the manual timing of each swim set were recorded. Additionally, video footage was taken to validate both the manual counting and timing and the accelerometer data for the 50-m IM swim set (used for the stroke phases differentiation).

Using the stroke count and lap time information gathered during the data collection process, the following equations were used to determine the kinematic parameters mentioned above. The equations were extracted from Hay (1993) and Callaway (2014).

- *Average velocity:*

The average velocity (m/s) was calculated by dividing the lap distance (d = 50-m) by the total lap time (t):

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

- *Stroke rate:*

The average stroke rate (stroke/sec) was calculated by dividing the number of completed arm cycles for the total lap distance by the time spent stroking (i.e. total lap time):

$$\overline{SR} = \frac{number\ of\ completed\ arm\ cycles}{time\ spent\ stroking} = \frac{Stroke\ Count}{Lap\ time}$$

- *Stroke length:*

The average stroke length (m/stroke) was calculated by dividing the average velocity by the average stroke rate:

$$\overline{SL} = \frac{\bar{v}}{\overline{SR}}$$

- *Critical swim speed:*

The critical swim speed (m/s) was calculated by dividing the difference between the shortest distance (50-m = D1) by the longest distance (400-m = D2) and the time taken (in seconds) for these respective distances (T2= 400-m time; T1= 50-m time) (Wakayoshi *et al.*, 1992).

$$CSS = \frac{D2 - D1}{T2 - T1}$$

3.7.2 Accelerometer data interpretation

The information derived from the tri-axial accelerometers has unprecedented research potential. However, the raw data it produces must undergo, various processing and analysis procedures, before it is ready for interpretation. In the sub-sections below, the following procedures were followed to allow for the investigation of the above-mentioned kinematic parameters.

3.7.2.1 Accelerometer data extraction

The GeneActiv software was used to extract the raw data files from the left wrist and upper-back accelerometers. Additional to the data extraction, the GeneActiv software allowed the researcher to set-up the accelerometers according to the swimmer's specifications (which included their height and weight), during the data collection process. Once the extraction of the raw data files was completed, the software was used to convert the data into comma-separated value (csv) compressed epoch files. The csv files were then used in multiple software's and analysis tools, to interpret the accelerometer data. These software and analysis tools include Microsoft Excel (version: 2019), Dartfish TeamPro Data (2019, version: classic 10) and Origin Pro (2019b, version: 9.65).

3.7.2.2 Video and accelerometer axis synchronisation point

To understand the complexity of the accelerometer data and its association with the swimmer's stroke mechanics and kinematics, video validation was used to help in the interpretation of this data. Therefore, live integration of the video footage and accelerometer data was required to carry out this interpretation. Specific software, namely Dartfish TeamPro Data (2019, version: Classic 10) was used for the integration. The software linked the csv external accelerometer data files for the left wrist and upper back to the corresponding video footage taken. However, with the synchronization method used (see section 3.6.2), an offset between the accelerometer data and the video was observed. This led the researcher to use an alternate method to synchronize the linked data to the video for the analysis process.

A synchronisation point was pre-determined by the researcher at the exact point at which the swimmer began to stroke (see Figure 25). As freestyle was the first stroke performed by the swimmer, a “stand-out” event corresponding with a specific axis was used as the primary synchronisation point between the video and accelerometer data. Therefore, the “stand-out” event for the left wrist was chosen by the first stroke phase of freestyle, namely the hand entry point after the recovery phase was completed. The chosen “stand-out’ point was consistent with previous research by Ohgi (2002), Ohgi et. al. (2003) and Callaway (2014), who used the hand entry as a marker to automate the stroke phase detection. The “stand-out” event for the upper back was chosen by the point at which the swimmer had completed their last stroke marked at the equivalent point at which their upper back rolled to its maximum on the swimmer’s side.

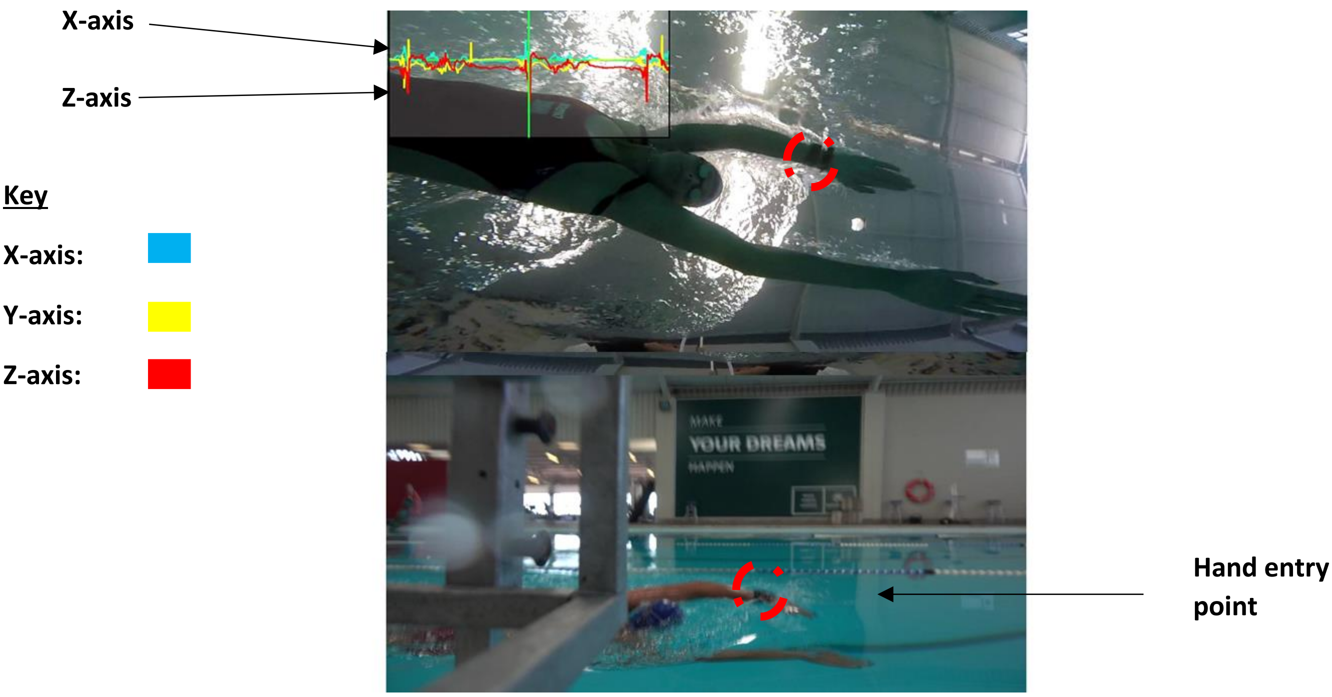


Figure 25: Illustration of video synchronization point with accelerometer data for the left wrist. Primary reference point - Z-axis (red line) with large negative spike and secondary point - X-axis (blue line) with a positive spike.

As seen in Figure 25, the primary synchronisation point at hand entry was marked by a negative inflection point (i.e. negative spike or trough) observed in the Z-axis. A secondary indicator was also noted in the X-axis with a corresponding positive inflection point (i.e. positive spike or peak) as the hand entered the water. The Y-axis was not used as a synchronisation point, due to the noise presented within the raw accelerometer data during the synchronisation process.

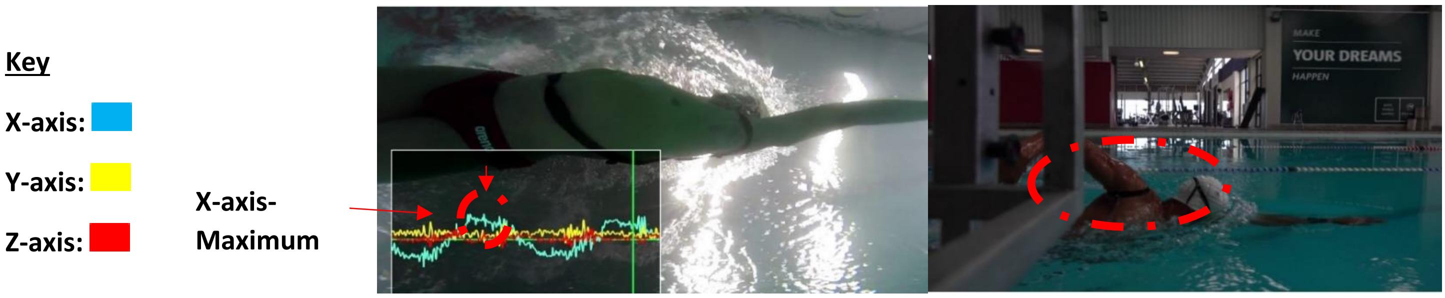


Figure 26: Illustration of video synchronization point with accelerometer data for the upper back. Primary reference point – X-axis (blue line) with a large maximum peak

As seen in Figure 26, the primary synchronisation point for the upper back was marked by a large peak or maximum in the X-axis. Only the X-axis could be used in the synchronisation process as minimal movement was observed in the Y- and Z-axis. This is consistent with the primary movement of the swimmer's upper-back only rolling medially and laterally (which is characteristic of the X-axis orientation).

Once the primary reference points were determined, the accelerometer data was synchronized and set, to ensure that the rest of the data corresponded with the remaining strokes. With the use of the live integration software, the analysis of the swimmer's stroke mechanics was performed. The analysis included associating the stroke phase events to a specific peak or trough events shown in a specific axis. However, the raw accelerometer data for the wrist presented with random spikes or "noise", which skewed the analysis of the axis characteristics associated with the stroke's phases. Hence, further steps were taken to filter the data, to account for this problem (see sub-section 3.7.2.3 to follow).

3.7.2.3 Filtering of accelerometer data for stroke phase differentiation

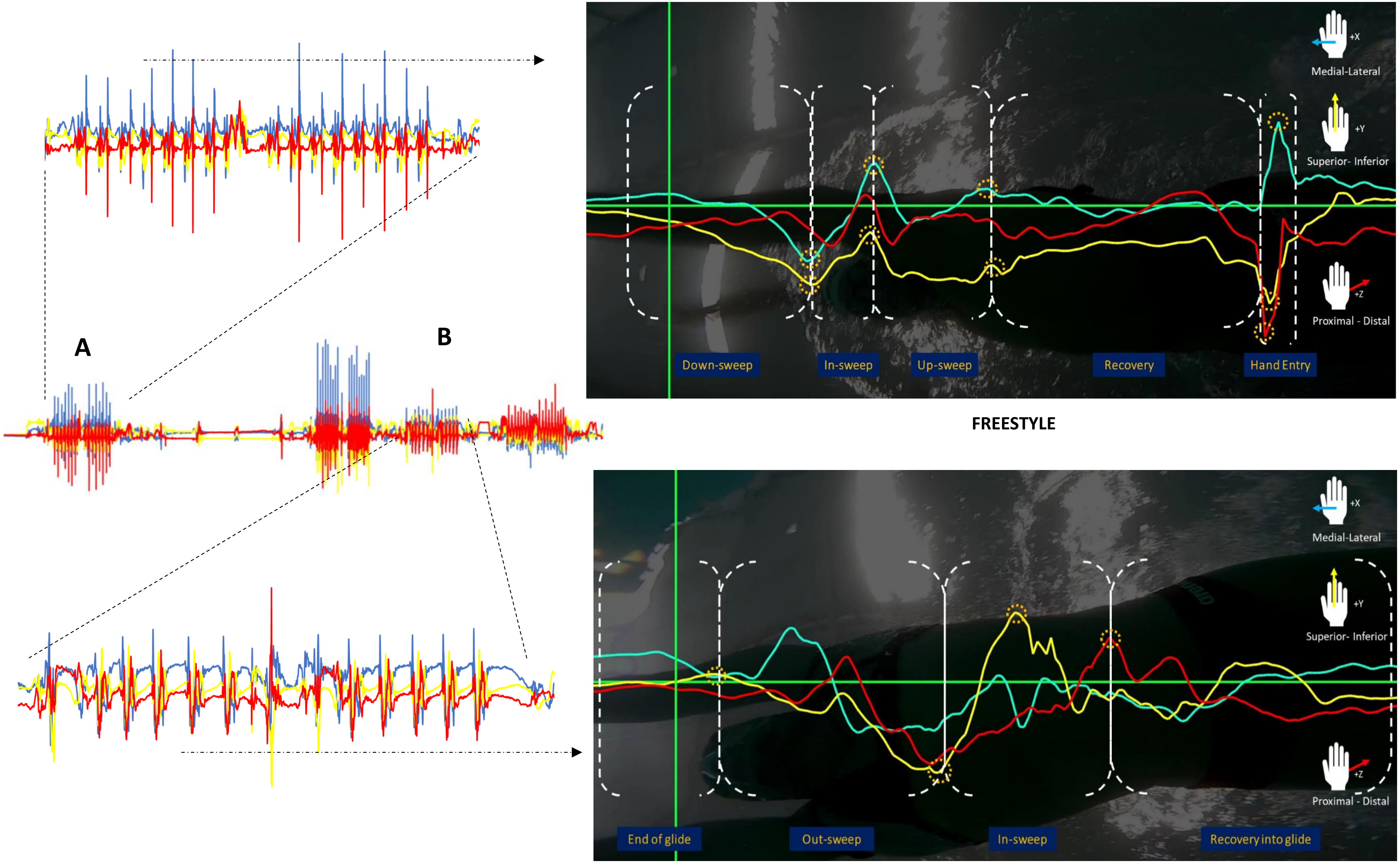
During the initial analysis, the raw accelerometer data presented with quite a substantial amount of "noise" or random acceleration spikes, especially with the left wrist data. Therefore, the data was filtered to help eliminate the random "noise" presented within the axis data. A *moving average filter* was applied to help smooth out the accelerometer data without losing important information. For the left wrist accelerometer data, the moving average filter was applied at *three intervals*. Intervals greater than three, were not ideal as it smoothed the accelerometer data, to the point that important information related to the swimmer's stroke phases were lost. Therefore, the moving average filter was applied in Excel (version: 2019). Once the data was filtered, the new csv data was linked with the video footage in Dartfish TeamPro data for the stroke phase differentiation.

3.7.2.4 Stroke phase association with axis characteristics

One of the main objectives of the present study was to be able to associate the relevant stroke mechanics, more specifically the stroke phases, of the swimmer to the accelerometer data. Before this association could be determined, a common description of the different stroke phases for the respective stroking styles was pre-appointed. These descriptions were chosen and adapted from Maglischo (1993), Didier and Seifert (2011) and Cortesi et. al. (2012) definitions, as they were the most suitable literary descriptions that met the present researchers chosen objectives. Therefore, the stroke phase descriptions for the four stroking styles were as follows:

- Freestyle: (i) Entry and stretch, (ii) down-sweep, (iii) in-sweep, (iv) up-sweep and (v) recovery
- Butterfly: (i) Entry, (ii) catch, (iii) shoulder (iv) release and (v) recovery
- Breaststroke: (i) Out-sweep, (ii) in-sweep and (iii) recovery
- Backstroke: (i) Entry and stretch, (ii) pull, (iii) push, (iv) hand lag time, (v) clearing and (vi) recovery

From the above descriptions, a minimum of two-stroke cycles per swimmer for 50-m IM swim set were analysed using the live integration software and the filtered accelerometer data. The relevant inflection points for each axis, characteristic of either a positively skewed peak or negatively skew trough, were associated with a specific stroke phase for a specific stroking style (see Figure 27 for stroke phase association).



BREASTSTROKE

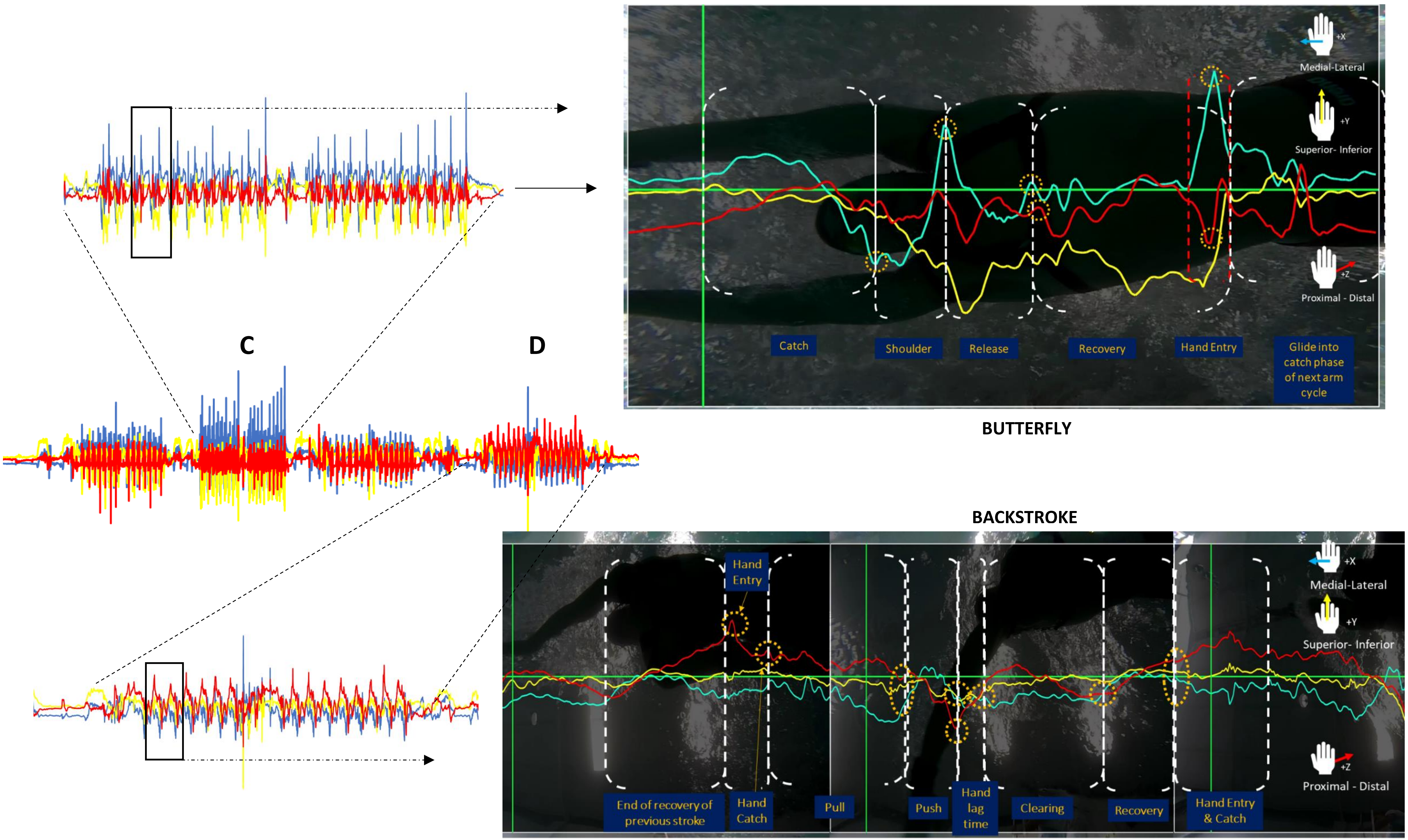


Figure 27: Stroke phase association with axes (A- Freestyle; B-Breaststroke; C-Butterfly; D-Backstroke), extracted from two swimmers

Research in the stroke phase detection and extraction for all four stroking styles using accelerometers has shown a pre-dominance for the stroke freestyle (Mooney *et al.*, 2015). The method, to which the stroke phases for each stroking style were detected and extracted (as seen in Figure 27) was guided by the studies performed by Ohgi (2002), Ohgi et. al. (2003) and Callaway (2014). Within these studies, the main objective was to automate the stroke phase detection, by developing an algorithm to perform this task. Hence, to start the automatic process, a primary starting point was chosen, which was defined by the "hand entry" of the stroke freestyle that was analysed. This starting point was consistent with the synchronisation "stand-out" point used within the present study to synchronize the accelerometer data with the video footage.

Hence, as seen in Figure 27, the stroke phase detection and extraction from the accelerometer data was performed manually using live integration software. Each hand entry point for the stroking styles that performed this action was associated with a key inflection point within the accelerometer data. For freestyle (Figure 27a), this was marked by a positively skewed peak and two negatively skewed troughs in the X-, Y- and Z-axes, respectively. Butterfly's (Figure 27c) hand entry was marked at the end of its recovery phase by a positively skewed peak and negatively skewed trough in the X- and Z-axes, respectively. Backstroke's (Figure 27d) hand entry was marked by a negatively skewed trough and positively skewed peak in the X- and Z-axis, respectively. However, for breaststroke (Figure 27b), the movement patterns performed did not allow for a definite hand entry to be observed, similar to that of the other three stroking styles. Therefore, the "in-sweep" phase of breaststroke was used as a key inflection point. The reason for this was that this phase displayed a major positively skewed peak, marked by the swimmer's arms tucking in towards their chest, before initiating the push phase. Once these key inflection points were identified, the relevant inflection points for the remaining stroke phases were detected and marked out. See Appendix E for a summary of the inflection points associations with the stroke phases for each stroking style.

Once the stroke phases were identified with their respective inflection points marked within the accelerometer data, differences amongst the swimmers were observed at these points associated with the magnitude of the relevant peak or trough (see Figure 28). An example of this difference was observed at the hand entry inflection point in freestyle, with the lower-ranked (i.e. lower 33%) swimmers displaying a smaller magnitude within their relative peak and trough compared to the higher-ranked (i.e. top 33%) swimmers at this inflection point.

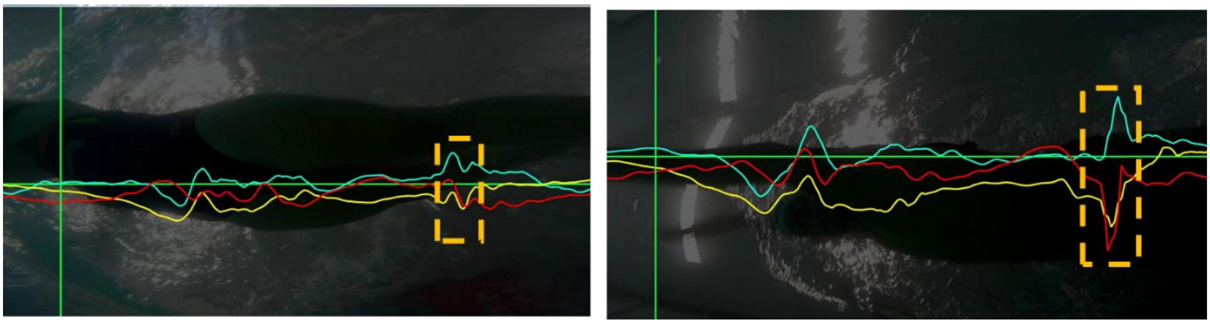


Figure 28: Differences in hand entry magnitude for freestyle (a) Lower ranked swimmer (b) Higher ranked swimmer

Therefore, further differences amongst the swimmers could be discerned from the magnitude of the relative peaks or troughs at the respective stroke phase junction points for the stroking styles.

3.7.2.5 Stroke kinematic parameters identification

One of the main objectives, set out for the present study was to identify the stroke kinematic parameters, using tri-axial accelerometers. Extensive research has been done in the identification of the stroke kinematic parameters of freestyle, using tri-axial accelerometers as the source (Callaway, 2015; Mooney *et al.*, 2015; Stamm, 2018). However, limited research has been completed in this regard, with the remaining three strokes. One study by Le Sage et. al. (2011), investigated the use of a system (i.e. accelerometer) to automatically determine the lap count, stroke count and stroke rate for all four strokes, with the results relayed to the coaches in real-time. Using the methodology of this study as a reference, the present researcher determined the following stroke kinematic parameters from the accelerometer data:

- Lap time (i.e. total time spent stroking)
- Stroke count
- Average stroke rate
- Average swimming velocity
- Average stroke length

The left wrist accelerometer data was disregarded in the identification of the stroke kinematic parameters, due to the variability presented within each of the swimmers' stroke mechanics. Hence, resulting in a higher possibility of misinterpretation of the stroke kinematic parameters in question, if the axis characteristics are constantly changing according to the swimmer's stroking action. Taking this into account, the upper-back sensor was used as the primary source, in the identification and determination of the stroke kinematic parameters, mentioned above. Origin Pro (2019b, version: 9.65) was used to filter and interpret the accelerometer data, to obtain the stroke kinematic parameters.

The first kinematic parameter investigated was the *stroke count* for each swimmer. The stroke count was determined by the marker characteristics within the accelerometer data that was consistent with the body movement or roll of the swimmer, for each respective stroke. Hence, two different types of body rolls were presented:

(i) Medial to lateral body roll (side to side movement): This is characteristic for the strokes freestyle and backstroke. The side to side movement is due to the bilateral arm movement performed by the swimmer, to complete the desired stroking action (Le Sage *et al.*, 2011)

(ii) Anterior to superior body roll (back to front movement): This is characteristic for the strokes' breaststroke and butterfly. The back to front movement is due to the unilateral arm movement performed by the swimmer, to complete the desire stroking action (Le Sage *et al.*, 2011)

Taking these two types of body rolls into account, only specific axes could be used to obtain the information required for the stroke kinematic parameters. These axes were the X- and Z-axis for the strokes freestyle and backstroke and breaststroke and butterfly, respectively. For all four strokes, the X- and Z-axis accelerometer data were filtered with a *low pass* 4^{th} *order Butterworth filter at a cut-off frequency of 1 Hz* (see Figure 29)

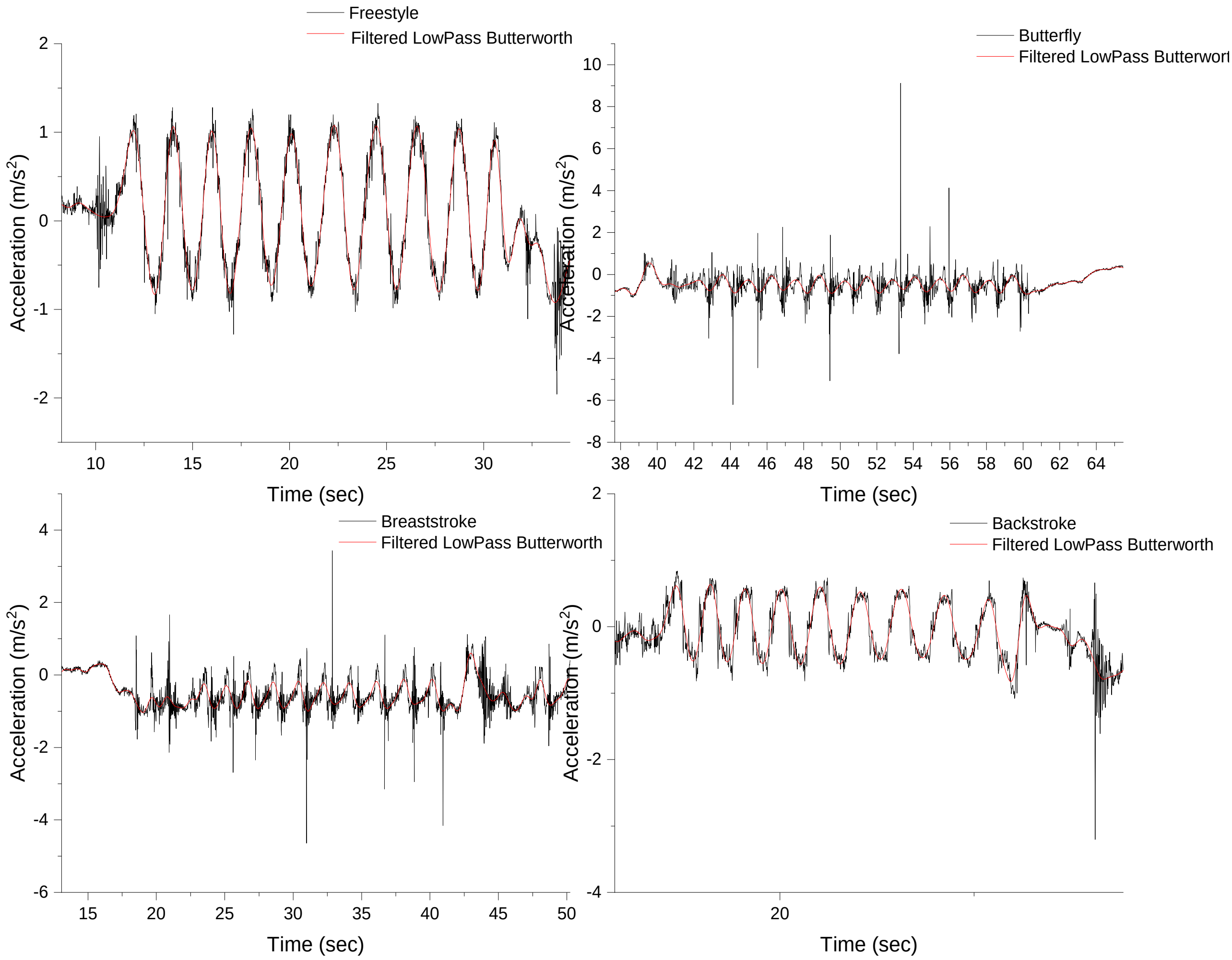


Figure 29: Graphical representation of the upper-back accelerometer data for each respective stroke, filtered with low-pass Butterworth 4^{th} order filter (cut-off frequency at 1 Hz)

As the upper-back sensor presented with substantial noise, the filter choice allowed for the exclusion of additional data points (not relevant to the analysis) at the relative peak and troughs in the data.

As seen in Figure 29, the use of the low-pass Butterworth filter, eliminated the relevant noise presented throughout each of the strokes, allowing for a smoother movement pattern to be observed. From the filtered data, the stroke count for each stroking style was determined by using the quick peak function on Origin Pro. Overall, the majority of the swimmer's presented with similar body roll mechanics. However, differences were observed amongst swimmers with regards to the magnitude of their relative peaks and troughs associated with their body rolls. With these peak magnitude changes, each stroke was given a different peak characteristic criterion.

The stroke count for the 50-m individual strokes was determined in the following manner:

- Freestyle and backstroke:

The detection of the relative positively skewed peaks and negatively skewed troughs was carried out using a *zero-crossing method* in conjunction with a *peak detection method*. The zero-crossing criterion was adapted to using the mean average of the data as the crossing, to account for different peak and trough magnitudes observed. Furthermore, the peak detection criterion was set for both negative and positive peaks to be detected, with peaks filtered at 50% of the magnitude of their relative peaks for freestyle. For backstroke, the peak magnitude ranged from 25% to 50%, with a majority of the swimmers being filtered at 50%, except if major magnitude differences were observed (see Figure 30a and d below for graphical illustration).

- Butterfly and breaststroke:

The detection of the relative positively skewed peaks was performed using a peak detection method. However, due to the nature of the body movement performed by the swimmer for butterfly and breaststroke, additional peaks were observed, over and above the primary peaks required for the stroke count. Therefore, to eliminate these peaks, a y-intercept crossing was used to eliminate these peaks. This intercept ranged between -0.5 and -1, with a majority of the swimmers using a -1 (y-intercept). Furthermore, the peak detection was set to observe positively skewed peaks (see Figure 30b and c below for graphical illustration). Although the -1 y-intercept disregarded a number of the additional peaks within the data set, a few of the swimmers' data presented with data points similar to the main stroke count data points. Therefore, the present researcher manually eliminated these points, as the system could not detect and differentiation these additional peaks in the data. A major discrepancy with this manual elimination method presented with an under- or over-estimation of the stroke count for these strokes. Hence, further research is required in eliminating this manual process, to decrease human error.

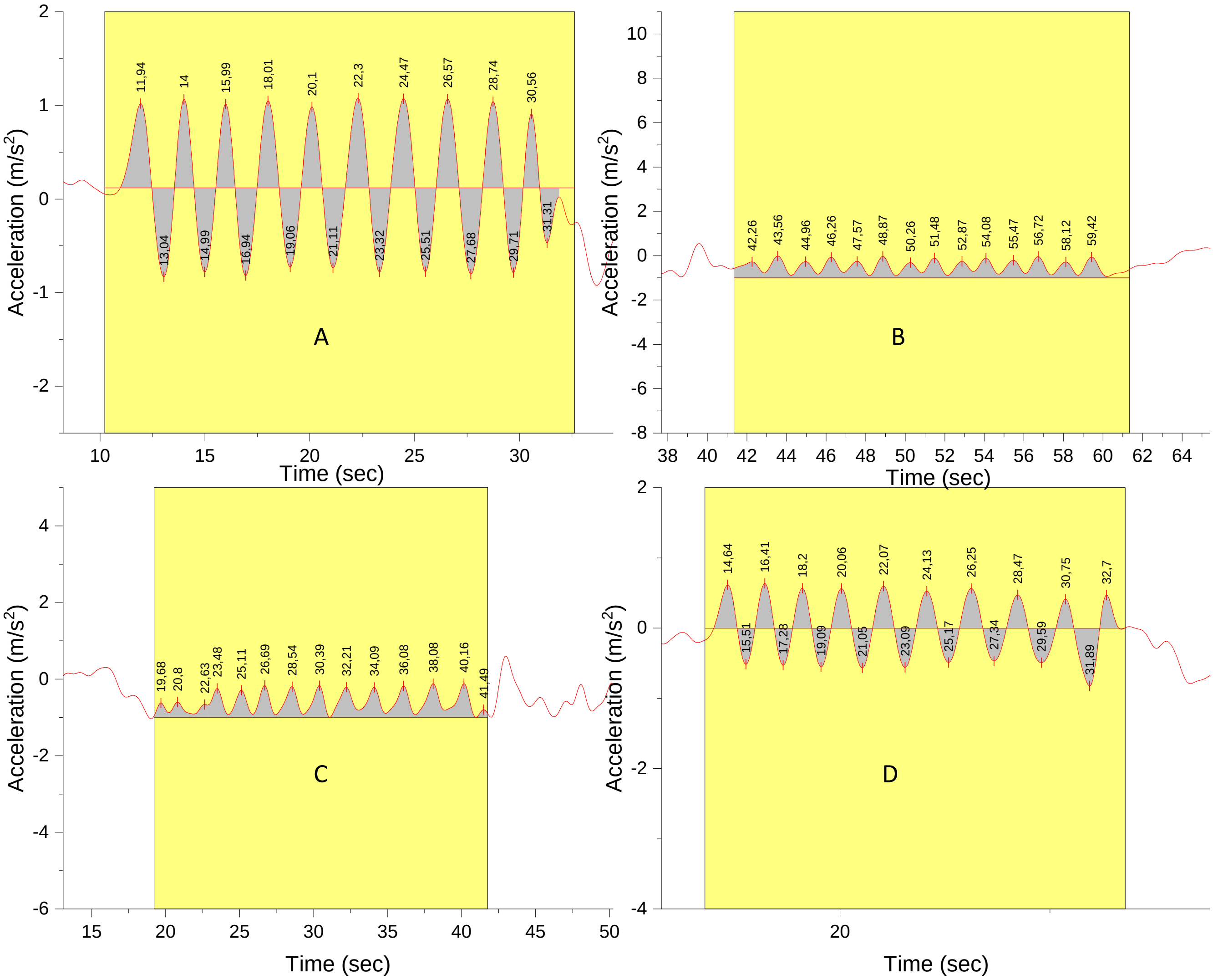


Figure 30: Graphical illustration of peak detection of stroke count for each respective stroke. (A) Freestyle, (B) Butterfly (C) Breaststroke (D) Backstroke

The stroke count for the 100-m freestyle sets used the same peak detection criteria as set for the 50-m freestyle and backstroke, with the peak magnitude set at 60%. However, one error was presented with the peak magnitude filter criterion chosen for all the swimmers. With the filter height, the tumble turns performed by the swimmer were counted as a stroke, as the difference between the magnitudes between the positively and negatively skewed peaks and troughs, didn't allow for the elimination of the turns if the threshold was set higher. Hence, posing a limitation on the peak magnitude filter criterion. Therefore, the three tumble turns performed by each swimmer was subtracted from the total stroke count estimated for the 100-m variation set.

The stroke count for the 200m-IM set could not be detected as one singular stroking group, due to the two different axes that were required for the respective strokes. Therefore, the 200m-IM was separated into each of the 50-m's for each individual stroke. Once this separation was performed, the stroke count criterion for the 50-m's (as stated above) was applied.

Once the stroke count for all three swim sets was determined, the equations (see section 3.7.1) were used to estimate the average swimming velocity, stroke rate and stroke length. The lap time for each swim set was measured by the time difference between the first stroke detected and the last stroke measured by the peak detection algorithm in Origin Pro.

3.7.2.6 Machine learning classification

The use of software's such as Microsoft Excel (version: 2019) and Origin Pro (2019b, version: 9.65) limited the researcher with regards to automating the stroke kinematics obtained from the accelerometer data. A major limitation was the time-consuming nature of extracting the relevant details from the data, to ensure the correct kinematics were interpreted. Henceforth, the help of Dr Seyed Salah Zadeh of the Computer Science Department at the Nelson Mandela University was sought out to overcome this limitation. Dr Salah Zadeh used artificial intelligence to interpret the accelerometer data by isolating the four primary stroking styles from the 50-m IM swim set. Therefore, for the present study, it was requested to observe if machine learning was able to extract and interpret the differences between each of the stroking styles from the raw accelerometer data. Dr Salah Zadeh performed an experiment on four of the swimmers 50-m IM data with an i5 3.4GHz CPU and 3 Cuda Core GPUs. As seen in Figure 31, a total of 289,273,784 blocks of one-second data was fed into the model. Of this, 60% of the data was used for training, 20% for the validation of the model and 20% for the test processes. The model included two Long Short-Term Memory Recurrent Neural Network layers, with each including 128 neurons. To prevent over-training, two dropout layers after each of the layers with the capacity of 50% were used. The limited number of swimmers used in the machine learning process was to prove a "proof of concept" for the present study.

Hence, further research and time would be dedicated to this aspect of the research study, in future research potentials.

The model architecture was recommended by researchers Mcdaniel and Quinn (2018), however unlike the tree-structured Parzen (TPE) expected improvement (EI) algorithm used in Mcdaniel and Quinn (2018) article, the *Adam optimisation algorithm* was used to train the above model (Figure 31). Why the Adam optimisation algorithm was chosen over the TPE algorithm, was that it is considered computationally more efficient as it requires little memory and is well suited for large data files or parameters. Additionally, the Adam method is typically used for non-stationary objectives which present with very noisy gradients (i.e. large accelerometer data files that present with excess noise across the axes caused by stroke vibrations) (Kingma & Ba, 2015).

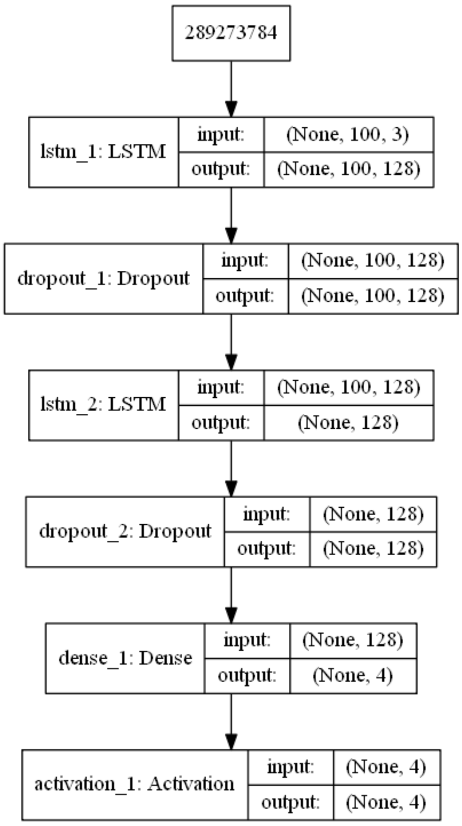


Figure 31: Architecture of the machine learning model used to identify the four individual stroking styles

Furthermore, for the model and results, a cross-entropy loss function was also used to reduce the uncertainty of the probability distributions amongst the data. Therefore, the accuracy of the custom implemented machine learning model by Dr Salah Zadeh is seen in Chapter 4, section 4.3.

3.8 Data Analysis

Descriptive statistics, in the form of tables, box charts and histograms, were used as measures of central tendency such as means, standard deviations, confidence intervals (95%) and standard errors to describe the data. Further inferential statistics were used to describe the relationship between the stroke kinematic parameters extracted from the accelerometer versus the manually estimated parameters. These inferential statistics included pair t-test, intra-class correlation (ICC), Cohen d and Bland Altman analysis (to assess bias amongst the two methods). Additionally, repeated measures one-way ANOVA, with post-hoc Tukey HSD test ($\alpha = 0.05$) was used for an inter-comparison between each of the stroking styles and the estimated stroke parameters from the accelerometer data. Similarly, a one-way ANOVA was used to compare selected stroke parameters obtained from the Polar V800 watch, accelerometer and the manually estimated parameters.

Simple linear regression was used to assess whether the critical swim speed and heart rate telemetry recorded during the swim sets account for any differences in swimming speed observed during the data collection. Therefore, to assess the linear fit the correlation coefficient (r) was used, with the statistical significance measured using an independent t-test. To assess the accuracy of the machine learning algorithm implemented, a confusion matrix was used to represent the findings of the classification model.

Both Statistica (software version 10.2) and Origin Pro (software version 9.3) were used in the statistical analyses. A qualified statistical consultant based at the Nelson Mandela University was consulted to ensure the validity and accuracy of the data interpretation.

3.9 Ethical Considerations

The present study adhered to the following ethical considerations to ensure the swimmers' safety and compliance: the avoidance of harm, informed consent, informed assent, confidentiality, action and competence of researcher and publications of findings (de Vos *et al.*, 2005).

Majority of the sample group was over the age of 18 years old, with 13% of the sample group under the age of 18 years old. Therefore, the younger swimmers and their parents were required to sign both informed consent and assent forms to participate in the present study, with additional consent sought out from coaches to gain access to their swimmers (see appendix C and D, respectively). The forms provided information with regards to the aim of the study, the expected duration of the swimmer's involvement, the procedures that were conducted and the possible advantages and disadvantages, as well as risks associated with the testing procedures. The gatekeepers were approached before the commencement of the study, namely the coaches of the prerequisite swimming clubs and in the case that a swimmer was under the age of 18 years old, the parents or guardians of the swimmer. All the above information was given to the gatekeepers, to ensure full transparency between the researcher and the gatekeepers. The swimmers' participation was voluntary and steps to ensure their confidentiality and anonymity were followed by the researcher. Therefore, the confidentiality and anonymity of each swimmer were safeguarded by the use of code names (de Vos *et al.*, 2005) within the present study.

The study was conducted at the Fitness and Aquatics Centre (FAC) on South Campus at the Nelson Mandela University. The tests were conducted by a qualified Sport Scientist and one assistant, under the guidance of a qualified Biokineticist to ensure reliable and competent testing. The research study gained ethical approval from the Research Ethics Committee-Human (REC-H) at the Nelson Mandela University in November 2018 (REC-H number: H18-HEA-HMS-007). Thereafter, testing was commenced.

3.10 Limitations

The novelty of this type of research within a South African context, the present study was met with various limitations in the data collection process and analysis. Due to the specific requirements of including "national" level swimmers within the Nelson Mandela Bay district, the sample size was invariably limited. Consequently, only 15 swimmers met the inclusion criteria and since this study was not a multi-centre national study, the results of the present study would not necessarily be transferable or generalisable to other swimmers at the national level.

Within the testing procedure, a major limitation was presented with the camera trolley, used to collect the video footage (above and below the water) of the swimmer. As the camera trolley was custom-made, a few problems arose from the structural design of the trolley. The first structural problem was the camera arm, holding the underwater camera. Due to the shape of the arm (i.e. straight lever arm), when the trolley was pushed alongside the pool, the arm caused excessive drag. Therefore, to limit this problem, a suggested curved lever arm would help to decrease the overall drag experienced by the researcher and the trolley itself. Additional to this drag force, the present researcher or research assistant had to counter the drag force by applying a counter torque on the trolley arm. This was to ensure that the trolley did not drive into the pool. Therefore, to try and limit the extra applied force by the researcher, alternative solutions were sought out, to help keep the trolley in a straight-line path alongside the pool. One solution found was the use of tracks to place the wheels of the trolley into, to secure it to the side of the pool and to maintain a straight-line pathway. This solution was presented in a study by Callaway (2014), who used a moving camera trolley, which had tracks to secure the trolley against the wall as it was pushed by the researcher during the testing. Therefore, in future research, the present researcher could look at adapting the current trolley, to a similar design used by Callaway (2014).

During the data analysis process, a time synchronisation error between the video footage and accelerometer data was found. This error included an undetermined off-set between the start of the accelerometer data recording in conjunction with what was recorded with camera one and two during the synchronisation process stipulated in section 3.6. Therefore, further research must be performed to identify a reliable and valid method in synchronising the present accelerometer used, with the recorded video footage without a time off-set delay.

An additional limitation related to the heart rate information obtained throughout the data collection found an inconsistency in collecting continuous heart rate data for the swimmers. The sensor location of the heart rate strap on the swimmer's chest produced a substantial amount of noise, limiting the instantaneous telemetry data. A potential solution was found recently with Polar releasing a new heart rate sensor called the Polar OH1 Optical heart rate sensor (Polar, 2019). The Polar OH1 Optical HR sensor is inclusive of an armband that can be placed on the athletes upper and lower arm (Polar, 2019). This HR sensor uses photoplethysmography (PPG) which uses LED lights and a light detector to measure the changes in the size of the blood vessels to measure heart rate readings. Whereas, the Polar H10 heart rate chest strap (used with the Polar V800) uses electrical activity (ECG) to measure heart rate readings (Polar, 2019). One triathlete found this new heart rate sensor to be more beneficial in obtaining continuous heart rate telemetry information throughout their swimming session, compared to that of the chest strap (Mclarty, 2019). Hence, for future research, it would be recommended to source this alternate heart rate sensor for more reliable heart rate telemetry information.

After the above the methods and procedures were implemented, Chapter 4 to follow will discuss the results of the present study, in correspondence with the objectives set-out.

CHAPTER 4: RESULTS

4.1 Introduction

The following results are based on the findings from the data collection defined in Chapter 3. Various descriptive and inferential statistics including the mean, standard deviation, confidence intervals (95%), intra-class correlation (ICC) and significance value and additional statistical tests were used to interpret and infer the relevant findings from the data. In the sections to follow, the comparison between the kinematics (including lap time, swimming velocity, stroke rate and length and stroke count) measured by the Polar watch, accelerometer and through manual methods (i.e. counting and video-based evidence) was completed. Additionally, an inference was made between the CSS and heart rate telemetry data against the stroke kinematics.

4.2 Identification of kinematic parameters

The primary method for the identification of kinematic parameters was carried out using the tri-axial accelerometers, with the accuracy compared against the kinematic parameters estimated by the present researcher through the manual calculations as stated in Chapter 3 (section 3.7.1).

4.2.1 Accelerometer and manual method comparison

The kinematic parameters identified and interpreted from the accelerometer data were as follows: stroke count, swimming lap time, swimming velocity, stroke rate and stroke length. The stroke count and swimming lap time were estimated from the accelerometer with the remainder of the kinematic parameters calculated using the equations in Chapter 3 (see section 3.7.1).

Three different swim sets were performed by each swimmer, 50-m IM, 100-m variation (maximum and self-selected set) and 200-m IM. For each swim set, a comparison between the accelerometer and manually estimated information was completed. Table 4 represents a summary of the statistical comparison between the accelerometer and manual method for each swim set, for each stroke kinematic parameter.

Table 4: Summary of the statistical comparison between the accelerometer and manually estimated stroke kinematic parameters for the 50-m IM, 100-m variations and 200-m IM swim sets (n = 13)

	ACCELEROMETER		MANUAL		BLAND-ALTMAN						
							LOA				
Variables	Mean ± SD	95% CI	Mean ± SD	95% CI	M_{diff}	SD_{diff}	95% CI (LL)	95% CI (UL)	d	ICC	p- value
50-m Freestyle											
*Stroke Count **	36.63 ± 6.67	32.59, 40.64	36.15 ± 6.94	31.96, 40.35	0.46	0.66	-0.83	1.76	0.70	0.99	0.027
*Lap time (sec) ****	42.06 ± 3.05	40.21, 43.90	46.67 ± 3.33	44.66, 48.68	-4.61	1.48	-7.51	-1.71	2.87	0.44	<0.001
*Velocity (m/s) ****	1.19 ± 0.09	1.14, 1.25	1.08 ± 0.08	1.03, 1.12	0.12	0.04	0.04	0.20	2.87	0.44	<0.001
*SR (str/sec) ****	0.87 ± 0.15	0.78, 0.96	0.78 ± 0.16	0.68, 0.88	0.09	0.03	0.04	0.15	3.49	0.84	<0.001
*SL (m/str) **	1.40 ± 0.23	1.27, 1.54	1.43 ± 0.24	1.28, 1.57	-0.02	0.03	-0.09	0.04	0.68	0.99	0.030
50-m Butterfly											
Stroke Count	24.38 ± 4.66	21.57, 27.20	23.85 ± 4.67	21.02 -26.67	0.54	1.13	-1.67	2.75	0.48	0.97	0.110
*Lap time (sec) ****	41.45 ± 4.65	38.64, 44.26	46.08 ± 3.63	43.88, 48.27	-4.62	2.61	-9.73	0.48	1.18	0.50	<0.001
*Velocity (m/s) ****	1.22 ± 0.14	1.13, 1.30	1.09 ± 0.00	1.04, 1.14	0.13	0.09	-0.05	0.31	1.43	0.44	<0.001
*SR (str/sec) ****	0.59 ± 0.1	0.53, 0.65	0.52 ± 0.10	0.46, 0.58	0.07	0.03	0.01	0.13	2.42	0.77	<0.001
SL (m/str)	2.12 ± 0.4	1.88, 2.36	2.17 ± 0.41	1.92, 2.41	-0.05	0.11	-0.27	0.17	0.43	0.96	0.145
50-m Breaststroke											
Stroke Count	20.46 ± 5.43	17.18, 23.74	20.54 ± 5.06	17.48, 23.6	-0.08	1.61	-3.22	3.07	0.05	0.96	0.866
*Lap time (sec) ****	44.88 ± 6.20	41.14, 48.63	50 ± 3.63	47.81, 52.20	-5.12	3.48	-11.95	1.71	1.47	0.51	<0.001
*Velocity (m/s) ***	1.14 ± 0.17	1.03, 1.24	1.00 ± 0.07	0.96, 1.05	0.13	0.12	-0.11	0.37	1.08	0.40	<0.001
*SR (str/sec) ****	0.45 ± 0.09	0.40, 0.51	0.41 ± 0.09	0.36, 0.46	0.04	0.02	0.00	0.09	1.78	0.86	<0.001
SL (m/str)	2.63 ± 0.81	2.14, 3.12	2.59 ± 0.41	2.15, 3.04	0.04	0.24	-0.44	0.52	0.16	0.95	0.568
50-m Backstroke											
*Stroke Count **	35.62 ± 5.03	32.58, 38.65	34.85 ± 5.13	31.75, 37.95	0.77	1.09	-1.37	2.91	0.70	0.97	0.026
*Lap time (sec) ****	44.39 ± 4.36	41.76, 47.02	48.42 ± 3.85	46.51, 51.16	-4.44	2.32	-8.99	0.10	1.92	0.54	<0.001
*Velocity (m/s) ****	1.14 ± 0.12	1.07, 1.21	1.03 ± 0.08	0.98, 1.08	0.11	0.06	-0.01	0.23	1.73	0.52	<0.001
*SR (str/sec) ****	0.81 ± 0.10	0.74, 0.87	0.72 ± 0.11	0.65, 0.78	0.09	0.04	0.00	0.17	2.03	0.68	<0.001
*SL (m/str) **	1.43 ± 0.20	1.31, 1.55	1.46 ± 0.73	1.34, 1.59	-0.03	0.05	-0.12	0.06	0.70	0.96	0.026
100-m Freestyle Maximum											
Stroke Count	77.15 ± 11.29	70.33, 83.98	77.54 ± 11.07	70.85, 84.23	-0.38	1.26	-2.86	2.09	0.31	0.99	0.293
*Lap time (sec) ****	67.68 ± 7.65	63.06, 72.30	71.55 ± 7.47	67.03, 76.06	-3.87	1.09	-6.00	-1.74	3.56	0.88	<0.001
*Velocity (m/s) ****	1.49 ± 0.18	1.39, 1.60	1.41 ± 0.15	1.32, 1.50	0.08	0.03	0.01	0.15	2.40	0.87	<0.001
*SR (str/sec) ****	1.14 ± 0.10	1.08, 1.20	1.08 ± 0.10	1.02, 1.15	0.06	0.02	0.02	0.09	3.00	0.86	<0.001

SL (m/str)	1.32 ± 0.19	1.20, 1.44	1.31 ± 0.19	1.20, 1.43	0.01	0.03	-0.04	0.06	0.24	0.99	0.411
100-m Freestyle Self-selected											
Stroke Count	68.08 ± 13.21	60.04, 76.06	67.54 ± 13.28	59.51, 75.57	0.54	1.20	-1.81	2.89	0.45	1	0.131
*Lap time (sec) ****	84.79 ± 7.71	80.13, 89.46	89.89 ± 7.37	85.44, 94.34	-5.10	1.78	-8.59	-1.61	3.00	0.79	<0.001
*Velocity (m/s) ****	1.19 ± 0.11	1.12, 1.26	1.12 ± 0.09	1.06, 1.18	0.07	0.03	0.01	0.13	2.30	0.79	<0.001
*SR (str/sec) ****	0.80 ± 0.12	0.73, 0.87	0.75 ± 0.13	0.67, 0.83	0.05	0.02	0.01	0.09	2.47	0.92	<0.001
SL (m/str)	1.52 ± 0.30	1.34, 1.70	1.53 ± 0.30	1.35, 1.72	-0.01	0.03	-0.08	0.05	0.43	0.99	0.145
200-m IM											
*Stroke Count **	131.54 ± 17.60	120.91, 142.17	128.23 ± 18.59	117, 139.47	3.31	4.31	-5.14	11.75	0.77	0.96	0.017
*Lap time (sec) ****	165.31 ± 21.65	152.23, 178.39	184.77 ± 19.12	173.22, 196.32	-19.46	5.44	-30.13	-8.79	3.57	0.66	<0.001
*Velocity (m/s) ****	1.25 ± 0.17	1.14, 1.35	1.09 ± 0.12	1.02, 1.17	0.15	0.07	0.03	0.28	2.36	0.60	<0.001
*SR (str/sec) ****	0.80 ± 0.05	0.77, 0.83	0.69 ± 0.06	0.66, 0.73	0.10	0.03	0.04	0.17	3.06	0.30	<0.001
SL (m/str)	1.57 ± 0.21	1.44, 1.69	1.59 ± 0.23	1.45, 1.73	-0.02	0.07	-0.17	0.12	0.32	0.94	0.272

*p<0.05, ** p<0.01, *** p<0.001; $M_{diff} = M_{accelerometer} – M_{manual}$; $SD_{diff} = SD_{accelerometer,}- SD_{manual}$; LOA = limits of agreements; LL = lower limit; UL = upper limit

The statistical significance between each of the variables for the accelerometer and manual estimated data were tested with a paired t-test at α = 0.05, with further statistical inferences measured with a Bland Altman analysis.

For the first stroke kinematic parameter, stroke count (SC), a strong reliability was found between the accelerometer derived and manual estimated SC for the 50-m IM swim set (ICC range 0.97 – 0.99). In support of this finding, the paired t-test showed no significant difference between each stroking style at α= 0.05 (butterfly p = 0.110 and breaststroke p = 0.866). However, a significant difference for the stroking styles freestyle (p= 0.027) and backstroke (p= 0.026) was found. Subsequently, a Bland Altman analysis was used to evaluate the reliability and agreement between the group means. The analysis results showed a bias of 0.46-, 0.54-, 0.77- and -0.08 strokes, for freestyle, butterfly, backstroke and breaststroke, respectively. The standard deviation difference (SD_{diff}) between the means per stroking style were within the recommended ±1.96 SD (freestyle SD_{diff} = 0.66, backstroke SD_{diff} = 1.09, butterfly SD_{diff} = 1.13 and breaststroke SD_{diff} = 1.61). Therefore, implying an agreement between the methods used (accelerometer versus manual counting) to measure the SC per swimmer.

Although breaststroke showed the least bias (-0.08 strokes) compared to backstroke with the highest (0.77 strokes) amongst the stroking styles, the SD_{diff} for breaststroke was the greatest (SD_{diff} = 1.61). The high SD_{diff} for breaststroke may be related to an under and over-estimation of the accelerometer to accurately extract the correct number of strokes executed by each swimmer. However, regardless of this SD_{diff}, the difference between the means for breaststroke was minimal as supported by Cohen d findings of 0.05, therefore emphasising that this difference was small even if there was a statistical significance between the two methods.

For the 100-m variation set, similar results to the 50-m IM swim set were found, with a strong reliability observed between the accelerometer and manual method for the 100-m maximum (max) and self-selected (SS) swim sets (ICC: 100-m Max = 0.99, 100-m SS = 1.00). The paired t-test supported the ICC for the respective swim sets, showing no significant difference for 100-m max (p= 0.30) and 100-m SS (p= 0.13). The Bland Altman analysis results showed a bias of -0.38- and 0.54 strokes, with a SD_{diff} between the group, means of 1.26 and 1.09 strokes for the 100-m max and 100-m SS, respectively. Therefore, indicating an agreement between the two methods in deriving the relative SC from these swim sets. For the last swim set (200-m IM), a strong reliability was found between the accelerometer and manual method (ICC = 0.96). However, a significant difference was found between the two methods (200-m IM: p= 0.017), which was supported by the Bland Altman analysis which showed lower reliability or agreement between the methods in deriving this kinematic parameter (bias = 3.31 strokes, SD_{diff} = 4.31, LOA: (LL) = -5.14 and (UL) 11.75). The large variation in the SC between the accelerometer and manual estimation was due to the method used to extract the relevant parameter from the accelerometer data. The method required extracting the SC from each individual 50-m within the 200-m IM, resulting in a misinterpreted under- or over-estimation of the total SC per 200-m IM per swimmer. Therefore, showing a limitation in the method used by the present researcher to extract this parameter from the accelerometer data reliably.

For the next stroke kinematic parameter (lap time), a moderate reliability was found between the accelerometer and manual method for the 50-m IM (ICC range = 0.44 – 0.54), whereas a moderate to strong reliability was found for the 100-m max (ICC = 0.88), 100-m SS (ICC = 0.76) and 200-m IM (ICC = 0.66) swim sets. The paired t-test showed that a significant difference was found between the accelerometer estimated lap time and the manually taken times across all three swim sets (p <0.001 for 50-m IM, 100-m variation, 200-m IM). This was supported by the results of Bland Altman analysis with the bias across all swim sets ranging from -5.12- to -4.44 seconds for the 50-m IM, -5.10- to -3.87 seconds for 100-m variation and -19.46 seconds for the 200-m IM. The SD_{diff} between the swim sets was greater than the recommended ±1.96 SD, therefore indicating a decreased reliability and agreement between the accelerometer derived lap time and manually taken times for each swim set. The decrease in reliability was further supported by Cohen d finding across all the swim sets with it ranging between 1.18 to 3.57, showing a strong meaningful difference between the group means for the lap time kinematic parameter. Moreover, the bias between each swim set showed a consistent underestimation of the lap time derived from the accelerometer versus the lap time taken manually. The underestimation was related to the inconsistency of the upper-back accelerometer to measure the lap boundaries accurately, therefore resulting in a reduced lap time estimation across all the swim sets performed.

The remaining stroke kinematic parameters (swimming velocity, stroke rate and length), were derived using the equations (see section 3.7.1). In the derivation of the average swimming velocity ($\bar{v}$), the formulae used the distance covered by the swimmer in the pool divided by the lap time estimation. However, due to the discrepancy with the accelerometer lap time estimation, the calculation for $\bar{v}$ was affected. This was found in the ICC findings across the 50-m IM swim set, which found weak-to-moderate reliability between the accelerometer derived $\bar{v}$ and the manually determined $\bar{v}$ (ICC range = 0.40 – 0.52). For the 100-m variations, a similar trend like the lap time estimation was found with moderate-to-strong reliability between the accelerometer and manually derived $\bar{v}$ (ICC 100-m max = 0.86, ICC 100-m SS = 0.79) and a moderate reliability for the 200-m IM (ICC = 0.60). However, the paired t-test findings showed a significant difference between the accelerometer and the manually derived $\bar{v}$ for all the swim sets (p <0.001 for 50-m IM, 100-m variation, 200-m IM). Despite this discrepancy in the derivation of the $\bar{v}$ from the lap time, the Bland Altman analysis results showed a relatively low bias across all the swim sets (50-m IM range = 0.11 – 0.13 m/s, 100-m max = 0.08 m/s, 100-m SS = 0.07 m/s and 200-m IM = 0.15 m/s), with the SD_{diff} falling within the recommended range (50-m IM range = 0.04 – 0.12 m/s, 100-m max and SS = 0.03 m/s and 200-m IM = 0.07 m/s). Therefore, indicating an agreement between the two methods in the differentiation of the $\bar{v}$. The same trend was found for the derivation of the average stroke rate ($\overline{SR}$) from the accelerometer data and through the manual calculations, as the method to calculate the $\overline{SR}$ included the same lap time estimation. Therefore, the same findings as the $\bar{v}$ were found between the accelerometer and the manually determined $\overline{SR}$.

Lastly, the average stroke length ($\overline{SL}$) was calculated using the estimated SC and the distance the swimmer covered in the pool. For all the swim sets performed, a strong reliability was found (ICC 50-m range = 0.96 – 0.99, 100-m max and SS = 0.99 and 200-m IM = 0.94). This was supported by the paired t-test, which found no significant difference between the two methods for butterfly and breaststroke in the 50-m IM set at α= 0.05 (butterfly p = 0.14 and breaststroke p = 0.57). Similar to the SC findings, a significant difference was found with freestyle and backstroke at α= 0.05, but this was due to the same SC estimation used within the calculation of the $\overline{SL}$. The Bland Altman results showed a relatively low bias between the means of the accelerometer and manually derived $\overline{SL}$ for all the swim sets (bias: 50-m IM = -0.02 to 0.04 m/str, 100-m max = 0.01 m/str, 100-m SS = -0.01 m/str and 200-m IM = -0.02 m/str). Therefore, indicating good agreement between the $\overline{SL}$ derived from the accelerometer and the manual method.

4.2.2 Comparison between stroking styles

The use of the accelerometer in the differentiation of the stroke kinematic parameters is important for both the coach and the swimmer in providing feedback related to their technique during training or competition. Each stroking style has definitive characteristics associated with their stroke kinematics; for example, freestyle would typically have the fastest average swimming velocity whereas breaststroke would typically have the greatest average stroke length based on its movement requirements. Using the accelerometer data, a comparison amongst each stroking style was performed, to detect characteristic trends associated with and between the stroking styles. Repeated measures one-way ANOVA was performed with a Tukey HSD test at α= 0.05 to compare the means of each stroking style per stroke kinematic parameter. Table 5 represents the summary of the statistical comparison between each of the stroking styles from the 50-m IM swim set.

Table 5: Summary of statistical comparison between the different stroking styles

Variables	Freestyle	Butterfly	Breaststroke	Backstroke	ANOVA
50-m IM					
SV (m/s)	1.19 (0.09)	1.22 (0.14)	1.14 (0.17)	1.14 (0.12)	F = 1789.37, p<0.001
SR (str/sec)	0.87 (0.15) $^{b***, c***}$	0.59 (0.10) $^{a***, c***, d***}$	0.45 (0.09) $^{a***, b***, d***}$	0.81 (0.10) $^{b***, c***}$	F = 671.60, p<0.001
SL (m/str)	1.40 (0.23) $^{b***, c***}$	2.12 (0.40) $^{a***, c***, d***}$	2.63 (0.81) $^{a***, b***, d***}$	1.43 (0.20) $^{b***, c***}$	F = 346.46 p<0.001

Mean (SD). Abbreviations: ANOVA: [a] significantly different from Freestyle. [b] significantly different from Butterfly. [c] significantly different from Breaststroke. [d] significantly different from Backstroke.
* p < 0.05. ** p < 0.01. *** p < 0.001

As per Table 5, the results showed a significant difference for the $\bar{v}$ between each of stroking styles (p< 0.001) for the population group tested. Further analysis using the post-hoc Tukey HSD test (α = 0.05) found that no significant difference was evident between the respective strokes (p > 0.05). This finding supports the speed-controlled protocol used with the swimmers, as they were instructed to maintain a set speed throughout the 50-m IM, resulting in a lower variability amongst the $\bar{v}$ of the stroking styles. Figure 32a represents a graphical illustration of the change in the $\bar{v}$ across all the swimmers for each stroking style. The typical trend across the 50-m IM depicted a decrease in swimming speed across the stroking styles with freestyle showing to be the fastest stroking style, followed by butterfly, backstroke and breaststroke. However, butterfly (1.22 m/s) was on average faster than freestyle (1.19 m/s) for the 50-m IM swim set, this was attributed to two to three swimmers, swimming above their 50-m freestyle speed resulting in a larger SD_{diff} (SD butterfly = 0.14 m/s) within the group tested. Hence, skewing the calculated average swimming velocity. If these outliers were averaged out the same trend would still be evident with freestyle presenting with the highest $\bar{v}$, followed by butterfly and the remaining strokes.

For the $\overline{SR}$ parameter, as seen in Table 5, a significant difference was found between the different stroking styles for this parameter (p < 0.001). Further analysis of the means using post-hoc Tukey HSD test, showed that freestyle and backstroke were not significantly different from each other (Tukey: p = 0.0968). Further comparisons between each of the stroking styles, found that each stroking style was significantly different from the remaining strokes it was not related too. In Figure 32b, the $\overline{SR}$ trend between each of the stroking styles were compared. The results showed a decrease in the $\overline{SR}$ across all the stroking styles, with freestyle presenting with the highest $\overline{SR}$, followed by backstroke, butterfly and breaststroke. This finding further supports the $\bar{v}$ trend seen in Figure 32a, with the increased $\overline{SR}$ results in a higher $\bar{v}$ achieved by the swimmer.

Lastly, a significant difference was found between the stroking styles for the $\overline{SL}$ ($p < 0.001$). Further analysis of the means per stroking style using post-hoc Tukey HSD test, showed no significant difference between freestyle and backstroke (Tukey test: $p = 0.997$). However, when the stroking styles were compared with the other remaining strokes, a significant difference was found between the means (Tukey test: $p<0.001$). In Figure 32c, the $\overline{SL}$ trend between each of the stroking styles was compared. The results found a decrease in the $\overline{SL}$ across all the stroking styles, with breaststroke presenting with the highest $\overline{SL}$, followed by butterfly, backstroke and freestyle.

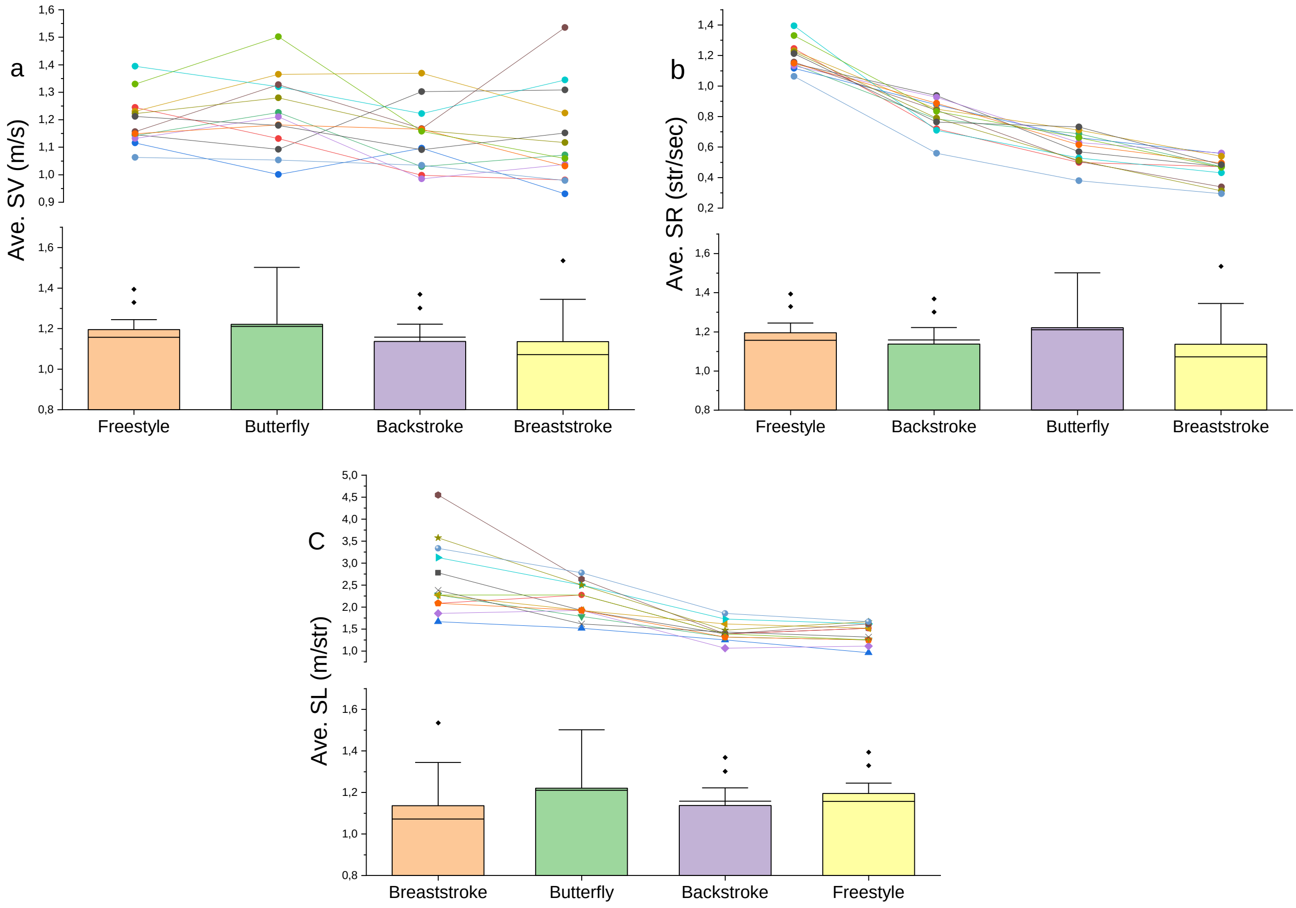


Figure 32: Repeated measure and difference plot of the different stroking styles from the 50-m IM (n = 13) accelerometer data. (a) average swimming velocity (m/s), (b) average stroke rate (str/sec), (c) average stroke length (m/str)

Based on the findings within the trends seen in Figure 32 the inter-dependent relationship between the SR and SL was evident in the maintenance of the $\bar{v}$, with the higher $\overline{SR}$, the $\overline{SL}$ decreased concomitantly to accommodate for this change to maintain a high $\bar{v}$**.** Therefore, supporting Hay (1993) theory on this inter-dependent relationship between the stroke parameters.

4.2.3 Comparison between polar watch and accelerometer

The use of the Polar V800 watch, allowed for the present researcher to compare the accelerometer kinematic parameters against the parameters obtained from the commercial watch. Only two-stroke kinematic parameters could be obtained from the Polar V800 watch during the swim sets, this included the estimated average swimming velocity and lap time, which matched the parameters extracted from the accelerometer data. These two kinematic parameters were then compared against the manually estimated parameters, as well as the accelerometer derived parameters. A one-way ANOVA ($\alpha = 0.05$) was used to compare the group means of the different techniques used to extract the stroke kinematic parameters. Additionally, a post-hoc Tukey HSD test was used to compare the means of different methods.

Figure 33, shows a graphical illustration of the mean group distribution of the population group tested with post-hoc Tukey HSD test for the $\bar{v}$ of the 50-m IM, 100-m variations and 200-m IM swim sets. It is evident from the results that no significant difference was found between the three different methods used to measure the $\bar{v}$, with the exception of the 50-m IM swim set. As seen in Figure 33a, a significant difference was found between the accelerometer and the manual method, with no difference observed between the Polar watch and manually estimated $\bar{v}$**.** This was due to the Polar watch including an additional inertial sensor (i.e. gyroscope) to allow for the instantaneous measurement of the swimmer's $\bar{v}$ as they perform the swim set. Therefore, resulting in a closer estimate of the swimmer's $\bar{v}$ when they performed the given swim set compared to that of the estimated $\bar{v}$ from the accelerometer.

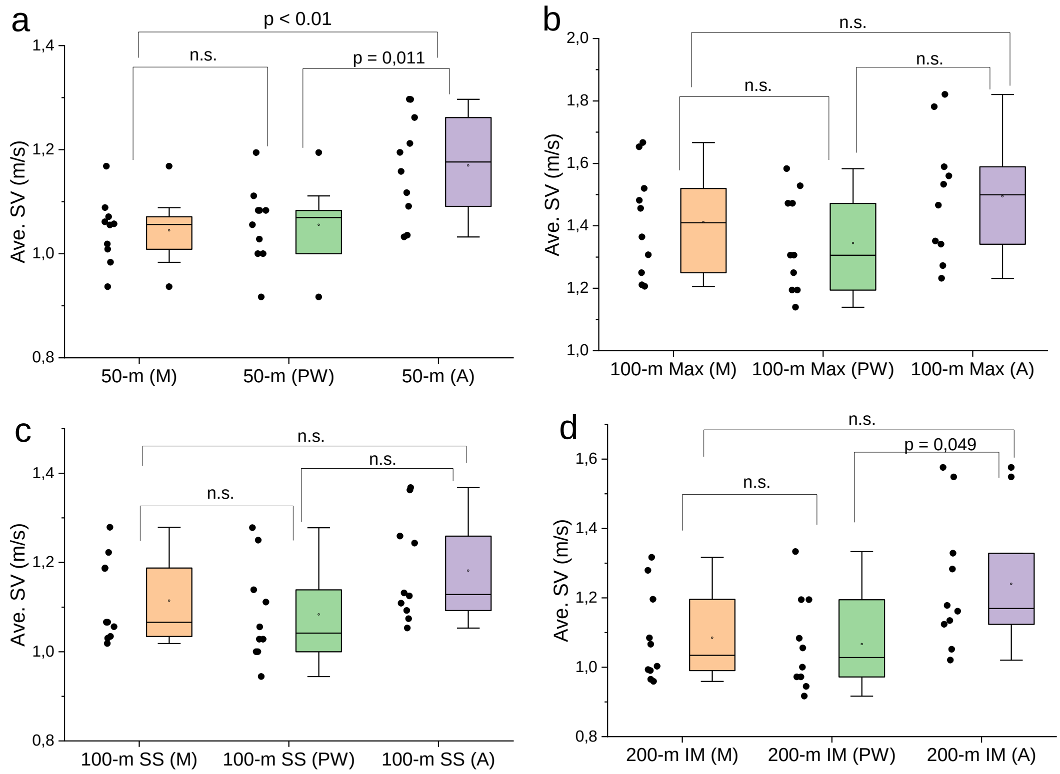


Figure 33: Box and whisker comparison, with statistical significance (Tukey HSD test at α = 0.05) of the relationship between the manually estimated (M), Polar watch (PW) and accelerometer (A) derived average swimming velocity (m/s) for (a) 50-m IM, (b) 100-m maximum, (c) 100-m self-selected (SS) and (d) 200-m IM swim set.

In the comparison between each method in the determination of the $\bar{v}$ and lap time, only 10 swimmers were used for the inter-comparison. The reduction in the group size was due to incomplete data retrieved by the Polar V800 to accurately measure the lap time for five of the swimmers. Therefore, this data was excluded from both parameters. It was found that no significant difference was found between either of three methods in the measuring of the lap time for the 100-m variation (100-m max: F-test: 0.45, p = 0.640; 100-m self-selected: F-test: 1.02, p= 0.370) and 200-m IM (F-test: 2.03, p= 0.150) swim sets. However, for the 50-m IM swim set, the Polar watch could not sufficiently measure the lap times as the lap boundaries for each 50-m were inaccurately measured. Hence, limiting the lap time data for the 50-m IM swim set that could be derived from the Polar watch. Therefore, this parameter could not be compared against the accelerometer derived lap time parameter.

4.2.4 Comparisons with heart rate telemetry and critical swim speed

The heart rate telemetry information was recorded during all three swimming sets by the Polar V800 watch and heart rate monitor. The heart rate telemetry information included the peak, minimum and average heart rate of the swimmer. Additional to these physiological parameters, the critical swim speed (CSS) for each swimmer was determined. Table 6 highlights the comparison between the CSS and the $\bar{v}$ per swim set performed by the population group.

Table 6: Correlation between the critical swim speed (m/s) and average swimming velocity for all the swim sets.

	Pearson r	p-value
50-m freestyle *	-0.13	0.023
50-m butterfly	0.08	0.160
50-m breaststroke *	0.47	0.012
50-m backstroke **	0.26	0.002
100m maximum **	0.36	0.002
100m self-selected *	0.25	0.026
200-m IM	0.45	0.455

*p<0.05, ** p<0.01, *** p<0.001

As seen in Table 6, a positive weak to moderate relationship was found between the swimming velocity of all the swim sets and the CSS. This was further supported by the t-test independent results with a significant difference found between the CSS and $\bar{v}$ of all the swim sets, except for the 200-m IM and 50-m butterfly. The determination of the CSS was based off the swimmer's fastest 50- and 400-m freestyle swim times, however, within the above comparison the CSS was compared against other stroking styles which may result in a weaker relationship to be found as the same strokes were not compared between each parameter. For the 50-m freestyle and the 100-m variation swim sets (in which freestyle was the primary stroke), a weak relationship was found between the CSS and the $\bar{v}$ of these swimming events. This weaker relationship may be resultant from the CSS determined from the swimmer's season-best times, which was then compared to their off-season swimming performance in the present study. Therefore, the swimming parameters were not tested within the same diurnal period, resulting in an inconsistent comparison and a weaker relationship between these parameters.

For the heart rate telemetry comparison, only 10 out of the 15 swimmers' results could be used for the statistical analysis. Reasons for the reduced number was caused by incomplete heart rate data collected during the swim sets, resultant from the heart rate monitor moving on the swimmer's chest and interfering with the heart rate telemetry retrieved. Therefore, these swimmers' results could not be used for comparison. Table 7 represents the summary of the comparison between the heart rate telemetry (maximum and average) and the $\bar{v}$ for the swimming sets performed by the swimming group tested.

Table 7: Correlation between the maximum and average heart rate response and average swimming velocity of all the swim sets

	Pearson r		p-value	
	HR max	HR Ave	HR max	HR Ave
50m- IM	-0.24 ***	-0.26 ***	<0.001	<0.001
100m maximum	-0.77 ***	-0.61 ***	<0.001	<0.001
100m self-selected	-0.42 ***	-0.50 ***	<0.001	<0.001
200m IM	-0.70 ***	-0.86 ***	<0.001	<0.001

*p<0.05, ** p<0.01, *** p<0.001; Abbreviations: HR max = heart rate maximum, HR Ave = heart rate average

As per Table 7, a significant difference and a negative relationship was observed between the maximum and average heart rate and the $\bar{v}$. The negative relationship indicates that when one parameter increases, the other concomitantly decreases (i.e. increase in heart rate, decrease in swimming velocity). Of the swim sets, the 50-m IM showed the weakest relationship between the heart rate responses and the $\bar{v}$, with the 100-m self-selected (SS) swim set also shows a moderate relationship between these parameters. For these two swim sets (50-m IM and 100-m SS), the swimmers were not required to swim at maximum pace, therefore the swimmers did not physically exert themselves resulting in a lower heart rate response and subsequently a weaker relationship between the heart rate responses and $\bar{v}$. Figure 34 represents a graphical illustration of the change in the $\bar{v}$ of the swimmers over the swimming sets, as well as the heart rate maximum achieved in the respective sets. A trend was found that the higher $\bar{v}$ resulted in a higher maximum heart rate to be achieved by the swimmer and vice versa. Therefore, as the 50-m IM and 100-m SS swim sets were swum at lower speed compared to the 200-m IM and 100-m maximum swim set, the maximum heart rate responses were subsequently lower for these swim sets for the population group tested.

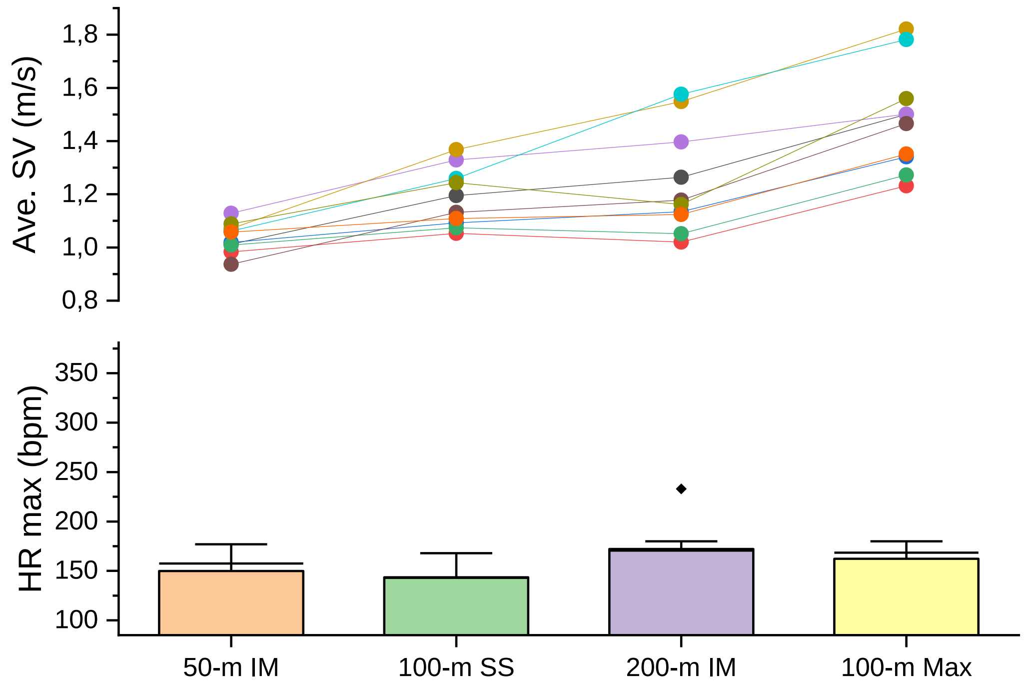


Figure 34: Repeated measures and difference plot of the average swimming velocity (m/s) and maximum heart rate (bpm) across all the swim sets (50-m IM; 100-m self-selected (SS), 200-m IM and 100m max) performed by the swimmers (n=10).

4.3 Use of machine learning for identification of stroke kinematics

A machine learning model was designed and implemented by Dr Salah Zadeh, to isolate and identify the four stroking styles from the 50-m IM swim set based on pure, unlabelled accelerometer data. For the present dissertation, four swimmer's data were used as a "proof of concept" to test the accuracy of the model.

It was found that the total classification accuracy for the model for the four swimmers was 96.6%. Figure 35 represents the model accuracy in predicting and identifying each of the stroking styles from the accelerometer data. It was found that there was a high correlation between the true stroking style and the predicted stroking style labelled by the model. Furthermore, it was observed that breaststroke had the lowest correlation of 0.86 compared to the remaining stroking styles of 1.00.

Figure 35: Confusion matrix representation of the labelling of each stroking style by the designed model by Dr Saleh Zadeh

For the above total classification accuracy, only 4 swimmers were used due to limited time and computer resources. Therefore, with further research, this classification accuracy may change with more data input given to the model.

In Chapter 5 to follow, the above results will be discussed in further detail in accordance with international literature and the objectives set out for the present study.

CHAPTER 5: DISCUSSION

5.1 Introduction

The present study aimed to differentiate the swimming stroke kinematic parameters and the stroke mechanics of the swimmer from the data retrieved from the use of tri-axial accelerometers. Therefore, following from Chapter 4 the findings will be discussed in conjunction with the objectives set out for the present study (see Chapter 1, section 1.2.3). These objectives will be discussed in sub-sections related to the accuracy of the accelerometer to identify and differentiation the swimming characteristics, mechanics and kinematics of the swimmers and the use of machine learning in automating the extraction of swimming characteristic information from the accelerometer data. In addition, the physiological response of the swimmers during their swimming performance will also be discussed.

5.2 Identification and differentiation of swimming characteristics using tri-axial accelerometers

Two tri-axial accelerometers were placed on the swimmers, one on the left wrist and the other on the upper back, from which specific stroke characteristics could be extracted. Based on the raw data extracted from the accelerometers, each stroking style has characteristic pattern profiles associated with the reference axes (i.e. X-, Y- and Z-axes). The pattern profile may be defined as the "observed" characteristics with or without filtering of the peaks and troughs which define and separate each stroking style from one another. It was found that the upper-back accelerometer within the present study displayed a common pattern profile for each individual stroking style which was supported by a similar pattern profile illustrated within Justham et. al. (2008) study, who used their accelerometer on the swimmer's lower-back (see Figure 10). Therefore, one can pre-determine pattern profiles for specific body regions, once these common patterns are discerned from the data. Subsequently, with further analysis of these pattern profiles of each stroking style, one can observe stroke mechanic differences amongst the swimmers by identifying changes pertaining to either the magnitude of the peak or troughs observed within the pattern profile. Therefore, in section 5.2.1, the differentiation of the stroke mechanics (i.e. stroke phases) from the accelerometer data will be discussed and how changes to the observed pattern profile may help to distinguish differences between the swimmers.

5.2.1 Stroke mechanics (i.e. stroke phase differentiation)

Coaches are constantly looking at ways to improve their swimmer's performance, however, their focus usually would be on the swimmer's time improvement in the pool, instead of factors pertaining to their stroking technique. A reason for this may be due to coaches having to monitor multiple swimmers in the pool at the same time, leaving little room for them to focus on the swimmer's technique and swimming inefficiencies (Wright & Stager, 2013). Therefore, accelerometers have been used as a platform to provide information to coaches and researchers in terms of the swimmer's kinematics and stroke mechanics, hence allowing coaches to focus more on other aspects in their training session (Ganzevles *et al.*, 2017). Therefore, the present study investigated the use of accelerometers in differentiating the stroke mechanics of each of the stroking styles. From the findings, it was observed that each stroking style had a common pattern profile with noticeable differences amongst swimmers associated with the magnitude of the peak and troughs, corresponding to certain stroke phase inflection points. This was most prevalent with the stroking style freestyle, in the stroke phase which marked the "hand entry" and beginning of the next stroke cycle for each swimmer. The "hand entry" was marked by a *negative trough in the Y- and Z-axis*, with a corresponding *positive peak in the X-axis*. It was found that the top 33% of the swimming group showed a greater peak magnitude overall in their axe's characteristics for this specific stroke phase inflection point compared to lower 33% of the group tested. This peak magnitude change was dictated by how the swimmer's hand entered the water after the recovery phase was ended. It was found that two types of hand entry styles were observed amongst the swimmers. These hand entry styles were as follows:

(i) When the hand entered *parallel* to the surface of the water (i.e. palm facing downwards).

(ii) When the hand entered *perpendicular* to the surface of the water.

Therefore, it was observed that the top 33% of the swimming group presented with style (i), with the lower 33% presenting with style (ii). Figure 28 illustrates the differences in hand entry magnitude between the lower and higher-ranked swimmers within the present study.

This difference in the peak magnitude observed with the diverse hand entry styles was supported by a study by Ohgi et. al. (2000), who found a difference in the Z-axis observation with different attack angles of the hand entry during freestyle swimming. In Figure 36, it was found within Ohgi et. al. (2000) study, that a smaller positive Z-axis acceleration was observed when the hand of the swimmer entered the water at a "pitched" angle (i.e. perpendicular) versus a larger positive Z-axis acceleration when the hand entered "flat palmed" (i.e. parallel) into the water. Therefore, the change in the peak magnitude of the Z-axis found in Ohgi et. al. (2000) was similar to that of the present study findings, with a larger Z-axis magnitude when the hand entered parallel to the surface of the water.

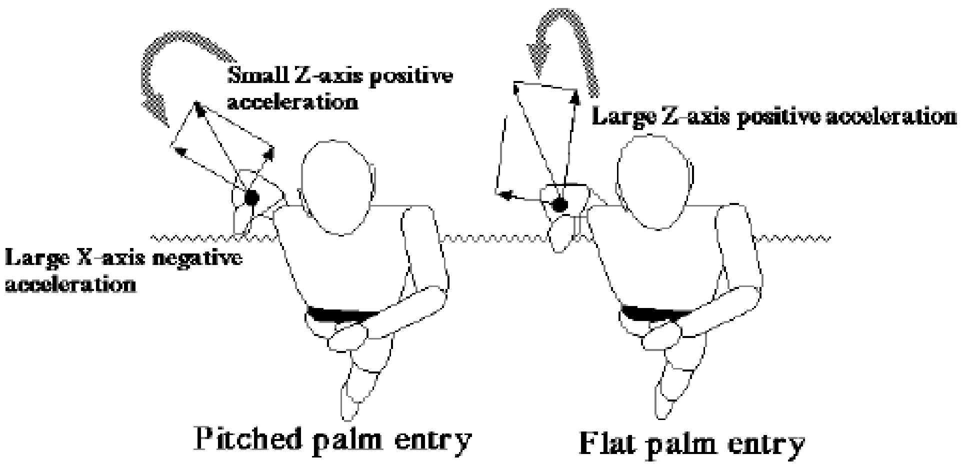


Figure 36: Visual depiction of hand entry styles, extracted from Ohgi et. al. (2000)

One difference between the present study and Ohgi et. al. (2000) was found in terms of the orientation of the Z-axis, with a positive orientation found with Ohgi et. al. (2000), versus a negative orientation with the present study. Reasons for this difference may be due to Ohgi et. al. (2000) using two monolithic bi-axial ADXL250 (Analog Devices, Inc.) accelerometers, which were placed together to form a tri-axial accelerometer sensor. Whereas, in the present study a GeneActiv (Activinsights, Cambridgeshire, England) tri-axial accelerometer was used.

Therefore, the orientation difference in the Z-axis may be associated with how each accelerometer differed in the measurement of the change in acceleration in the Z-axis plane of reference. However, the orientation of the axis does not affect the axes characteristics linked to the stroke phases, as one would observe the peak magnitude differences of the peaks or troughs in the respective axes to associate the performance characteristics and differences amongst the swimmers.

With the axis orientation discrepancy between the present study and Ohgi et. al. (2000), differences in axis labelling and orientation are important parameters to consider in the standardisation of and development of stroking style algorithms used in research and marketable products. If the goal is to develop stroking style algorithms that could be used universally, then such standardisation is a necessity to avoid potential errors and maximise the accuracy of these inertial sensory devices. Additional to these parameters, the type of accelerometer should be factored into the standardisation (i.e. bi-axial versus tri-axial accelerometer) to account for changes associated with the labelling of the pattern profiles linked to a given stroke characteristic. An example of different axes labelling was presented within Ohgi (2002), who used two bi-axial accelerometers together to differentiate the stroke phases for freestyle and breaststroke. In comparison with the present study (which used a tri-axial accelerometer), the same magnitude of each peak and trough was found for each stroke phase. However, the inflection points for these stroke phases were inverse of each other for the respective stroking styles observed in the comparison between Ohgi (2002) and the present study. The inversion of the stroke phases could then be associated with the labelling of the axes for the respective type of accelerometer used. Therefore, the type of accelerometer used would also affect the standardisation and development of algorithms to help in the stroke mechanic differentiation from the accelerometer data. These parameters which should ideally be considered in a standardisation process would be important for the inter-comparison between related research studies or inertial products. If all these parameters were considered, the designation of the accelerometer characteristic differences such as peak magnitude changes or alternate pattern profiles would ease the process in identifying these factors within the accelerometer data.

In the stroke phase differentiation from the accelerometer data within the present study, between all the stroking styles, backstroke showed to be the most complex with regards to the association of key inflection points to its respective stroke phases. The chosen stroke phases for backstroke were as follows: (i) hand entry and catch, (ii), pull phase, (iii) push phase, (iv) hand lag time, (v) clearing and (vi) recovery. It was observed that between all the swimmers tested, the push phase showed the most variance in the X-axis in differentiating the exact key inflection point as the swimmer's hand transitioned from the pull phase through the push phase into the hand lag time and clearing phase. The observed variance in the X-axis was related to a difference in magnitude of the peak that marked the transition into the push phase, with each swimmer presenting with a different X-axis peak magnitude throughout their stroke cycle. During these phase changes (pull phase to clearing phase) the swimmer's arm in the pull phase begins in a straight arm position, as the hand pulls down into the push phase, with the swimmer's arm bending approximately 90 degrees, to initiate the push phase (see Figure 6d) (Hay, 1993). The variance in the X-axis may be due to the extent to which the swimmer bends their arm as they transition from the pull phase into the push phase. The bending of the arm allows the swimmer to position their hand to apply a "push" force through the water to increase the propulsion through their stroke cycle. Therefore, a smaller propulsive force would be generated if the swimmer transitioned through the pull phase into the push phase with their arm remaining relatively straight, therefore preventing the swimmer in applying an adequate palmar pressure through the push phase. It was further observed amongst the swimmers tested, that the lower-ranked swimmers (i.e. lower 33%) presented with a relatively straight arm cycle through their backstroke stroking action with the higher-ranked swimmers (i.e. top 33%) bending their arm approximately 90 degrees through their pull phase to execute an adequate propulsive force in the water. This change in the swimmer's stroking action, varied the X-axis findings, therefore, not allowing for a consistent observation of the key inflection points for the push phase.

The observed discrepancy found within the push phase for backstroke, emphasises the importance of using alternative technology in swimming performance monitoring as characteristic differences amongst swimmers can be detected. This was prevalent within the present study, as the lower 33% of the swimming group presented with the "straight arm" stroke cycle, compared to the top 33% of the group. Support for using accelerometers as an alternative for technique observation was found in a study by Anthony and Chalfant (2010), who emphasised the use of the stroke phases and the relative "timing" between each phase, to differentiate key differences amongst elite versus novice level swimmers. Therefore, showing a field of research with the potential for coaches and researchers to use accelerometers as a means to help discern characteristic or technique differences which separate the elite from the novice swimmers. Subsequently, allowing for coaches to apply technique adaptation or corrections with their swimmers during practice, or alternatively, finding stroke mechanic errors affecting their swimmer's performance.

It is important to note however that simple tri-axial accelerometers show clear limitations given that accelerometer orientation cannot be accounted for. Subsequently, the use of accelerometers containing built-in gyroscopes is motivated for as this may provide additional information currently unavailable. Moreover, the data presented in this study required significant processing times which would invalidate timeous feedback between the coach and athlete. Hence, the development of accelerometers with Bluetooth capabilities would allow for instantaneous feedback to be carried out, advocating the need for this addition based on the results of the present study.

5.2.2 Stroke kinematic parameters

In daily swimming training, coaches would observe and monitor their swimmers stroke kinematics such as their stroke count, stroke rate and most importantly their lap time to measure their swimmer's performance in the water (Ganzevles *et al.*, 2017; Mooney *et al.*, 2015). The monitoring of these stroke kinematic parameters is done manually by coaches leaving little room for technique correction to be done to improve the swimmer's performance in the pool, especially if the coach has to oversee multiple swimmers in a practice (Wright & Stager, 2013). As previously mentioned, the use of the tri-axial accelerometers was then sought out as a performance monitoring tool for coaches to use as a measure of the swimmer's stroke kinematics during their training session (Ganzevles *et al.*, 2017). Therefore, research has focused on the accuracy of the accelerometers in measuring swimming performance kinematics against alternative methods such as video-based observations or the manual estimation of certain stroke kinematic parameters (Callaway *et al.*, 2009; Ganzevles *et al.*, 2017; Mooney *et al.*, 2015). In the present study, one of the objectives was to determine if the stroke kinematic parameters could be extracted and differentiated from the tri-axial accelerometers used. The findings from the tri-axial accelerometer data were measured against the same stroke kinematic parameters estimated manually by the present researcher, as well as certain stroke parameters measured by the Polar V800 watch. The stroke kinematic parameters differentiated from the tri-axial accelerometers were as follows: stroke count, average swimming velocity, average stroke rate, average stroke length and estimated lap time. From the two tri-axial accelerometers placed on the swimmer's left wrist and upper-back respectively, only the upper-back sensor could be used to extract the stroke kinematic parameters. The upper-back sensor was chosen as it displayed the least variance in its pattern profile in the extraction of the stroke kinematic parameters compared to the left wrist sensor. It was found that the left wrist sensor pattern profile was more suited for the extraction of the stroke mechanics (i.e. stroke phase characteristics) of the swimmer, which corresponded with studies by Magalhaes et. al. (2014) and Zhao et. al. (2015). Therefore, all the stroke kinematic findings were extracted from the upper-back tri-axial accelerometer.

5.2.2.1 Comparison between accelerometer and manually derived stroke kinematics

The swimmers' in the present study performed three different swimming sets: 50-m IM, 100-m variation and 200-m IM, of which the above-mentioned stroke kinematic parameters were extracted from the respective swimming sets (see Chapter 4, section 4.2.1). For the stroke count extracted from the accelerometer data, no significant difference ($p > 0.05$) and strong reliability (ICC > 0.96) was found between the accelerometer and the manually estimated SC for all three swimming sets. The 50-m IM set breaststroke had the smallest bias (-0.08 strokes) according to the Bland Altman analysis, with backstroke showing the greatest bias (0.77 strokes) amongst the accelerometer and manually estimated SC. However, the Bland Altman analysis revealed that breaststroke had the greatest SD_{diff} of 1.61 for the mean group tested ($n = 13$), with limits of agreements (LOA) ranging from -3.22 to 3.07. Therefore, the accelerometer on average under- or over-estimated the SC of the group by ± 1.61 strokes, compared to the remaining stroking styles which showed an error estimation of approximately ± 1.00 stroke on average. In the differentiation of the SC for breaststroke from the accelerometer data, variations in the magnitude of the peaks and troughs during the peak detection method were found. The peak magnitude variation links to the body roll mechanics of the swimmer as they performed the stroking action. For breaststroke and butterfly, a negative peak was observed to mark each stroke throughout the swim set. Hence, for breaststroke the greatest negative peak observed in the upper-back, corresponded at the point at which the swimmer's arms were tucked into their body (end of phase ii: in-sweep), before the recovery phase and glide was initiated. The variations in the body movement in these phases were observed as the extent to which the swimmer may tuck their arms in during the in-sweep phase, which may be lesser or greater, depending on their body roll mechanics. Alternatively, the swimmer may not use their upper-back in the desired manner, to execute the stroking action correctly revealing a technique error. For example, the swimmer may extend their upper back less, reducing the extent to which their arms can tuck into their sides before initiating the recovery phase. In Figure 37, shows the difference in peak magnitudes found between one of the swimmers within the top 33% for breaststroke versus one of the lower 33% within the group tested. As seen in Figure 37, observable magnitude differences amongst the associated peaks were seen between the two swimmers with swimmer A (Figure 37a) showing a magnitude range of -1 m/s^2 and 0 m/s^2, with swimmer B (Figure 37c) between -1 m/s^2 and -0.5 m/s^2. These magnitude differences are affected by the extent to which the swimmer extends their upper-back in the water, to execute their (ii) in-sweep and (iii) recovery phases for breaststroke, as well as the rate at which this movement was executed in the water. As seen in Figure 37d, swimmer B displayed an upper-back extension of 36°, compared to that of swimmer A, who presented with a back extension angle of 50° (Figure 37b). It could be assumed, with the higher degree of extension by the swimmers upper-back to execute the (ii) in-sweep phase to its greatest limit (i.e. tucking their arms into their torso as much as possible), the higher peak magnitude observed in the accelerometer data (as seen in Figure 37a and b). Therefore, observed differences amongst the swimmers with regards to their body roll mechanics can be derived from the accelerometer data. Further research is then required to validate the findings associated with these body roll mechanics. However, at present, the researcher requires video footage to validate these findings, which poses a limitation for future use by coaches. This limitation may include the use of video footage in a public area, violating the privacy of public swimmers (Wright & Stager, 2013). Therefore, one would have to investigate alternative methods of validation which eliminates the use of video validation from the analysis process or seeking alternative sensors (i.e. gyroscope) to add to the accelerometer unit to obtain the required information.

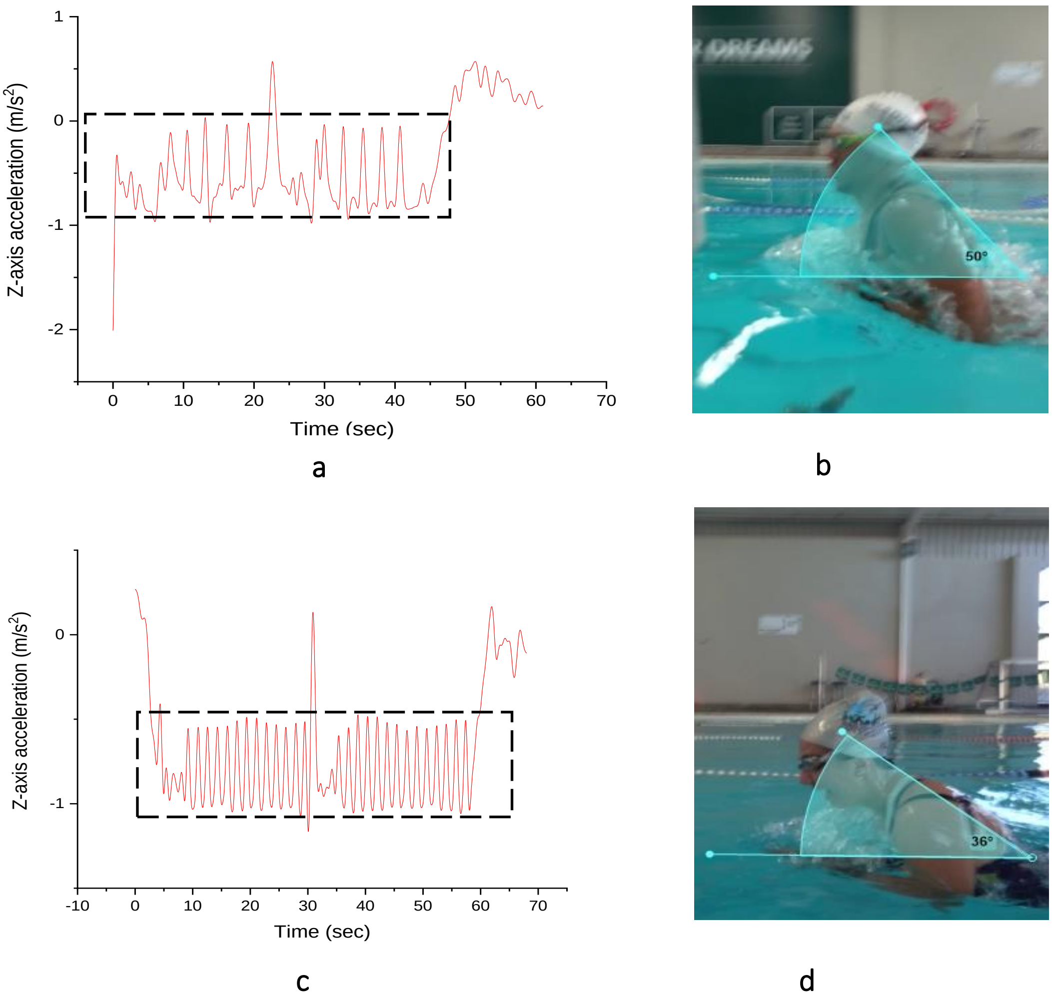


Figure 37: Graphical illustration of the breaststroke body roll mechanics during 50-m IM set for the Z-axis. (a) swimmer A peak magnitude per stroke; (b) upper-back extension angle of swimmer A; (c) swimmer B peak magnitude per stroke; (d) upper-back extension angle of swimmer B

Although breaststroke showed the greatest variance in the SC estimation between the accelerometer and manually counted SC, no difference was found between the means for both methods based on the Cohen d finding of 0.05. For the 100-m variations swim set, very strong reliability (ICC >0.99) and no significant difference (p>0.30) was found between the estimated SC through manual counting and the accelerometer extracted value. The 200-m IM swim set showed similar findings to that of the previous swim sets with strong reliability (ICC = 0.96) between the manual count and the accelerometer extracted SC, however, it was shown that a significant difference was found (p = 0.017) which was supported by the Bland Altman analysis with a bias of 3.31 strokes and SD_{diff} of 4.31 strokes. Therefore, as the SD_{diff} was greater than the recommended ±1.96, showing a low agreement between the two methods for the estimated SC. The large variation in the SC between the accelerometer and manual estimation may be due to the method used to extract the relevant parameter from the accelerometer data (see Chapter 3, section 3.7.2.5). The method required extracting the SC from each individual 50-m within the 200-m IM, resulting in an under- or over-estimation of the total SC per 200-m IM per swimmer. As two different axes were used to extract the SC estimation from the accelerometer data, one algorithm could not be applied to the data stream to extract the respective parameter. Therefore, showing a limitation in the method used in the present study to extract this parameter from the accelerometer data reliably and efficiently. It was found in certain studies that researchers opted to use different filter frequencies (Le Sage *et al.*, 2011) or different threshold heights (magnitude of peak or trough) in the peak detection method (Siirtola *et al.*, 2011), to isolate the different stroking styles from the accelerometer. For both Le Sage et. al. (2011) and Siirtola et. al. (2011), the accelerometer was placed on the upper back of the swimmer, with the findings showing a >95% accuracy in the extraction of the SC from the accelerometer data for all the stroking styles. Supported by the findings within the present study, the upper-back accelerometer was the most suited in the extraction of SC, as the body roll mechanics of the swimmers allowed for a more accurate interpretation of the actual SC performed. However, with the method used to extract the SC from a continuous stream of data containing all four stroking styles, a limitation was prevalent within the present study. Subsequently, with the studies by Le Sage et. al. (2011) and Siirtola et. al. (2011), although a high accuracy was found with using the accelerometer in the SC differentiation, the methods used to extract the parameter requires additional manual input by either the researcher or coach. For example in Le Sage et. al. (2011), the researcher was required to manually change the filter frequency to isolate and extract the respective SC for each stroking style. Similarly, in the present study manual input was required to eliminate "strokes" which were mislabelled as an actual stroke, to ensure the correct information was retrieved from the accelerometer data. Therefore, the data acquisition became a lengthy process, which would limit the instantaneous feedback which coaches would require, if similar methods were used. Ideally, researchers would want to extract the SC or stroke parameters automatically, without manual input to allow for a "real-time" feedback to occur. To overcome this problem, the use of machine learning (i.e. artificial intelligence) may be recommended, to learn and program the necessary algorithms to extract the SC and further stroke kinematic parameters from the accelerometer data, without additional “human” support. This concept was applied within the present study with the extraction of the different stroking styles using machine learning (discussed further in section 5.4 below).

Based on the results, it was shown that the extraction of the SC from each swim set was successful, with high reliability between the manually counted SC taken by the present researcher and the accelerometer-derived SC. However, for the lap time estimation extracted from the accelerometer data, a significant difference ($p < 0.001$) was found between the accelerometer versus the manually taken lap times. The Bland Altman analysis showed that there was a recurring bias within the means, with an underestimation of the lap time derived from the accelerometer data versus the manually taken times. In the method used to extract the lap time from the accelerometer data, the data points used to estimate the SC for the respective swim sets were used to determine the lap time by calculating the time difference between the first observed stroke to the last observed stroke within the swim set. However, with this method it neglected the lap boundaries or the moments at which the swimmer contacted the wall, indicating the start or end of the swim set. Therefore, it was concluded that the lap time derived from the accelerometer data was more indicative of the *time spent stroking* by each swimmer during the swim set, rather than the total lap time. With the accelerometer placed on the upper back, the lap boundaries could not be easily detected, hence affecting the estimated lap time. In support of this finding, a study by Davey et. al. (2008), with the accelerometer placed in the same body region, it was found that there was a constant error with the under-estimation of the time between the accelerometer measured lap time and the manually taken lap time. Davey et. al. (2008) found that the lap time error by the accelerometer was caused by the inability of the upper-back sensor to detect the wall touch by the swimmer at the end of the lap. It was observed that the swimmer would glide into the wall at the end of their last stroke cycle, with most of the impact of hitting the wall absorbed by the swimmer’s arm, with very little vibrations reaching the swimmer’s torso (or upper-back), resulting in undetectable peaks or troughs in the data to mark the end of the lap boundary. Hence, the lap boundary detection error found with using an accelerometer on the swimmers upper-back, poses a limitation in obtaining an accurate lap time estimation for coaches and researchers. Alternatively, Callaway (2015), detected the lap time boundary by using the wall-push off event detected by the accelerometer placed on the swimmers lower back. This event was marked by a large trough in the Y-axis of the accelerometer data. Using this method and sensor placement, Callaway (2015) found a mean percentage error of 2.15% between the accelerometer and the video validation, with a strong positive correlation between the video recorded time and the accelerometer-derived lap time (r = 0.97). An alternative to using the lower or upper back region, researchers or coaches may use an accelerometer placed on the swimmer's wrist or ankle to detect the lap boundaries with higher accuracy in order to gain a better indication of the lap time. This was supported by the Bächlin and Tröster (2012) study, where the wrist acceleration change in Y-axis a was used to detect the wall-push off, wall- turn and wall-strike events during the prescribed swim set. These events were characterised by specific axes patterns such as a large peak in the acceleration to mark wall-push off with a similar peak trend found for the wall-strike at the end of the swimmer's last stroke cycle. Therefore, the wrist accelerometer may be used as an alternate source to derive the lap time of the swimmer. However, it was found within the present study, the wrist sensor was limited in the stroke parameter differentiation, with the wrist accelerometer used primarily for stroke phase extraction.

For the remainder of the stroke parameters such as the average swimming velocity ($\bar{v}$), stroke rate ($\overline{SR}$) and stroke length ($\overline{SL}$), these parameters were derived from the SC and lap time parameters using the equations seen in Chapter 3 section 3.7.1. In the derivation of the $\bar{v}$ and $\overline{SR}$ parameters from the accelerometer data, a significant difference was found between the accelerometer derived and manually estimated parameters ($p < 0.001$) for all the swim sets. This may primarily be ascribed to the lap time differences derived from the accelerometer which, as mentioned previously, was not a true reflection of the swimmer's actual lap time. However, despite the significant difference found, the Bland Altman analysis results showed a relatively low bias across all the swim sets. Furthermore, for the last stroke parameter $\overline{SL}$, no significant difference (50m IM: $p > 0.05$; 100-m variations: $p > 0.05$ and 200-m IM: $p = 0.272$) and strong reliability was found between the accelerometer and the manually derived $\overline{SL}$ (ICC: 0.94 – 0.99). Similar, to that of the $\bar{v}$ and $\overline{SR}$ derived parameters, the Bland Altman analysis showed a relatively low bias between the two methods, with SD_{diff} supporting that an agreement was found between the means of each method. Therefore, based on the results the accelerometer was relatively successful in the differentiation of the stroke kinematic parameters when compared against the manually estimated values, despite the discrepancy with the lap time estimation.

5.2.2.2 *Inter-comparison between the stroking styles stroke parameters*

The use of accelerometer as an alternative source for coaches has shown research potential within swimming kinematic differentiation. Studies have looked at using accelerometers as a coaching aid during training, to monitor and support the coaches, either when they are not present at a practice or as a tool to assess the swimmer's performance (Ganzevles *et al.*, 2017; Wright & Stager, 2013). As seen in section 5.2.2.1, the accelerometer was relatively successful in the differentiation of the respective stroke parameters from the different swim sets. However, could further differences between the stroking styles be derived from the accelerometer data? For example, detecting the swimming velocity differences between the stroking styles. Each stroking style has definitive characteristics linked to its stroke mechanics and kinematics. The inter-comparison between the stroking styles and their respective stroke kinematic parameters were performed within the 50-m IM swim set. The results found that for the $\bar{v}$, a significant difference was found (repeated measures one-way ANOVA: $p< 0.001$) however, the post-hoc Tukey HSD test revealed that there was no significant difference between the relative stroking styles ($p> 0.05$) in this pairwise analysis. Reasons for this was due to the swimmers being given instructions within the data collection for the 50-m IM in which their swimming pace was speed controlled. The swimmers were instructed to pace themselves based on the sustainable speed of the camera trolley. The pace was set at a slow to medium speed for each stroking style, as the camera trolley arm that held the underwater camera produced excessive drag, thereby hindering the pace the trolley could be pushed. Subsequently, a slow average speed across each of the 50-m was performed by each swimmer. Further investigation between the stroking styles showed a trend amongst the stroking styles for $\bar{v}$ which showed that on average, freestyle showed the highest $\bar{v}$, followed by butterfly, backstroke and breaststroke. This was supported by Neiva et. al. (2011) who found that freestyle showed the fastest times and $\bar{v}$, followed by butterfly, backstroke and breaststroke. For the $\overline{SR}$, a significant difference was found between each of the stroking styles (repeated measures one-way ANOVA: $p <0.001$). However, it was found that the $\overline{SR}$ between freestyle and backstroke weren't significantly different from each other supported by the post-hoc Tukey HSD test (p= 0.0968). However, a significant difference was found between the remaining strokes when compared to each other. Freestyle and backstroke are described as bilateral or asymmetrical strokes, with butterfly and breaststroke described as unilateral or symmetrical strokes (Hay, 1993; Reilly *et al.*, 2005). Therefore, with these arm movement characteristics, these stroking styles would typically present with equivalent stroke rates. This was especially true for freestyle and backstroke, which showed no significant difference for their $\overline{SR}$. However, with breaststroke and butterfly, although both strokes are unilateral in their arm movement, the body position during the stroking action for each stroke resulted in a greater surface area exposed to the oncoming flow in the water, therefore increasing the drag forces on the swimmer. This was especially prominent with breaststroke, with the stroking action requiring a balance in optimal propulsion in the water, with the swimmer trying to achieve a streamline position during their arm stroking action without hindering the legs kicking force to generate maximal propulsion through the water. Hay (1993) then stated that the changes in the swimmer's body position, relevant to their limb's, has the greatest influence on the swimmer's resistance experienced in the water for breaststroke, compared to the other stroking styles. Therefore, with the increased drag attributed to the temporal characteristics of the arm and leg action for breaststroke, this may account for the significant difference found between breaststroke and the remaining strokes for $\overline{SR}$.

Figure 32b illustrated a decreasing trend which was observed amongst the stroking styles, with freestyle recording the highest $\overline{SR}$, followed by backstroke, butterfly and breaststroke. This trend confirms the findings of Hay (1993), who stated for the stroking styles freestyle and backstroke, the swimmer uses 90% of their arms to generate the propulsion in the water. Therefore, increasing the number of strokes per second, the swimmer would be able to generate with their arms during the given length in the pool. Whereas with butterfly the propulsive force is generated through equal usage of the swimmer's arms and legs, with breaststrokes propulsion contributed largely by the swimmer's legs. Therefore, based on these propulsion concepts for each stroking style by Hay (1993), the $\overline{SR}$ findings (Figure 32b) were characteristic of the contribution of the swimmer's arms during the 50-m IM swim set. A similar finding to that of the $\overline{SR}$ was found with the $\overline{SL}$ inter-comparison, with freestyle and backstroke showing no significant difference between their $\overline{SL}$ (Tukey HSD test: p = 0.997).

However, a significant difference was found between the remaining strokes during the pairwise comparison (Tukey HSD test: $p < 0.05$). It was observed in Figure 32c, that the reverse trend to the $\overline{SR}$ was found, with breaststroke showing the highest or longest $\overline{SL}$, followed by butterfly, backstroke and freestyle. The observed $\overline{SL}$ trend supports the inter-relationship between the swimmer's stroke rate and stroke length, in maintaining a constant swimming velocity. As stated in Hay (1993) and supported by Figueiredo, Morais, et. al. (2013), the $\overline{SR}$ and $\overline{SL}$ have an interdependent relationship. Therefore, as one parameter increases the other concomitantly decreases. Therefore, within the observed findings the upper-back tri-axial accelerometer showed to be adequate in measuring and depicting definite stroke parameter characteristics and trends amongst the stroking styles.

5.2.2.3 Inter-comparison between the commercial inertial sensor (Polar V800 watch) and accelerometer

Commercialised inertial sensors have become increasingly popular amongst all athletes and disciplines, to monitor and assess their sporting performance. These commercialised devices allow for manufacturers to design a multi-disciplinary sensory device at an affordable cost for both the recreational and competitive athlete (Yang & Hsu, 2010). One would then question which would be a better source of information for coaches to use as a training tool, accelerometer-based sensors versus commercial fitness watches? In the present study, a Polar V800 fitness watch was used to monitor the heart rate telemetry of the swimmers' during the swim sets, while recording additional kinematic information. The kinematic information included the swimmer's average and maximum swimming speed, swimming distance covered in the pool and their average pace during the swim set. Based on the kinematic parameters which were measured by the Polar V800 and derived from the accelerometer data, only two parameters were compared between the two sensory devices namely, average swimming velocity and estimated lap time. These two parameters were compared against the manually estimated values to ensure standardisation. For the $\bar{v}$ it was found that there was a significant difference between each of the methods (one-way ANOVA: $p = 0.003$). With further comparisons using post-hoc Tukey HSD test, it was found that the $\bar{v}$ obtained using the Polar V800 watch was not significantly different from the manually estimated $\bar{v}$ for the 50-m IM swim set; whereas a significant difference was found between the accelerometer derived $\bar{v}$ and the manually estimated $\bar{v}$ (see Figure 33a). The Polar V800 system includes a GPS and gyroscope system and proprietary algorithms to monitor movement and speed changes during the physical activity performed by the individual (Polar, 2018). Therefore, the measured $\bar{v}$ by the Polar V800 was a more accurate reflection of the speed swum by the swimmer in the pool, thereby emphasising the limitation of the accelerometer to accurately measure the instantaneous speed of the swimmer without the addition of other inertial sensors. However, for the remaining swimming sets, it was found that no significant difference was found between either inertial device for the $\bar{v}$. This finding requires further investigation with regards to the accelerometer derived $\bar{v}$ with distances swum above 50-m. As the accelerometer used did not have additional gyroscopic information, therefore; the non-significant findings for the 100-m and 200-m swim sets $\bar{v}$ could be explained by the accelerometer obtaining a greater data set with the increased distance swum by the swimmers, to which the average velocity could be derived, regardless of the lap time error found in section 5.2.2.1 above.

For the lap time parameter, it was shown that no significant difference was found between the Polar V800 and the accelerometer versus the manually taken times (Tukey HSD test: $p > 0.05$) for the 100-m variations and 200-m IM swim set. However, for the 50-m IM swim set, a lap time estimation from the Polar V800 could not be derived as the watch could not accurately measure the lap boundaries between each 50-m. Reasons for this may be similar to that of the accelerometer findings, with the swimmer gliding into the wall at the end of their last stroke cycle and with the variance in the speed performed with each 50-m, hence the lap time could not be accurately determined. It was also noted that the lap time estimation by the Polar V800 and accelerometer across all three swim sets were underestimated compared to the manually taken times. Hence, both inertial devices could not accurately measure the complete lap time as the lap boundaries, at the start and finish of the set, could not be attained. Therefore, emphasising a limitation with both devices in the accurate measurement of the swimmer's lap time performance.

If one were to compare the Polar V800 versus accelerometer, both devices provide information which would be beneficial to both the coach and researcher. However, further research must be done to account for the lap time error found with both sensors, to ensure that elite swimming performance monitoring is accurately measured. A study by Mooney et. al. (2017)

stated that elite swimmers require their lap time estimate to be within ±0.3 seconds of the manually taken time (i.e. stopwatch). Based on the findings within the present study, both the accelerometer and Polar V800 would not suit this criterion. However, both these inertial sensors would be suited for recreational and triathletes, who only require an estimation of their swimming performance, to monitor their progression. One of the benefits of using tri-axial accelerometers to measure swimming performance is that it provides insights into the stroke mechanics of the swimmer, which commercial devices do not possess. However, further research must still be performed to account for the lack of instantaneous feedback, which commercial devices include. Subsequently, with this limitation in the feedback process, it has given commercial technology the edge over specialised inertial devices, with swimmers and athlete alike, opting to use fitness watches as their performance monitoring tool (Zhao *et al.*, 2015). Therefore, to promote the use of specialised inertial equipment in swimming performance monitoring, one would have to provide ample information to coaches and athletes alike, to see the benefit in these types of sensory devices versus the commercial fitness watch. However, with accelerometers, it may be used more in a research capacity rather than as a training tool in swimming until further research is performed to account for the limitations associated with the instantaneous feedback and the cumbersome processing of the data (i.e. require faster algorithms) observed within findings of the present study.

5.3 Heart rate telemetry and critical swim speed comparison

A swimmer's performance is dictated by the interplay between their biomechanical and physiological parameters. Heart rate, which is typically used as a physiological monitoring tool, provides an objective measure of a swimmer's effort throughout their performance (Ganzevles *et al.*, 2014). Therefore, the higher the heart rate, the greater the physical exertion required from the swimming event performed by the swimmer. In the present study, the critical swim speed (CSS) and heart rate of the group tested were measured and compared to the average swimming velocity achieved within each of the swim sets performed. The reason for this comparison was to determine the extent to which these physiological parameters affect the swimmer's performance capacity.

The CSS is the measure of the swimming speed corresponding to the swimmer's maximal lactate steady state, which separates the sustainable from the non-sustainable swimming speeds, indicative of the upper limit of their aerobic steady-state (Akşit *et al.*, 2017; Takahashi *et al.*, 2009). Therefore, it has been used as a determinant of their endurance capacity. The results revealed that the CSS and the $\bar{v}$ for each swim set (except 200-m IM and 50-m butterfly) were significantly different (t-test independent: 50-m IM (except butterfly) range: p= 0.002-0.023; 100-m variation: p= 0.002 – 0.026). All the swim sets showed a weak to moderate relationship between the CSS and the $\bar{v}$ achieved within the respective sets. The weak relationship between these parameters may be due to the estimation of the CSS of each swimmer being determined off their season best times (for their 50- and 400-m freestyle), which was compared then to their swimming performance in the present study during their off-season. The gap between the season best times and the testing period was four to six months approximately. Therefore, the CSS during the testing period was not a true reflection of their actual CSS, ultimately affecting the comparison between these two parameters. One study by Marinho et. al. (2011), found a strong relationship (r >0.85) between each 50-m of each stroking style and the calculated CSS of the population group (Club level swimmers: 12 males and 8 females; age: 12.1 ±0.72 years) tested. The swimmer's CSS was calculated off their best swim times with a three-month time gap between their times and the given testing period. The CSS was correlated against the swimmer's performance in various short distances swum at *maximum* pace. Hence, resulting in a higher correlation amongst the two parameters. Therefore, it is important for future comparisons, that the CSS determined be estimated during the same testing period, or with a shorter period between the CSS estimation and the actual testing, to ensure consistent and reliable results.

Heart rate has been used as a physiological indicator of the swimmer's response to their swimming training and to monitor their swim performance, without the use of invasive methods (Ganzevles *et al.*, 2014). Within the present study, the heart rate of the swimmers, including their minimum, maximum and average heart rate was measured during the swim sets. A comparison between the maximum and average heart rate and the average swimming velocity achieved by the group during each of the swim sets showed a negative relationship between the heart rate measured and the $\bar{v}$ of the group. Therefore, as the one-parameter increases (i.e. heart rate), the other would concomitantly decrease (i.e. $\bar{v}$). The decrease in the

$\bar{v}$ with the higher average heart rate, may be related to the fitness levels of the swimmers. Therefore, swimmers who are less fit would exhibit a higher average HR response compared to a fitter individual (Reilly *et al.*, 2005). As the swimmers were all tested in their off-season, their fitness levels were not at their peak, hence they would exhibit a higher average HR overall throughout the swimming sets performed, supporting the present study findings. It was further found that a strong relationship was observed between the swim sets (100-m maximum and 200-m IM) that were swum at maximum pace and the heart rate maximum and the average response recorded. Therefore, indicating that the swimmers were performing at a maximum pace in correspondence with their heart rate response. Further investigation into the heart rate response of the swimmers could not be attained as portions of the heart rate telemetry recorded was disrupted during the swim sets. This was due to the problem of securing the heart rate strap to the swimmer's chest. Hence, during the data collection the heart rate belt would move, causing a disruption to the heart rate telemetry and subsequently affecting the heart rate results observed. Therefore, alternative solutions have been developed as of recent to account for the chest strap problem. Developed by Polar, a new strap namely, Polar OH1 heart rate sensor, was designed by attaching to the athlete's arm, to allow for a better heart rate reading via telemetry (Mclarty, 2019; Polar, 2019). Hence, this new innovative design by Polar emphasises the ever-growing commercial market, which aims to satisfy the needs of the athlete in obtaining reliable and valid observations of their performance. Therefore, this new strap could be used in future research to obtain a consistent heart rate telemetry reading throughout the testing procedure. Despite the heart rate telemetry problem found within the present study, the heart rate responses on average for the group was accurately measured by the chest strap.

5.4 Implementation of machine learning in the automation of stroke extraction

Tri-axial accelerometers have proven beneficial in the interpretation and viewing of the stroke mechanics of the swimmer, to help correct for technique or to determine differences amongst novice and elite swimmers (Anthony & Chalfant, 2010; Mooney *et al.*, 2015). However, the processes required to extract the relevant swimming information from the accelerometer data has proven to be both time consuming and “undefined” in the correct method of analysis. Within the present study, the methods used to extract the accelerometer data were in accordance with various studies with similar backgrounds. However, a level of novelty was still evident with several limitations arising in the extraction of the stroke kinematic parameters from the accelerometer data. These limitations include (i) the manual filtering and interpretation of all the swimmer’s data, and (ii) the use of two different axes in the SC extraction due to the stroke mechanics of the different stroking styles. Therefore, posing a limitation on the extraction of the relevant parameters from a continuous stream of data containing more than one stroking style. Additionally, manual elimination of excess peaks or troughs were required by the present researcher, after the peak detection algorithm was applied to the filtered accelerometer data. The addition of erroneous peaks observed during the analysis process was due to the stroke mechanics of the swimmer and each swimmer presenting with different peak magnitudes within their data. Although the data was filtered, the present researcher had to ensure the data was not over-smoothed to the point that important information related to the swimmer’s stroke kinematics was lost. Therefore, choosing the correct filtering technique was important in the stroke kinematic extraction process. Considering these limitations, the aid of the machine learning (i.e. artificial intelligence) was sought out to help automate the processes of data extraction of the relevant stroke kinematics and stroke mechanics from the accelerometer data. However, due to the novelty of the data used and with “no defined template”, a computer algorithm was implemented to isolate and label the four stroking styles from the raw, unlabelled accelerometer data. It was found that the designed computer model had a total classification accuracy of 96.6% (n = 4), in the labelling of the four stroking styles within the swimming data. Further analysis found that a strong relationship was observed between the predicted and actual stroking style within the data for all four strokes (see Figure 35). Therefore, the use of machine learning is an unprecedented field of research, which could be vital in the understanding and interpretation of the accelerometer data for both the researcher and the coach. Hence, with the initial findings presented from the machine learning model in the present study, one could design an artificial intelligence template to read the accelerometer data, to account for the limitations reported above. Once these are accounted for, the use of the machine learning models could allow for programs to be designed to help aid coaches in their daily training, by providing the necessary kinematic and stroke mechanic information related to their swimmer once the input data is extracted from the accelerometer. Therefore, representing future benefits of implementing machine learning as a means to automate and help interpret the accelerometer data process. However, in conjunction with machine learning, live or instantaneous feedback should also be implemented to increase the user-friendliness of these inertial sensors for coaches.

5.5 Future recommendations

For the present study, the novelty of this type of research was evident in a South African context, with the research process encountering various limitations which affected the end research goal. Despite these limitations, the benefits of this type of research and the use of accelerometers in swimming kinematic differentiation shows substantial potential, therefore motivating the need for further research. To overcome the limitations met within the present study, the following future recommendations are advised to ease the research process and to improve the research results: (i) increasing the sample size and the expertise level of the sample group to allow for an inter-comparison between the swimmers (i.e. novice versus national-level swimmers) (ii) a re-design of the camera trolley used for the video validation to allow for a better data collection process (iii) to formalise a “common” or standardised method of analysis and interpretation, which can be derived for most studies with similar methods (iv) to implement some form of machine learning to automate the labelling and extraction of the relevant stroke kinematic parameters and stroke mechanics, and (iv) to implement a real-time “live feedback” system in swimming practice for coaches to use, eliminating the time-consuming post-practice analysis, allowing for technique corrections to be done during training.

5.6 Conclusion

Based on the findings from the present study, it was found that the accelerometers used were adequate in the differentiation of the stroking styles, stroke kinematics and stroke mechanics from its data for the swimming group tested. The major limitation was the time-consuming aspect of the data extraction and interpretation which may limit mainstream appeal. It is important to note, however, that the present study would serve as a foundation for future research given the strides that have been made in identifying key accelerometer thresholds for the various stroking styles. Furthermore, the use of machine learning was successful in the auto-labelling of these stroking styles within the accelerometer data. The present study proved the benefits of using accelerometers as a tool to provide key information related to the swimmer's performance. This information included the breakdown of the swimmer's stroke mechanics (i.e. stroke phases), with characteristic differences found between the swimmers within the analysis. Additionally, technique-based differences between the swimmers in the performance of the stroke were also depicted within the accelerometer data, thereby emphasising further benefits of this specialised inertial sensor as a coaching and research tool in swimming performance monitoring. Therefore, accelerometers have unprecedented potential in discerning swimming characteristics, which commercial technology at present does not produce with the necessary in-depth analysis. The present study should serve as the grounding for the use of accelerometers as an additional kinematic tool in research to further enhance the swimming performance information given to both the researcher and the coach which is especially important in the differentiation of the stroke mechanics and discerning specific differences amongst elite and novice swimmers.

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APPENDIX A: Information Sheet

NELSON MANDELA UNIVERSITY

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Date: January 2019

To whom it may concern:

RE: SWIMMING STUDY

This study will be conducted by Courtney Musson under the supervision of Mr Mark Kramer from the Department of Human Movement Science (Faculty of Health Sciences) at the Nelson Mandela University. The testing will be conducted at the Nelson Mandela University High Performance Complex, specifically at the Fitness and Aquatics Centre.

The study aims to determine the differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers.

The swimmers will be required to partake in a swimming evaluation, with the addition of three anthropometric measurements (height, weight and arm span). The swimming assessment includes 4 x 50-m individual medley, 2 x 100-m freestyle (one at maximum intensity and one at a self-selected pace) and 200-m individual medley at maximum intensity. The testing will be conducted in accordance with the swimmers training regime and schooling.

The risks associated with the testing may include over-exertion by the swimmers during the maximal effort bouts during the swimming evaluation, but these risks are no different than those experienced during a traditional IM event. The potential benefits include: the swimmers gaining information with regards to their kinematic parameters associated with their swimming performance and exposure to the use of tri-axial accelerometers in their daily swimming training.

The swimmer will be required to wear one tri-accelerometer, Polar V800 watch, Polar H7 heart rate monitor and the use will be made of two video cameras, one above and below the water to collect the above-mentioned data.

All the information collected within this study will be coded with a unique personal identification and stored in a safe locked place. Only the primary researcher and their supervisor of the study will have access to the data. The members of the committee of ethics and research at Nelson Mandela University may ask for access to the collected information for the monitoring of the studies progress. The key findings of the study may be published, and the names and personal identities of the swimmers will not be revealed to ensure anonymity.

Participation in this study is voluntary, hence one has no obligation to partake in the study. Consent is required for the participation of your child/children. If they wish to withdraw at any time, they may do so even after you have signed the consent form.

Please do not hesitate to contact us should have any further questions or concerns.

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APPENDIX B: Pre-testing guidelines

NELSON MANDELA UNIVERSITY

Pre-testing guidelines

The following pre-testing protocol serves as a guideline before the testing day. Each guideline is only a recommendation and does not have to be adhered too. These guidelines serve, to inform each swimmer, who is to partake in this research study, of the same information. Therefore, to ensure a similar pre-testing routine and warm-up is performed by each swimmer.

Standardised pre-test preparation guidelines:

Diet: Swimmers are required to abstain from food and beverages containing caffeine or alcohol, at least 2 hours prior to testing. Adequate hydration (water or sports drink) is recommended.

Training: Swimmers are required to not participate in high-intensity training 18 hours before testing. It is also recommended that no heavyweight training or exercise with which the swimmer may not be accustomed too, to be undertaken 24 hours preceding testing.

Testing: Swimmers are required to be reasonably well-rested and free of illness and injury (at least six months) prior to testing. If the swimmer is unable to take part in the testing due to one of these variables, testing would be postponed to a further date, to ensure the athlete is adequately prepared.

Warm-up: Swimmers may perform their own standard practice warm-up before the testing commences. Swimmers should complete the same warm-up prior to all pool sessions if testing is not completed on the allocated day.

APPENDIX C: Informed consent

NELSON MANDELA UNIVERSITY

INFORMATION AND INFORMED CONSENT FORM

RESEARCHER'S DETAILS	
Title of the research project	**Differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers**
Principal investigator	**Courtney Musson**
Address	**30 Dyason Street, Mount Croix, Port Elizabeth**
Postal Code	**6001**
Contact telephone number (private numbers not advisable)	**073 66 55 681**

A. DECLARATION BY OR ON BEHALF OF PARTICIPANT		**Initial**
I, the participant and the undersigned	(full names)	
ID number		
OR		
I, in my capacity as	(parent or guardian)	
of the participant	(full names)	
ID number		
Address (of participant)		

A.1 HEREBY CONFIRM AS FOLLOWS:		**Initial**
I, the participant, was invited to participate in the above-mentioned research project		
that is being undertaken by	Courtney Musson	
From	Faculty of Health Science	
of the Nelson Mandela University.		

THE FOLLOWING ASPECTS HAVE BEEN EXPLAINED TO ME, THE PARTICIPANT:					**Initial**
2.1	**Aim:**	The primary aim of the present study is to determine differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-m IM event in South African national level swimmers			
2.2	**Procedures:**	The participant will be required to partake in a swimming evaluation, with the addition of three anthropometric measurements (height, weight and arm span). The swimming assessment includes 4 x 50-m individual medley, 2 x 100-m freestyle (one at maximum intensity and one at a self-selected pace) and 200-m individual medley at maximum intensity			
2.3	**Risks:**	The possibility of injury during the swimming and anthropometric assessments are extremely low and would be associated with delayed onset of muscle soreness that may accrue because of maximal effort requirements within the swimming procedure			
2.4	**Possible benefits:**	There is a lack of research on the kinematic parameters associated with the swimmer, with the use of tri-axial accelerometers to investigate these factors. Hence, this study will be conducted to fill this gap. A detailed swim report will be made available for each participant.			
2.5	**Confidentiality:**	My identity will not be revealed in any discussion, description or scientific publications by the investigators.			
2.6	**Access to findings:**	Should you be interested in the findings or advancement of this research, you may contact the head researcher whose details appear at the top of this document			
2.7	**Future use of data:**	I hereby consent that my data may be used for future research, as long as anonymity is maintained.			
2.8	**Filming:**	I hereby consent to the use of a camera system for the recording of my stroke mechanics during my swimming. I am aware that the sole purpose of the filming is to time-synchronize the accelerometer data for the accurate analysis of my swimming technique			
2.9	**Voluntary participation / refusal / discontinuation:**	My participation is voluntary	**YES**	**NO**	
		My decision whether or not to participate will in no way affect my present or future care/employment/lifestyle	**TRUE**	**FALSE**	

3.	**THE INFORMATION ABOVE WAS EXPLAINED TO ME/THE PARTICIPANT BY:**								**Initial**
in	**Afrikaans**		**English**		**Xhosa**		**Other**		
and I am in command of this language, **or** it was satisfactorily translated to me by									

(name of translator)	
I was given the opportunity to ask questions and all these questions were answered satisfactorily.	

4.	No pressure was exerted on me to consent to participation and I understand that I may withdraw at any stage without penalisation.	

5.	Participation in this study will not result in any additional cost to myself.	

A.2 I HEREBY VOLUNTARILY CONSENT TO PARTICIPATE IN THE ABOVE-MENTIONED PROJECT:	
Signed/confirmed at on 20	
Signature or right thumb print of participant	Signature of witness:
	Full name of witness:

B. STATEMENT BY OR ON BEHALF OF INVESTIGATOR(S)									
I,	(name of interviewer)			declare that:					
1.	I have explained the information given in this document to			(name of patient/participant)					
	and / or his / her representative			(name of representative)					
2.	He / she was encouraged and given ample time to ask me any questions;								
3.	This conversation was conducted in	**Afrikaans**		**English**		**Xhosa**		**Other**	
	And no translator was used <u>OR</u> this conversation was translated into								
	(language)	by	(name of translator)						
4.	I have detached Section D and handed it to the participant		YES		NO				
Signed/confirmed at on 20									

Signature of interviewer	Signature of witness:
	Full name of witness:

C. IMPORTANT MESSAGE TO REPRESENTATIVE OF PARTICIPANT	
Dear participant/representative of the participant Thank you for your/the participant's participation in this study. Should, at any time during the study: - an emergency arise as a result of the research, or - you require any further information with regard to the study, or - the following occur (indicate any circumstances which should be reported to the investigator)	
Kindly contact	
at telephone number	(it must be a number where help will be available on a 24 hour basis, if the research project warrants it)

NELSON MANDELA UNIVERSITY

Faculty of Health Sciences
Department of Human Movement Science
School of Lifestyle Science
Tel . +27 (0)41 504 4754
E-mail: crmusson@gmail.com

GATEKEEPER CONSENT FORM

Dear Club Coach

This letter serves to invite your swimmer to participate in a study focused on identifying differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers. The study consists of three anthropometric tests (height, weight and arm span) and set of swimming assessments chosen to derive the kinematic parameters. The swimming assessments consists of 4 x 50-m individual medley at maximum intensity, 2 x 100-m freestyle (one at maximum intensity and one at a self-selected pace) and 200-m individual medley at maximum intensity. These tests are selected to determine various parameters such as stroke length and rate, stroke phases and defining stroking styles using tri-axial accelerometers.

The following ethical considerations will be adhered to:

- No name will be mentioned throughout the study.
- All swimmers will have to be granted permission by their parents/ guardians or club coach.
- Participation in this study is on a voluntary basis and no rewards will be offered to swimmers.
- Swimmers will be allowed to withdraw their participation at any stage with no penalties.
- This study does not involve any risk or harm to the swimmer (physically and emotionally). However, the swimmer may experience delayed onset of muscle soreness (DOMS) the day after the assessment.
- All information collected will be treated in a highly professional manner with respect to confidentiality and privacy.
- Video recordings will be used to obtain certain parameters in the study.

Your permission is required to allow your swimmer to participate in the above study. Your swimmer can still withdraw from the study at any time and he/she will not be prejudiced.

Name of Club Coach……………………………………………………

Signature……………………………………………. Date: ……………………………..

I…………………………………………………………… (Please print full name), in my capacity as Club coach of

………………………………………………………………………………….. (Please print full names) a swimmer at

…………………………………………………………………………….. swim club (Full name of club), agree that my swimmer may take part in the research project entitled: Differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers.

I understand that:

- My swimmer is under no obligation to participate in this study
- There would be no incentive to my swimmer for participating in this study.
- My swimmer's anonymity will be protected at all times.
- There are no risks involved in taking part in this study.

I fully understand what participating in this study involves, and hereby give informed agreement for my swimmer to participate in this study.

………………………………………
Signature

………./………/……….
Date

…………………………………
Witness

…../………/……….
Date

APPENDIX D: Assent forms and parental consent

NELSON MANDELA UNIVERSITY

Faculty of Health Sciences
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School of Lifestyle Science
Tel . +27 (0)41 504 4754
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Date: December 2018

ASSENT FORM FOR LEARNER

Please initial each box below:

☐ I confirm that I have read and understand the information letter dated December 2018 for the study focusing on the differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily.

☐ I understand that my participation is voluntary and that I am free to withdraw from this study at any time without giving any reason and without any consequences to me.

☐ I agree to allow the researcher to take video recordings in conjunction with the study aim and objectives

☐ I agree to take part in the above study.

_________________________	______________________________________	_________________
Name of Participant	Signature of Participant	Date
_________________________	______________________________________	_________________
Name of Researcher	Signature of Researcher	Date

Faculty of Health Sciences
Department of Human Movement Science
School of Lifestyle Science
Tel . +27 (0)41 504 4754
E-mail: crmusson@gmail.com

GATEKEEPER CONSENT FORM

Dear Parent/ Guardian

This letter serves to invite your child to participate in a study focused on identifying differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers. The study consists of three anthropometric tests (height, weight and arm span) and set of swimming assessments chosen to derive the kinematic parameters. The swimming assessments consists of 4 x 50-m individual medley at maximum intensity, 2 x 100-m freestyle (one at maximum intensity and one at a self-selected pace) and 200-m individual medley at maximum intensity. These tests are selected to determine various parameters such as stroke length and rate, stroke phases and defining stroking styles using tri-axial accelerometers.

The following ethical considerations will be adhered to:

- No name will be mentioned throughout the study.
- All swimmers will have to be granted permission by their parents/ guardians or club coach.
- Participation in this study is on a voluntary basis and no rewards will be offered to swimmers.
- Swimmers will be allowed to withdraw their participation at any stage with no penalties.
- This study does not involve any risk or harm to the swimmer (physically and emotionally). However, the swimmer may experience delayed onset of muscle soreness (DOMS) the day after the assessment.
- All information collected will be treated in a highly professional manner with respect to confidentiality and privacy.
- Video recordings will be used to obtain certain parameters in the study.
- You will be required to transport your child to the testing facility as stated in the information sheet.

Your permission is required, your child can still withdraw from the study at any time and he/she will not be prejudiced.

Name of Parent/ Guardian ……………………………………………………

Signature…………………………………………….. Date: ……………………………

I……………………………………………………….. (Please print full name), in my capacity as parent/guardian of

………………………………………………………………………………… (Please print full names) a swimmer at

…………………………………………………………………………… swim club (Full name of the club), agree that my child may take part in the research project entitled: Differences in swimming stroke mechanics and kinematics derived from tri-axial accelerometers during a 200-IM event in South African national swimmers.

I understand that:

- My child is under no obligation to participate in this study
- There would be no incentive for my child for participating in this study.
- My child's anonymity will be protected at all times.
- Own transport to the testing facility is required
- There are no risks involved in taking part in this study.

I fully understand what participating in this study involves, and hereby give informed agreement for my child to participate in this study.

…………………………………………
Signature

………./………/……….
Date

……………………………………
Witness

…../………/……….
Date

APPENDIX E: Summary of stroke phases

	FREESTYLE
	i- Hand Entry
X-axis:	Marked by a positively skewed peak. **Additional characteristic:** The magnitude of the peak is dictated by the orientation of the swimmer's wrist as it enters the water. The magnitude of the peak was greater if the swimmer's hand entered perpendicular to the surface of the water.
Y-axis:	Marked by a negatively skewed trough.
Z-axis:	Marked by a negatively skewed trough. **Additional characteristic:** The magnitude of the trough is dictated by the swimmer's hand entering parallel to the surface of the water and the driving force the swimmer applied into the water after the recovery phase was completed. This axis was used as the *primary* indicator of the hand entry for each swimmer, as it is the most distinctive axis across all swimmers tested.
	ii- Down-sweep
X-axis:	Remains relatively unchanged for the duration of this phase, until the inflection point between the down-sweep and in-sweep phase. The inflection point is marked by a negatively skewed trough. The change in the axis is characteristic of the swimmer's hand moving inwards, as they transition into the in-sweep phase begins.
Y-axis:	This axis represents the *primary* hand movement within this phase by the swimmer. This movement was indicated by a negatively skewed change in the axis, as the swimmer's hand moved in a downward movement through the water. The end of the phase is marked by the negatively skewed trough at the inflection point between the down- and in-sweep phases.
Z-axis:	Remains relatively unchanged for the duration of this phase
	iii- In-sweep
X-axis:	Marked between two inflections points: negatively skewed trough and positively skewed peak. This axis represents the hand movement of the swimmer as it moves inward and outward, to transition into the up-sweep phase.
Y-axis:	Marked between two inflection points: negatively skewed trough and positively skewed peak.
Z-axis:	Marked by a positively skewed peak. This represents the hand of the swimmer beginning to move into a position to apply an upward force through the water, for the transition into the up-sweep phase.
	iv- Up-sweep
X-axis:	Marked between two inflection points: positively skewed peak and the next highest positively skewed peak. The second positive peak represents the hand exiting perpendicular to the surface of the water, as it transitions into the recovery phase.

Y-axis:	Marked between two inflection points: positively skewed peak and the next highest positively skewed peak.
Z-axis:	This axis remains relatively unchanged throughout this phase, as the primary movement of the swimmer's hand is measured by changes in the X- and Y-axis.
	v- Recovery
X-axis:	This axis remains relatively unchanged throughout this phase as the hand of the swimmer rotates to a position of their choice, to re-enter the water, to complete the arm cycle.
Y-axis:	This axis remains relatively unchanged throughout this phase.
Z-axis:	This axis presents with a positively skewed increase as the hand rotates to re-enter the water
	The primary hand movement of the swimmer occurs in the sagittal plane as the hand movements are superior and inferior in stroking action. However, phase ii occurs in the coronal plane as the hand performs an inverted question mark ("?") movement, moving medially and laterally to execute the stroking motion.
	BUTTERFLY
	i- Catch
X-axis:	Marked by the positively skewed peak followed by the (lowest) negatively skewed trough. This axis represents the swimmer's hand movement as it moves laterally (outward) to initiate the catch movement before moving medially (inward), to transition into the shoulder phase.
Y-axis:	This axis remains relatively unchanged.
Z-axis:	This axis is skewed positively throughout this phase, as the swimmer's hand applies a force distally, to help increase the power-driven through this push phase.
	ii- Shoulder
X-axis:	Marked between two inflection points: negatively skewed trough and positively skewed peak. This change between the inflection points represents the rotation of the swimmer's hand orientation as they prepare for the release phase.
Y-axis:	Marks the change in the swimmer's hand orientation in conjunction with the X-axis. The hand orientation of the swimmer changes from facing palm down to palm up, to initiate the release phase. Hence, a negatively skewed decrease to a negatively skewed trough (in the release phase).
Z-axis:	*This axis requires further analysis, as the axis characteristics for this phase amongst all the tested swimmers, changes with every stroke cycle. This may be due to the different stroke mechanics presented by each swimmer, within this phase.*
	iii- Release
X-axis:	Marked between two inflection points: positively skewed peak followed by the next, first highest positively skewed peak.
Y-axis:	Marks the change of the swimmer's hand from palm facing up to palm facing down as the hand enters the recovery phase. A positively skewed increase indicates the movement of the hand upward and out the water, as it enters the recovery phase
Z-axis:	*This axis requires further analysis, due to the different stroke mechanics presented by each swimmer. On initial analysis, the end of the release phase is marked by a positively skewed peak corresponding with the X-axis positive peak.*
	iv- Recovery
X-axis:	Marked between two inflection points: positively skewed peak followed by the highest positively skewed peak (marking hand entry).

Y-axis:	This axis remains relatively unchanged as the swimmer's hand rotates back to their palm facing downward to re-enter the water, to begin the glide into the catch phase
Z-axis:	Marked between two inflection points: positively skewed peak followed by the lowest negatively skewed trough (marking hand entry) before initiation of the glide into catch phase
	Glide phase
	The glide phase is marked by the unchanged movement on all three axes. During this phase, the swimmers kick is initiated to allow for additional propulsion in the water.
	BREASTSTROKE
	i- Out-sweep
X-axis:	This axis represents the hand movement as it executes the out-sweep. It is marked by a positively skewed peak as the hand moves laterally (outward). The transition into the in-sweep is marked by the negatively skewed change, as the hand begins to move medially (inward), as the swimmer's arms bend towards their chest.
Y-axis:	Marked by the negatively skewed decrease towards a negatively skewed trough. The trough indicates the transition into the in-sweep phase as the swimmer's arms are bent towards their chest.
Z-axis:	Follows the same trend as the Y-axis
	ii- In-sweep
X-axis:	Marks the rotation of the hand as it moves towards the swimmer's chest, before the initiation of the recovery phase (i.e. push into recovery phase). This is represented by the negatively skewed change in the X-axis acceleration, as the hand moves medially (inwards). The transition into the push phase (recovery phase), is marked by the positively skewed increase at the end of the phase. This change represents the hand rotation laterally, to become parallel with the surface of the water before executing the recovery phase.
Y-axis:	Marked between two inflection points: negatively skewed trough and positively skewed peak, as the swimmer's arms tuck into their chest before initiating the recovery phase (i.e. push phase). The positive peak represents the change in the swimmer's arms acceleration to initiate the push phase (start of the recovery phase)
Z-axis:	Follows the same trend as the Y-axis. The initiation of the hands into the recovery phase is marked by the positive peak within this axis.
	iii- Recovery
X-axis:	Axis remains relatively unchanged, with minimal changes in acceleration as the swimmer initiates their kick to glide through the water during their push phase.
Y-axis:	Same as the X-axis
Z-axis:	Initiation of the push phase into the glide marked by the positively skewed peak, before becoming stable as the swimmer continues their recovery phase.
	Glide
	The glide is characterised by the length of time at which the accelerations in all three axes, remains unchanged. During this phase, the swimmer is executing their kick to gain additional distance in the pool.
	BACKSTROKE
	i- Hand Entry and Catch
X-axis:	Hand entry marked by the negatively skewed trough corresponding at the same point as the positively skew peak in the Z-axis. The Hand catch is marked by the positively skewed peak as the swimmer's hand rotates laterally to help initiate the pull phase.

Y-axis:	Remains relatively unchanged throughout this phase
Z-axis:	Hand entry marked by a positively skewed peak. Hand catch marked by the next positively skewed peak.
	ii- Pull
X-axis:	Marked between two inflection points: positively skewed peak followed by a negatively skewed trough corresponding with the Z-axis negatively skewed trough. This change represents how the swimmer's hand rotates medially, into the push phase. The transition into the push phase is initiated with a positively skewed increase as the swimmer's hand rotates perpendicular to the surface of the water.
Y-axis:	Remains relatively unchanged throughout this phase
Z-axis:	Marked between two inflection points: positively skewed peak followed by a negatively skewed trough at the same point as the X-axis negatively skewed trough
	iii- Push
X-axis:	*This axis requires further analysis, as the stroke mechanics of each swimmer differ in terms of how the swimmer initiates the pushing movement throughout the water.*
Y-axis:	Remains relatively unchanged throughout this phase
Z-axis:	Marked between two inflection points: Negatively skewed trough followed by the next greatest negatively skewed trough, as the swimmer's hand enters the hand lag time phase.
	iv- Hand lag time
X-axis:	Very little change observed during this short phase
Y-axis:	Remains relatively unchanged throughout this short phase
Z-axis:	Marked by two inflection points: negatively skewed trough followed by the positively skewed increase into the clearing phase as the hand pushes to clear the water.
	v- Clearing
X-axis:	This axis remains relatively unchanged throughout this phase.
Y-axis:	This axis remains relatively unchanged throughout this phase.
Z-axis:	Marked by the change in the axis, as the hand clears the water presenting with positive to negative transition into the recovery phase
	vi- Recovery
X-axis:	Remains relatively unchanged until the hand entry, which is marked by the negatively skewed trough as the hand enters perpendicular to the surface of the water
Y-axis:	Remains relatively unchanged throughout this phase
Z-axis:	Marked by the positively skewed increase towards the positively skewed peak, marking hand entry