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SmartSwim: A novel approach to swimming analysis and coaching assistance based on wearable inertial sensors

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To my Wife Solmaz for her Endless Love,

My Mother Mahin for her Infinite Kindness,

And my Father Hamid for his Everlasting Memories

ABSTRACT

As one of the three most popular sports in the Summer Olympics, competitive swimming has always been an attractive subject of study for sports scientists. The intricate nature of the swimmer's movements and the variety of techniques have led coaches to require analysis systems to gain a more detailed understanding of swimmers' performances, to plan training sessions as efficiently as possible and closely monitor the swimmer's progress. Surveys have shown that despite recent technological advances in sports, swimming coaches still need a measurement device that is accessible, easy to use, and provides easy-to-understand results. Conventional analysis systems such as high resolution cameras, while accurate, are too time consuming and cumbersome for daily use.

With the advent of wearable sensors, especially inertial measurement units (IMU), motion analysis has gained the ability to not only study new aspects of motion, but also cover in-field applications. IMUs have been used to study swimming and provided a credible solution for extracting kinematic and spatio-temporal features. However, researchers focused primarily on extracting features rather than using them to evaluate performance and provide feedback in the field. Free-swimming is the phase that has been most studied with IMUs, and among the major swimming styles, front crawl has attracted more attention. However, to win competitions, swimmers need to master all phases of swimming in each style. Therefore, a comprehensive analysis approach based on IMUs covering all swimming styles and phases can provide the swimming community with deeper insight into swimmers' performance and a better solution to training needs.

This thesis presents a novel methodology for swimming training analysis based on inertial wearable sensors. The proposed method uses a unified macro-micro analysis approach that scans the entire training session for swimming bouts and then narrows down to separating the swimming phases from wall to wall. The method is implemented using the IMU data from different sensor positions on the swimmer's body for comparison. Based on the results of the developed algorithms, sacrum position was determined to be optimal for detecting all swimming phases. As a result, the analysis then detects a set of spatio-temporal and kinematic parameters based on the IMU data on the sacrum at each phase, which are used for the swimmers' phase-based performance evaluation. Furthermore, the extracted parameters were shown to reflect different aspects of the swimmer's performance, such as propulsion, posture, or efficiency. The developed performance evaluation method estimates a set of velocity-based goal metrics, validated against the reference system, that represent how well the swimmer performed during the corresponding phase. These goal metrics can provide coaches with knowledge-of-result feedback so that they can focus on the swimmers' weaknesses and guide them more efficiently. Finally, the system is used to provide weekly feedback to a team of young swimmers to evaluate the application of feedback in practice and its impact on swimmers' progress.

Overall, this thesis proposes a new approach to swimming performance evaluation based on IMUs, with a broader scope of application to all phases and styles of swimming. It aims to expand the application of IMUs in swimming by providing spatio-temporal and kinematic parameters that represent critical aspects of swimming and objectively evaluate swimmers' performance. The estimated goal metrics are sensitive to swimmers' progress during weeks of training. In addition, the potential of such an analysis system for in-field training sessions is tested and showed promising results. Finally, coaches can obtain a more detailed view of swimmers' techniques at both macro and micro levels using a single IMU sensor on a daily basis.

Keywords: Sports biomechanics, swimming, wearable system, inertial sensor, IMU, Macro-micro analysis, spatio-temporal parameters, kinematics, swimming phases, lap segmentation, performance evaluation, swimmer progress, efficient training, feedback.

RÉSUMÉ

En tant que l'un des trois sports les plus populaires des Jeux Olympiques d'été, la natation a toujours été un sujet d'étude attrayant pour les scientifiques du sport. La nature complexe des mouvements du nageur et la variété des techniques ont conduit les entraîneurs à exiger des systèmes d'analyse pour acquérir une compréhension plus détaillée des performances des nageurs, pour planifier les séances d'entraînement le plus efficacement possible et suivre de près les progrès du nageur. Des enquêtes ont montré que malgré les récentes avancées technologiques dans le sport, les entraîneurs de natation ont toujours besoin d'un appareil de mesure accessible, facile à utiliser et fournissant des résultats faciles à comprendre. Les systèmes d'analyse conventionnels tels que les caméras à haute résolution, bien que précis, sont trop chronophages et encombrants pour une utilisation quotidienne.

Avec l'avènement des capteurs portables, en particulier des unités de mesure inertielle (IMU), l'analyse du mouvement a acquis la capacité non seulement d'étudier de nouveaux aspects du mouvement, mais également de couvrir des applications sur le terrain. Les IMUs ont été utilisés pour étudier la natation et ont fourni une solution crédible pour extraire des caractéristiques cinématiques et spatio-temporelles. Cependant, les chercheurs se sont concentrés principalement sur l'extraction de paramètres biomécaniques plutôt que sur leur utilisation pour évaluer les performances et fournir des retours sur le terrain. La nage libre est la phase qui a été la plus étudiée avec les IMUs, et parmi les principaux styles de nage, le crawl a attiré plus d'attention. Cependant, pour gagner des compétitions, les nageurs doivent maîtriser toutes les phases de la natation dans chaque style. Par conséquent, une approche complète basée sur des IMUs couvrant tous les styles et toutes les phases de nage peut fournir à la communauté un aperçu plus approfondi des performances des nageurs et une meilleure solution aux besoins d'entraînement.

Cette thèse présente une nouvelle méthodologie d'analyse de l'entraînement à la natation basée sur des capteurs portables inertiels. La méthode proposée utilise une approche d'analyse macro-micro unifiée qui analyse, dans un premier temps, l'ensemble de la séance d'entraînement afin de détecter les épisodes de natation. Puis, dans un deuxième temps, l'algorithme sépare les phases de nage d'un mur à l'autre au sein d'un même épisode. Le procédé est mis en œuvre en utilisant les données provenant de capteurs placés à différentes positions sur le corps du nageur à des fins de comparaison. Sur la base des résultats des algorithmes développés, la position du sacrum a été déterminée comme étant optimale pour détecter toutes les phases de nage. En conséquence, l'analyse détecte ensuite un ensemble de paramètres spatio-temporels et cinématiques basés sur les données du IMU sur le sacrum, qui sont utilisés pour l'évaluation de la performance des nageurs dans chaque phase. De plus, il a été démontré que les paramètres extraits reflètent différents aspects de la performance du nageur, tels que la propulsion, la posture ou l'efficacité. La méthode d'évaluation des performances développée estime un ensemble de mesures d'objectifs, basées sur la vitesse de nage, afin de quantifier la performance du nageur au cours de chaque phase. Les précisions d'estimation de chacune de ces métriques ont été validées par rapport à un système de référence. Ces métriques peuvent fournir aux entraîneurs un feedback concret afin qu'ils puissent se concentrer sur les faiblesses des nageurs et les guider plus efficacement. Enfin, le système est utilisé pour fournir un feedback hebdomadaire à une équipe de jeunes nageurs, dont l'objectif est d'évaluer les effets du feedback dans la pratique et son impact sur les progrès des nageurs.

En général, cette thèse propose une nouvelle approche de l'évaluation des performances de nage basée sur des IMUs, avec une portée d'application à toutes les phases et à tous les styles de nage. La méthode développée vise à étendre l'application des IMUs à la natation en fournissant des paramètres spatio-temporels et cinématiques pertinents à l'évaluation objective de certains aspects critiques des techniques de nage et des performances des nageurs. Les mesures d'objectifs estimés sont sensibles aux progrès des nageurs au cours des semaines d'entraînement. De plus, le potentiel d'un tel système d'analyse pour le suivi des sessions d'entrainement sur le terrain a été testé et a montré des résultats prometteurs. Enfin, les entraîneurs peuvent obtenir une vue plus détaillée de la technique des nageurs aux niveaux macro et micro en utilisant quotidiennement un seul capteur IMU.

Mots clés : Biomécanique du sport, natation, système portable, capteur inertiel, IMU, Analyse macro-micro, paramètres spatio-temporels, cinématique, phases de nage, segmentation des longueurs, évaluation des performances, progression du nageur, entraînement efficace, feedback.

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

PART I – INTRODUCTION AND BACKGROUND

Chapter 1 Introduction

1.1 Overview

At the 1972 Olympic Games in Munich, Gunnar Larsson won the gold medal in the men's 400-meter individual medley swimming event by a margin of two thousandths of a second over Tim McKee of the United States. The international swimming rules have been changed to use a hundredth of a second as the record resolution, allowing for ties between swimmers with identical times. At the 2016 Olympics, the difference between the first and last swimmer in the men's 50m front crawl was just 0.68s. Swimming is one of the most competitive sports, where the loss of a hundredth of a second can decide the color of a swimmer's medal. Winning such a close competition requires months of intense training and extensive preparation. To achieve peak performance, elite swimmers gradually increase their training intensity and volume, beginning several months before each competition (Hellard et al., 2019).

There are different distance events in the four main styles of breaststroke, butterfly, backstroke, front crawl, and individual medley. Front crawl, medley or mixed relays are team events in which four athletes swim consecutively. The international swimming federation (FINA) has established several rules for the competitions concerning the acceptable form of stroke in each swimming style or phase that swimmers should follow. Sequencing the phases of swimming within the limits established for each, swimming underwater versus swimming above water, turning at the wrong time, and touching the wall incorrectly can all result in the swimmer being disqualified. Therefore, although the main goal of swimming is to be as fast as possible, swimmers must consider much more than technique to outperform others, as every detail is intensely scrutinized by the referees.

Beating top competitors while playing by the rules requires a flawless performance. For decades, sports scientists and researchers have studied the performance of swimmers from various angles, such as energetics and biomechanics (Ferreira et al., 2016), strength and conditioning (Amaro et al., 2019), nutrition (Shaw et al., 2014) or psychology (Sheard and Golby, 2006). However, biomechanics have been shown to be more important and more easily improved through training (Mooney et al., 2016a). Compared to aquatic mammals and fish, humans are inefficient and clumsy in water due to their different evolution and musculoskeletal system. As a result, they have always struggled to find the optimal swimming techniques to increase propulsion and reduce drag, which is the main goal of biomechanical analysis of swimming locomotion (Takagi et al., 2021).

In the study of swimming biomechanics, the kinematics, kinetics, and energy expenditure of swimmers with different performance levels are compared and then related to performance. Thanks to the increasing knowledge of sports science, man has learned to swim more efficiently by understanding the governing rules of swimming biomechanics. From the analysis of the movement of the swimmer's body segments using Newton's second law of motion (Maglischo, 2003; Bao et al., 2021) to the application of computational fluid dynamics models (Barbosa et al., 2010; Takagi et al., 2016), we now better understand how to generate the greatest possible propulsion, avoid water resistance, and increase swimming efficiency. The achievement of new world records in international events almost every year is a clear sign of this progress. In addition, minute differences in race times between finalists in swimming competitions have forced coaches and swimmers to work harder to achieve a "fraction of a second" improvement in performance (James et al., 2004). Given the limitations of the human body for fast swimming, it is becoming increasingly difficult for swimmers to make worthwhile progress as a competitive advantage, and the role of the coach in training is therefore becoming more important.

1.2 Coaching importance in training

Efficient training is the basis for swimmers' success in competitions. Therefore, it is important for a swimmer to be carefully organized and strictly supervised by the coach. The training plan should be adapted to many factors, such as the swimmer's age, performance level and potential, and the time remaining until the competitions. The coach should create a detailed, long-term training plan and improve various aspects of swimmer’s performance through continuous assessment. The coach is responsible for bringing about a positive change in the swimmer's performance. This is accomplished through an appropriate and timed training program that addresses physical, tactical, mental, and technical aspects (Nathan and Scobell, 2012). At an advanced level, swimmers are trained for specific events and can be divided into sprinters or short-, middle-, and long-distance swimmers, each of which should be trained differently in terms of intensity and volume. Swimmers also perform strength training out of the water and aerobic exercise between swim sessions. The coach should determine the profile of each swimmer, identify their strengths and weaknesses, and guide them to achieve the best results. In doing so, the coach should focus on specific metrics that affect the swimmer's performance to accurately identify technique errors and then intervene to improve them.

1.2.1 Technique analysis and feedback

"Technique analysis" is the term for a method of analysis used by coaches to understand how athletic skills are learned and then to lay the foundation for improved performance. The goal of technique analysis is achieved by determining the parameters that characterize technique and using them to represent the athlete's performance (Lees, 2002). A complete process of technique analysis includes the three steps of observation and information gathering, diagnosis or identification of technique errors, and remediation or intervention to improve performance and achieve the desired outcome (McPherson, 1990; Knudson and Morrison, 1997). However, some authors believe that the complicated process of diagnosis and intervention requires even more steps than technique analysis, especially when it comes to quantitative analysis (Carr and Carr, 1997; McGinnis, 2013). Given the little attention authors pay to this distinction, we can conclude that the role of technique analysis is limited to laying the groundwork for providing feedback and should be separated from it.

Approaches to technique analysis can be either qualitative or quantitative. Starting from qualitative analysis, technique analysis develops primarily on the basis of the application of mechanical principles, also known as "biomechanical principles of movement," in addition to subjective observation and interpretation of movement. As a basis for the systematic approach, the ideas of phase analysis, temporal analysis (Knudson, 2013), and critical feature extraction (Sewell et al., 2014) have emerged to assist coaches in technique evaluation. With the increase of data collection methods in sports, it has become more practical to use them in technique evaluation, commonly referred to as quantitative technique evaluation which provides the coach with more accurate and detailed information. According to the common approach, a wide range of instrumented data collection methods are used to quantify performance skills, such as kinematic, and kinetic analysis. By analyzing the collected data, key parameters related to technique can be identified.

One of the most important roles of coaches is to provide regular feedback to the athletes and guide them efficiently during training sessions. Using a variety of visualization tools, a coach tries to help athletes understand and correct their mistakes. The positive effects of feedback on motor learning have been supported by many studies, especially when it comes to complex tasks such as sports activities (Wulf and Shea, 2002; Sigrist et al., 2013). New feedback devices such as cameras and virtual reality platforms (Mestre et al., 2011), smartwatches (Lopez et al., 2019), or data visualization tools (Blandin et al., 2008) combined with data analytics and artificial intelligence methods help coaches provide quantitative, more accurate, and detailed feedback to athletes, resulting in efficient training sessions.

To better discuss the metrics a swim coach must consider, the swimming phases a swimmer goes through during a trial should be examined. Looking at a complete trial, shown qualitatively in Figure 1.1, competitive swimming can be segmented into three main phases start, free-swimming, and turn (Figure 1.1, A-I to A-III) (Mooney et al., 2016b). From the moment the buzzer sounds until the swimmer reaches the 15-metre mark, the start is distinguished, which is usually subdivided into more detailed sub-phases such as block, flight, entry, glide, and leg kicking or stroke preparation (Figure 1.1, B-I), based on the kinematic motion profile (Vantorre et al., 2010). When the swimmer starts swimming from inside the water, the three phases before glide should be replaced by the wall push-off phase (Figure 1.1, B-II). According to FINA rules, the start phases can continue to a maximum of 15 m from the wall. The free-swimming phase consists of stroke cycles divided into different sub-phases depending on the style. The example for front crawl style is described in Figure 1.1, C-I to C-IV on the right arm. The arm phases are entry, pull, push, and recovery (Chollet et al., 2000). The turn (tumble turn for front crawl and backstroke or simple turn for butterfly and breaststroke) can also be divided into smaller phases (Figure 1.1, D-I to D-V) of wall approach, rotation, wall contact or push-off, glide, and stroke preparation (Slawson et al., 2012).

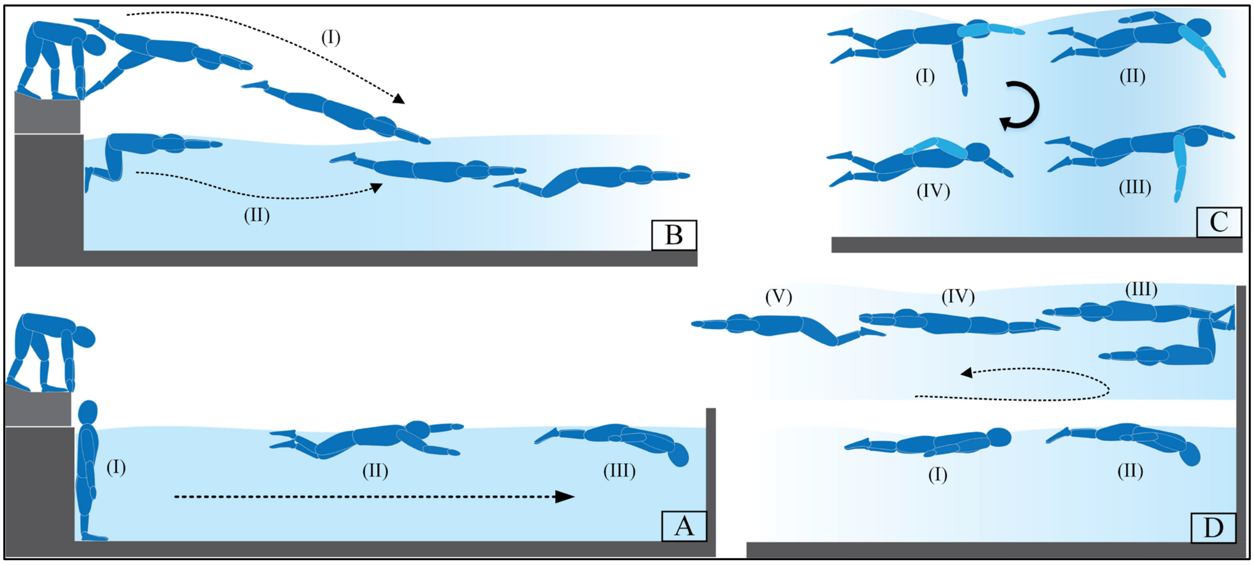

Figure 1.1 – Competitive swimming phases from wall to wall for a trial in front crawl. (A) The three main phases of start, free-swimming and turn. (B) Start phases (I) from the block or (II) from inside the water. (C) Stroke cycle phases of (I) entry, (II) pull, (III) push and (IV) recovery on the right arm for front crawl style. (D) Turn phases including (I) wall approach, (II) rotation, (III) wall contact or push-off, (IV) glide, and (V) stroke preparation.

Since a swimmer must master all phases to win the race, a detailed training plan to improve swimmer's performance in all phases is necessary to prepare them for competition. Coaches can be considered as the link between research and practice, and it is important to understand their views on optimizing training sessions (Lyle and Cushion, 2010). A survey of 298 competitive swimming coaches in the United States was conducted to obtain a general picture of coaching practices and perceptions during training sessions (Mooney et al., 2016a). They were asked about their coaching experience, key sport science areas they consider during training sessions, and the types of analytic devices they commonly use. Based on the survey results, biomechanics (motion kinematics and kinetics) was indicated as the most significant area of sport science on the coaches' priority list. Given the importance of proper technique in swimming and decades of research on the biomechanical principles of the sport, understanding the biomechanics of swimming has contributed much to current coaching techniques (Payton et al., 2002; Toussaint and Truijens, 2005). Among the performance-related indices considered most important in swimming, there were the most responses for temporal parameters (e.g., splits), body positioning and posture, start and turn phases specific parameters, and kinematic parameters (e.g., stroke length, velocity, acceleration). Although start and turn parameters overlap with the temporal and kinematic groups, they are listed separately due to the high response rate among participants. As a result, each coach must monitor a variety of metrics to effectively analyse swimmers' technique and provide feedback.

1.3 Objective evaluation for coaching assistance

Dealing with a team of swimmers with a variety of strengths and weaknesses in each phase, coaches must keep detailed records of each individual. They gather information about the swimmers' performance, such as body posture, duration and velocity of each phase, velocity loss due to drag, body coordination, and stroke efficiency to name a few. In addition to the swimming technique, the coach must also consider other aspects such as the physics and physiology of the swimmer (Zamparo et al., 2020), the training plan, workload adaptation, fatigue, and injury prevention (Matthews et al., 2017) during the training sessions. Coaches usually collect all this information through observation and simple measuring tools (e.g., stopwatch), which is subjective and prone to error. As a result, accurately obtaining such a large amount of information cannot be guaranteed and requires proper measurement systems to monitor the swimmer's performance and response to training instructions.

Swimming locomotion analysis is a powerful tool that can provide detailed information about a swimmer's technique and motion biomechanics, helping the coach provide more accurate feedback to the swimmer. In-pool stationary instruments such as tethered devices for propulsion force (Morouço et al., 2014) or velocity measurement (Clément et al., 2021) are still used as reference for velocity measurement. However, it is known that these devices require controlled conditions and cause many interventions in the pool to transform it into a laboratory, which in most cases changes the natural technique of the swimmers (Samson et al., 2018). Vision-based systems are another class of measurement systems that are less intrusive on swimming activity and are still considered as the gold standard for swimmers’ motion analysis.

With the development of cinematography in the last century, the use of motion picture cameras has increased in sports (Wilson, 2008). Optoelectronic systems can track the position of reflective markers attached to swimmer’s body and analyze the movement. The accuracy of these systems depends on the position of the cameras relative to each other, the position, number, and type of markers, and the movement of the markers within the capture volume (Maletsky et al., 2007). The use of optoelectronic systems is complicated in swimming due to the numerous practical shortcomings in aquatic environments. In addition to the time-consuming calibration, manual or automatic digitization of landmarks, and complicated procedure of transportation and installation underwater, it is inevitable that image distortions and the bubbles in water can cause the occlusion of markers in certain body orientations (Magalhaes et al., 2015). Swimming is classified as an individual indoor sport that requires a relatively large capture volume for motion analysis (Van der Kruk and Reijne, 2018), while optoelectronic systems are limited in terms of capturing volume to a few stroke cycles. The use of several reflective markers on swimmer's body increases drag, which significantly impedes swimming movements (Washino et al., 2019).

Considering the limitations of marker-based motion analysis in aquatic sports, the marker-less image processing are more suitable for motion analysis in swimming. The results of feasibility studies have shown that marker-less techniques are as reliable as manual digitization approaches in swimming, but further research is needed to prove this (Monnet et al., 2014). Thanks to recent advances in automatic image processing, new marker-less methods for motion analysis have been developed based on the extraction of the swimmer's silhouette in and out of the water and matching of the 3D kinematic models (Ceseracciu et al., 2011). The accuracy of silhouette recognition has been improved using a new convolutional neural network (Ascenso et al., 2020). However, these method needs to have the whole body in view to work properly. It also did not allow for the integration of underwater cameras with the cameras out of the water. Because marker-less techniques require a great deal of processing, and specialized cameras, they are still too expensive for daily training in swimming clubs.

Novel analysis systems that have emerged as a result of improvements in accuracy, size, and cost of microelectromechanical systems (MEMS) have received much attention in both the research and commercial communities as alternatives to previous approaches to motion analysis. Wearable inertial measurement units (IMUs) are used to measure motion kinematic parameters in a variety of activities including swimming. In conjunction with an accelerometer, gyroscope, and sometimes a magnetometer, IMUs are now adapted to aquatic environments with waterproof coatings and offer a new approach to swim coaching (Mooney et al., 2016b). This technology has facilitated the analysis of stroke mechanics, race performance, and training intensity, allowing for more efficient coaching with less trial and error. Despite the shortcomings of IMUs for motion analysis (e.g., random noise, signal bias and drift effect), IMUs can offer a highly portable and cost-effective solution to motion analysis and provide detailed information about a swimmer's technique while having minimal impact on performance. They do not impose any restriction to the capture volume, can even be a credible option as a replacement for high-precision optoelectronic systems if carefully positioned and calibrated (Guignard et al., 2021). IMUs can also be used to better analyse the fast swimming phases, such as start by the dive or turn, where visibility is limited by the change of medium or by bubbles and water reflections.

1.3.1 IMU-based technique evaluation and feedback

IMUs have been used to study swimming motion and extract spatio-temporal, kinematic, and kinetic parameters from both a general (e.g., number of laps and swimming time in each style) and a detailed perspective (e.g., hand trajectory in stroke cycles). Coaches should strive to gather information about a team's swimmers at both levels through observation, which is also inaccurate and prone to subjectivity. In a general view of the training, IMUs were used to detect major events in the pool such as turns (Jensen et al., 2013) between swimming laps or to differentiate between swimming styles (Wang et al., 2019). This information can help coaches guide training, but is not useful for competitive swimmers because it does not provide detailed information about their performance and coaches are less concerned about them following the training plan.

In a more detailed level, IMUs have been most commonly used to estimate the number and rate of strokes (Mooney et al., 2016b). The acceleration and angular velocity profiles obtained with IMU on the wrist revealed subtle changes in motion and its variation during multiple cycles. The hand pitch angle at the entry point, the effects of fatigue, and the angle of the elbow (Seifert et al., 2014) are examples of observable variables that facilitate a detailed and specific analysis of swimmers' hand movements. Quantifying the swimmer's kicking pattern is another relevant factor in free-swimming phase for coaches, especially for alternating swimming styles (front crawl and backstroke), where the movements of the upper and lower limbs are independent. IMUs were used to help the coach by estimating the rate and number of kicks (Fulton et al., 2011). With the introduction of advanced signal processing and machine learning techniques, IMUs have been used to estimate instantaneous velocity (Clément et al., 2021) or average velocity per stroke (Dadashi et al., 2015). Apart from the fact that researchers focus mainly on free-swimming phase, most of the extracted parameters are studied in isolation and are less related to swimmer's performance (denoted by propulsion, posture and efficiency), which is necessary to show IMUs application for performance evaluation.

Continuous acquisition of swimming characteristics is another advantage of IMUs over vision-based systems that makes it possible to study the inter-cyclic variability of a performance-related parameter such as velocity which is important for the coach to design of pacing strategies (Dadashi, 2014). High variability in performance has been shown to indicate fatigue and lack of endurance in athletes, which may be particularly the case in long-distance swimmers. The use of multiple IMUs on arms and legs allows the temporal phases of arms for alternating styles (Dadashi et al., 2013c) or arm and leg for simultaneous styles (Dadashi et al., 2013b) to be compared and the coordination index to be defined as a performance-related metric (Chollet et al., 2000, 2004), representing the inter-segmental delay of propulsive phases. However, the use of multiple wearable sensors is not practical in swimming because of the additional impact on the swimmer's technique and the complexity of their use during training sessions.

Coaches need to spend a lot of time working on start and turn techniques during training sessions, as these phases have been shown to be significantly related to a swimmer's overall performance. Due to the high speed of motion and visual errors caused by air bubbles and water reflections, these phases are difficult to study by vision-based methods (Guignard et al., 2017b), whereas IMUs are not affected by such limitations. Using IMUs to study start and turn phases is still at its preliminary stages. Qualitative detection of start sub-phases (block, flight, and glide phases) (Le Sage et al., 2012) and turn sub-phases (start and end of rotation) (Lee et al., 2011) for technique visualization are examples of studies conducted to date by IMUs on start and turn phases. Coaches, however, need more detailed analysis of start and turn, which is currently performed qualitatively, such as swimmer timing for turn (Nicol et al., 2019), or push force and acceleration (Hermosilla Perona et al., 2020).

The next step would be frequent, high-quality feedback at the same time or shortly after the activity, which can be considered a goal for successful coaching in swimming (Jefferies et al., 2012). IMUs have made the process of providing feedback easier and faster by providing low-volume data that can be easily transferred to other platforms for analysis and visualization with lower computational power needed. Therefore, the development of real-time methods for providing feedback with IMUs has attracted much attention (Lecoutere and Puers, 2016; Jeng, 2021). Examples of using IMUs for feedback are communicating the style, laps, and strokes (Silva et al., 2011) or hand movement during strokes (Ehab et al., 2020) to the coach. Given the challenges of data transmission in aquatic environments, it is expected the time delay between training and feedback to decrease as communication protocols achieve viable real-time performance (Rana and Mittal, 2021). IMUs can improve the coach feedback effect on swimmer's performance by providing autonomous feedback directly to themselves. A well-known example of this mode is movement sonification, which is used to support motor perception, motor control, and learning (Effenberg, 2007). Although the application of IMUs to provide feedback in sports is profound, swimming coaches do not benefit enough from it and there are fewer studies that focused on transferring to the coach. Furthermore, the effect of IMU-based feedback on performance has not been well studied in the literature, and researchers have mainly focused on the feasibility of swimming analysis with IMUs and have hardly gotten around to applying it in practice.

In general, studies focused more on front crawl style and free-swimming phase than start and turn phases when extracting parameters with IMUs. There are not enough data-based studies that demonstrate the usefulness of such parameters in practice by relating them to the swimmer's performance in each swimming phase. As a result, by providing superficial parameters, current solutions are tailored to the needs of recreational swimmers rather than competitive swimmers and coaches still rely on their own experience for performance evaluation. The use of IMUs for feedback to coaches and swimmers and their impact on performance improvement should also be investigated more. Further details on the current gaps in the literature will be provided in Chapter 2.

1.4 Thesis objectives

In this chapter, swimming was presented as one of the most competitive Olympic disciplines. The importance of training and the important role of coaches in the success of swimmers was emphasized. It is more difficult for swimmers to gain a worthwhile advantage over their competitors as they approach human body limits in swimming with our increasing knowledge of swimming biomechanics and its underlying mechanisms. The importance of focusing on all swimming phases is explained, and the critical role of the coach in analyzing technique and providing feedback for each phase is clarified. Considering the vast amount of information needed to manage a team of swimmers, the additional help of new technological analysis systems for swimming coaches becomes inevitable.

Through a brief introduction to current methods of evaluating swimmer performance, IMUs have been shown to be a credible replacement for vision-based or stationary in-pool measurement systems as they have overcome the limitations of these systems and are more suitable for use as coaching assistance in daily training. They have been used to extract parameters related to swimming performance that are useful for technique analysis. These studies have mainly focused on validating the extraction of free-swimming phase parameters. However, swimmers need to master all swimming phases, and the need for comprehensive performance evaluation with IMUs has not yet been met. It should also be considered that front crawl is the most commonly studied swimming style, as it is the most common even among recreational swimmers. Also, the use of IMUs to convey feedback to coaches and swimmers as the end goal of any analysis system has not been adequately explored, and its impact on swimmer performance should be evaluated.

Considering the above gaps and challenges, the research presented in this dissertation aims to develop a novel IMU-based analysis system for swimming that can be used in training. In order to develop a research strategy beneficial to the coach, their roles during a training session should be investigated. Three different but complementary roles can be identified for the coach (displayed in Figure 1.2), the first of which is to observe and gather as much information as possible about the swimmer’s performance. The coach observes the swimmer or uses simple measuring instruments such as a stopwatch to record the swimmer's timing in various exercises. They must devote considerable time to each swimmer on the team to extract and record the specific data for further analysis, which is usually impractical and results in more qualitative data collection. IMUs can contribute to this task by automatically collecting data in all swimming phases and swimming styles from multiple swimmers in parallel, giving the coach a comprehensive overview of the training session through quantitative values (Figure 1.2 - I).

Second, after gathering input through observation and measuring devices, there is a subjective evaluation of the swimmer's performance based on coach experiences to identify strengths and weaknesses. The coach performs this task in parallel with data collection, as the evaluation is ongoing while continuously receiving data from the swimmer. Because subjective performance evaluation is prone to error due to bias or misconceptions, IMUs can help coaches to improve the evaluation by an objective and quantitative analysis. They can verify their advice by a subsequent assessment of the swimmer using the IMU results again. Thus, the next main contribution of this study is to lay the foundation for comprehensive, objective technique analysis by estimating performance-related metrics at each phase, regardless of swimming style (Figure 1.2 - II).

The third role of the coach is to communicate to the swimmer the choices they are making to improve their performance. Verbal comments combined with a visual illustration of the correct movement or recorded times are common methods of feedback communication. However, the effect of such feedback communication methods is compromised by possible misunderstandings, and the swimmer's learning and progress can only be monitored qualitatively. The third contribution that IMUs can make is to provide quantitative feedback to both the coach and the swimmer to engage them more effectively in the learning loop. Even though the coach strives to remain objective in all three roles, the coach's inherent limitations in taking in information, subjectivity in analyzing the swimmer's technique, and inefficiency in providing feedback should be considered (Figure 1.2 - III).

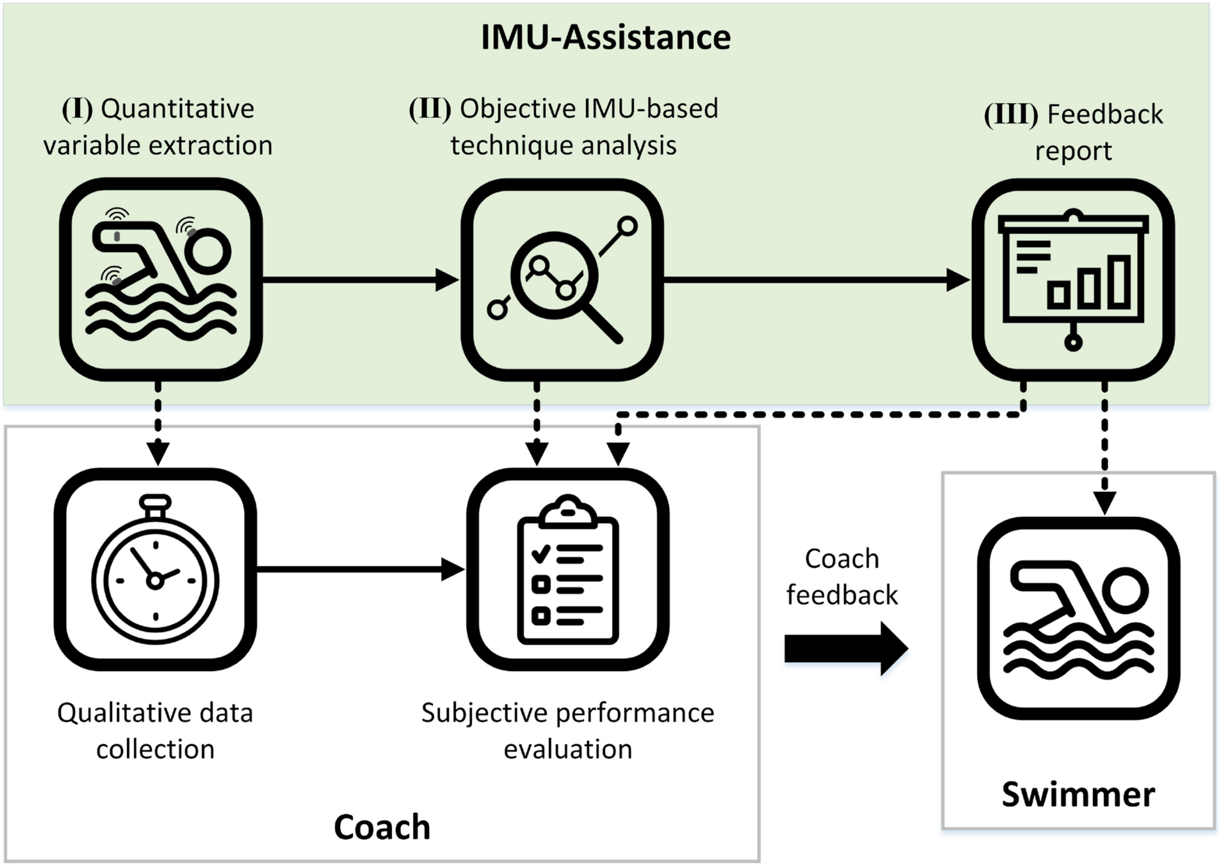

Figure 1.2 – Thesis principal objectives and contributions to the roles of swimming coaches in a training session.

With this thesis, I plan to contribute to each of the three roles of the coach in training sessions by using wearables for more efficient training and filling the existing gaps in the literature. The following objectives are addressed in this thesis:

i. Development of an easy-to-use novel analysis method that extracts quantitative information about swimming without impeding or minimally affecting the swimmer. This implies to capture all phases of wall-to-wall swimming with a single IMU in order to provide the coach with a comprehensive and detailed overview at the end. The method is intended to provide valid information covering the four major swimming styles for competitive swimmers.

ii. Objective technique analysis and performance evaluation of swimmers using the developed analysis method. Considering the complexity of evaluating all swimming phases simultaneously based on a single sensor, the method aims to provide a phase-based performance evaluation allowing the coach a more explicit and individual advice based on the swimmer's strengths and weaknesses in each phase.

iii. Development of a practical strategy for providing feedback to the coach and swimmer during training sessions using objective metrics of performance and assessment of the effectiveness of such feedback - as an assistant to the coach - on swimmer's progress.

1.5 Thesis outline

This thesis first reviews the current state of the art in swimming assessment with IMUs and the challenges involved. The three main aspects of acquiring kinematic parameters of swimming, evaluating swimmer's performance, and providing feedback with IMUs will be addressed, along with their limitations. We will then propose a novel approach to swimming analysis in a training session that commences by scanning the entire training session for swimming bout detection and extends to the detection of wall-to-wall swimming phases. Based on this approach, the best sensor position for subsequent steps is determined. This approach is then used to extract the kinematic and spatio-temporal parameters of each swimming phase and perform a comprehensive performance evaluation by estimating phase-based goal metrics in each swimming phase. The proposed goal metrics will then be evaluated for monitoring swimmers in training sessions and tracking their progress. Finally, the proposed performance evaluation method is provided to the coach as an assistant named SmartSwim to guide the swimmers more efficiently, the effects of which is evaluated on swimmers' performance.

This thesis consists of seven main chapters divided into four parts, shown in Figure 1.3. For clarity, shorter versions of the names of the parts and chapters are used in this figure.

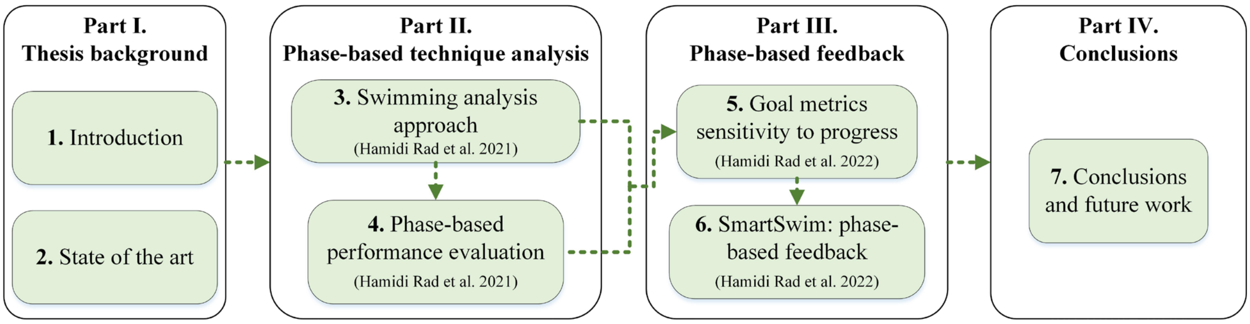

Figure 1.3 – Outline of the dissertation, including four parts and seven chapters. Chapters 3, 4, 5, and 6 are based on published work, as indicated in parentheses.

Part I – Introduction and Background: this part explains the objectives of the work and gives an insight into the state-of-the-art studies using IMUs for the analysis of swimming.

- **Chapter 1 –** (current chapter) presents the importance of coaching in a competitive sport such as swimming. It provides a comprehensive overview of the needs of swimming coaches, the role of technology to provide objective evaluation to swimmers, and their existing challenges. Among the existing measurement systems, IMUs were given more focus with an introduction to the literature. To define the objectives of this thesis, this chapter briefly describes these studies and highlights the main existing research gaps that this thesis aims to address. These gaps are more clarified in the next chapter.

- **Chapter 2 –** presents the current state of the art in swim training with measurement systems, focusing on IMUs. First, the tasks of a sports coach are explained and it is clarified how technology can contribute to their duties. Then, the role of IMUs in sports is examined in more detail and the types of parameters they can extract are discussed. The chapter continues with a detailed overview of the applications of IMUs in swimming analysis and the existing gaps on the way to an IMU-based performance evaluation system. Finally, a brief overview of existing measurement systems on the market is provided to support the coaches' need for a novel approach to the use of IMUs in swimming analysis.

Part II – Phase-based technique analysis with IMU: the second part discusses the proposed IMU-based approach to the technique analysis of swimmers and its application to the phase-based performance evaluation of swimming in all four swimming styles.

- **Chapter 3 –** proposes a macro-micro approach to swimming analysis that first deals with the entire training session and narrows down to the detection of swimming phases based on the IMU signals. The developed algorithms for this approach are discussed in four different swimming styles for the acceleration and angular velocity signals of the four main sensor positions of wrists, head, sacrum and shanks. The results of the algorithms are validated using a series of cameras mounted on the pool wall and recording all swimming laps. Event detection errors of the four sensor positions are also compared to find an optimal position for a single-sensor measurement system.

- **Chapter 4 –** introduces a phase-based performance evaluation method using the algorithms developed in Chapter 3. The method proposed in this chapter is an extension of the macro-micro approach to extract a set of spatio-temporal parameters in each swimming phase. A feature selection algorithm is used to select the parameters that are highly associated with the swimmer's performance in each phase. A swimmer's performance is quantified based on a set of phase-specific goal metrics defined using the actual swimmer's velocity as measured by a reference tethered speedometer. The selected parameters are then used to estimate the goal metrics based on regression models. In this chapter, performance evaluation models are developed for each swimming phase in the four main swimming styles.

Part III – Phase-based feedback for coaching with IMU: using the models developed in the previous part, we first analyzed the sensitivity of the estimated goal metrics in relation to the progress of a swimmer during several months of training. We then provided the goal metrics as feedback for a swim team to evaluate its effect on progress.

- **Chapter 5 –** describes the change in phase-based goal metrics in front crawl style during two and a half months of training measured by weekly tests. The performance level of each swimmer is quantified using lap times recorded by the coach, and the association between the phase-based goal metrics obtained by IMU and performance level is examined in this chapter.

- **Chapter 6 –** investigates the effect of SmartSwim feedback, used as an assistant to the coach, on the progress of young front crawl swimmers. Swimmers on a team are divided into two groups, an experimental group and a control group, and the coach receives feedback only for swimmers in the experimental group. During the study, the coach adjusted the swimmers' training based on the feedback and the performances of the two groups were compared.

Part IV – Conclusions: this part summarizes the main achievements of this work for the field, the limitations of the proposed analysis system, and future work and perspective.

- **Chapter 7 –** discusses the contributions of the current work to swimming analysis with IMUs, its limitations, and possible future work.

Chapter 2 Coaching and Technology: IMU in sports with a focus on competitive swimming

The purpose of this chapter is to provide an overview of the current state of the art regarding the contribution of IMUs to competitive swimmer training and the existing gaps that need to be addressed. Since this thesis proposes a novel approach based on wearable IMUs to support swim coaches, the first step is to identify the duties of a coach and clarify the contribution of IMU technology to them. Therefore, the overview begins with the roles of a coach in training and how technology can assist them to enhance the quality of a training session. Among the various technologies that have been developed for motion analysis, emphasis will be placed on IMU and its role in technique analysis and feedback for swimming analysis. The studies in which IMUs have been used for parameter extraction, performance evaluation and feedback for competitive swimming will be discussed to provide an overview of the latest developments and the existing gaps in this field. A brief overview of the IMU-based measurement systems available on the market and the parameters they provide follows. The concluding remarks present the gaps that this study aims to fill.

2.1 Sports coaching roles and technology

Motion analysis is a tool frequently used by coaches that includes personal observation or cameras and more sophisticated measurement systems. Since the approach to swimming analysis taken in this thesis is based on motion analysis, it is necessary to examine how this approach contributes to the coach's duties in training sessions.

2.1.1 Coaching duties and motion analysis

To obtain a comprehensive overview of the needs of coaches, the assessments they perform in training sessions should be first examined. According to "Sports training principles" by Frank W. Dick (Dick, 2007), a coach always struggles with answering four main questions: **(i)** "What does it take to win?", **(ii)** "What is the athlete's path to success?", **(iii)** "What are the risks along the path?", and **(iv)** "How do we learn from the process and affect change?". The author indicates that the coach should regularly conduct multiple evaluations and analyses to answer these questions and guide athletes through the training sessions.

To determine what it takes to win, the coach should first conduct a competition analysis that focuses on the strengths of competitors to realistically situate the athletes among their rivals

(Luteberget et al., 2018). The coach should continuously analyze the athletes' technique during training to identify the strengths and weaknesses. In fact, the coach measures the mechanical features to explain the results of the competition analysis (Lees, 2002). To measure the underlying maximal physiological capacity that supports proper technique, the coach should analyze the physical and physiological condition of athletes. Developing training programs based on sound physiological principles requires an understanding of acute metabolic responses to training and their changes over time (Opondo et al., 2015).

The training plan and comparison between the actual and planned training of each athlete is necessary to increase the efficiency of the training sessions, which is the next responsibility of the coach to determine the athlete's path to success. Appropriate training load combined with adequate recovery is essential to achieve optimal performance while minimizing the risk of overexertion, overtraining, injury, and illness (Hamlin et al., 2019). To monitor the potential risks on an athlete's path to success, coaches must place safety and injury prevention at the center of their training strategies (Verhagen et al., 2010). The simplest method of monitoring injuries and illnesses is to record the occurrence and healing process of an athlete's injury and use it to adjust the training plan. Finally, the athlete's learning process is tracked by the coach and improved through regular feedback, the benefits of which have been demonstrated by numerous studies, especially in complex tasks such as most athletic activities (Sigrist et al., 2013).

Based on the above analyses required for answering the four coaching questions and the relationships between them, a block diagram can be conceptualized (Figure 2.1). Coaches begin by analyzing competitions to determine the characteristics of success and set realistic goals for athletes. The required characteristics are considered in both technique and physiological analysis. The coach decides on the required skills or "mechanics" and the underlying physiology to achieve the defined goals. By this point, the coach knows what is needed to win the competition and uses these ideas to define the training goals. Training should be planned and continuously analyzed to achieve the goals set before the competition. The results of the training analysis are also relevant to assessing the risk of injury and should be continually updated based on athlete's progress. Finally, providing feedback to athletes and helping them learn and improve is a task that is ongoing parallel to all coaching responsibilities. Training objectives should be updated based on feedback to make training sessions as efficient as possible.

The correct accomplishment of the above tasks for each athlete requires the support of measurement systems and monitoring devices. Based on the current methods and technologies used to accomplish each coaching duty, Table 2.1 provides a summary of the analyses with examples of technology used for each task.

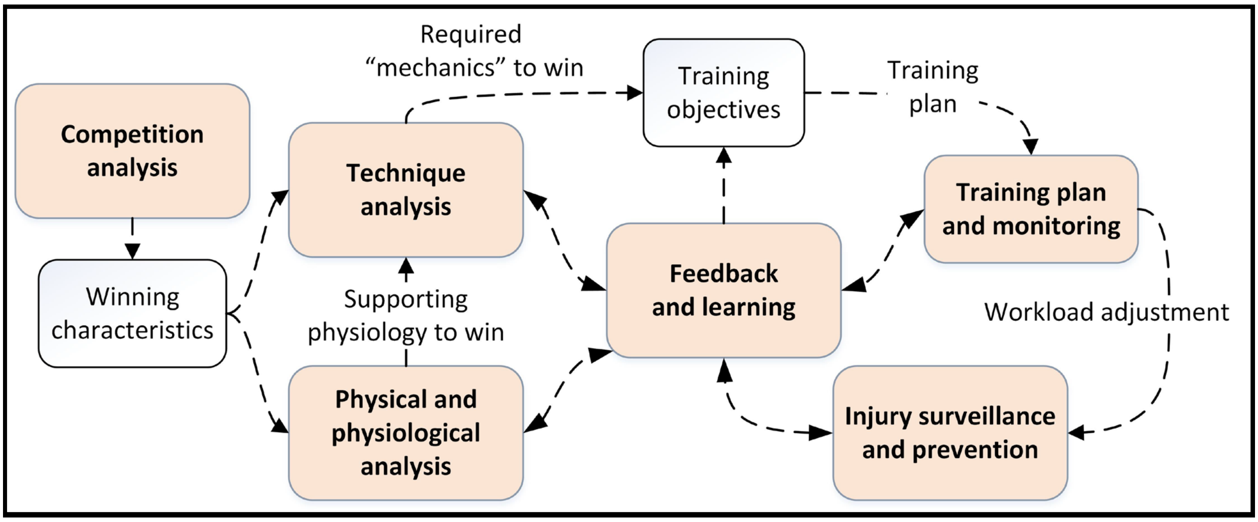

Figure 2.1 – Block diagram of coaching roles (colored blocks) in a training session

Table 2.1 – The tasks of a coach to answer the four main coaching questions. Examples are given of the technical tools used for each evaluation. Adapted from (Dick, 2007).

Coaching question	Relevant evaluations and analyses	Examples of current technology
(i)	Competition analysis	GPS-based measurement systems, Software based analysis tools
	Technique analysis	kinematic and kinetic analysis
	Physical and physiological analysis	VO_2 max and other max capability assessments, speed-HR-lactate assessments, power consumption measurement
(ii)	Training plan and monitoring	Spread sheets, training management platforms
(iii)	Injury surveillance and prevention	Software based recording systems, isokinetic dynamometer, goniometer, force plate, kinematic assessment
(iv)	Feedback and learning	Various data feedback tools such as smartwatches and other wearables with data visualizations

According to Figure 2.1 and Table 2.1, the coach's roles are interrelated, and the results of each role influence the others. Based on this categorization, motion analysis can be found among the examples of several coaching tasks, such as technique analysis, injury surveillance and feedback. It can also contribute indirectly to competition analysis or the planning of the training sessions. However, the immediate importance of motion analysis technologies in everyday training can be identified in the two blocks of technique analysis and feedback and learning. Depending on the motor task, nuances in movement technique that are difficult for human to perceive can determine victory or defeat. This is where motion analysis can help coaches by capturing the movements with high accuracy and resolution (Pueo, 2016). Since providing feedback is related to different roles of a coach, it was separated from technique analysis. However, these two duties are closely related, as the results of technique analysis form the basis for intervention and feedback. Consequently, the use of motion analysis for technique analysis is also directly beneficial for feedback to athletes.

2.1.2 Feedback for sports coaching

Feedback can be categorized by different components such as the origin, modality, and timing. From the origin perspective, the feedback can be intrinsic or extrinsic (Magill, 1994). Intrinsic or inherent feedback comes from within the body, while extrinsic or augmented feedback is additional information provided by an external source, such as a coach or measurement systems. Visual, auditory, and tactile modalities are the most commonly used for providing feedback (Sigrist et al., 2013). Choosing the correct feedback modality depends on human perceptual and cognition abilities during the activity (Jakus et al., 2017). The cognitive load of feedback should not be too high, as this leads to a negative effect of distraction (Stojmenova et al., 2018). From another important aspect, feedback can be given in three different times: before, during (real-time or concurrent feedback), and after the movement (terminal feedback) (Mononen, 2007). Feedback given before the movement reflects previous tasks the person has performed, such as notes from the last session. Concurrent feedback can be received intrinsically or extrinsically during the task, in real-time or with a certain short or longer delay depending on the time needed for computation and communication. Terminal feedback is given when the task is completed or even some time later.

Feedback is proven to have a positive impact on the motor learning process if understandable feedback is given in an appropriate form at the right time (Kos and Umek, 2018a). Sport activities are defined as complex learning tasks (Sigrist et al., 2013) and the use of feedback is a proven means to enhance the learning process of athletes. The main purpose of using feedback in sport is to support and accelerate the motor learning process of athletes (Effenberg and Schmitz, 2018). Three types of feedback loops are presented in Figure 2.2 depending on the involvement of the coach and technical equipment (Kos and Umek, 2018a). In traditional coaching, the coach analyses the technique of the athletes by observation and then provides feedback to them directly using his/her own expertise (Figure 2.2, A). Using technological devices, the coach can obtain more detailed technical information and then gives a more objective and precise feedback to the athlete (Figure 2.2, B). The athlete can receive feedback directly from the measurement equipment in different modalities, detect their weaknesses and then learn the motor task in an autonomous manner (Figure 2.2, C).

Motion analysis methods have contributed much to this role of sports coaches. These technologies provide the coach with a detailed analysis of the athlete's performance and improve their decision-making process. The use of visual feedback from cameras was the first method to improve the quality of feedback that athletes receive from the coach. Cinematographic (Wilson, 2008) and markerless (Colyer et al., 2018) approaches have been used to quantify feedback from videos and increase accuracy, but they suffer from several limitations such as cumbersome installation and calibration or limited capture volume. Recent technological developments and improvements in accuracy, cost and size of MEMS have IMUs as a plausible alternative to other motion tracking systems for athletes and providing feedback to them. An IMU consists of an accelerometer, a gyroscope, and often a magnetometer. Together with the acceleration and angular velocity provided by the accelerometer and gyroscope modules, the orientation of the device can be determined by combining the two (data fusion). The magnetometer measures the earth's magnetic field like a compass and helps estimate the orientation of the sensor.

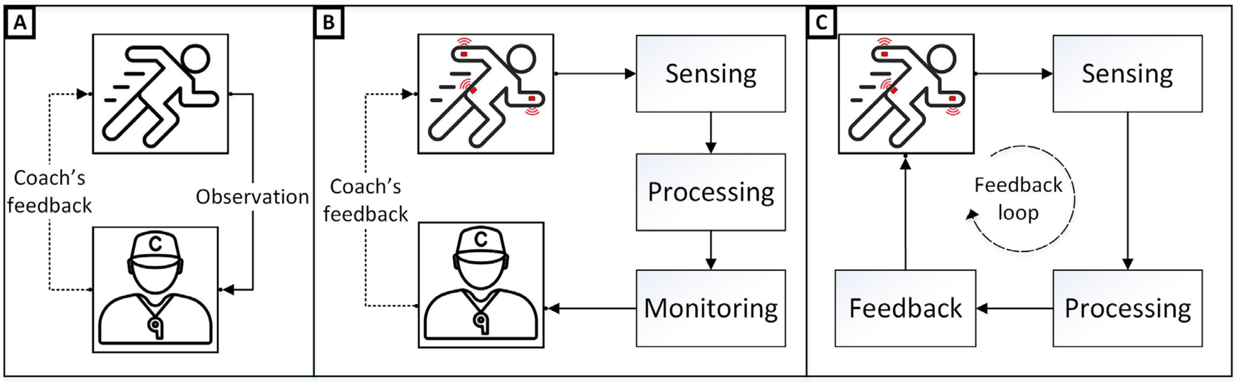

Figure 2.2 – Three types of technique analysis and feedback loops, based on coach involvement and measurement devices: **(A)** coach-based feedback, **(B)** coach-based feedback with technology equipment, and **(C)** autonomous feedback during technology-enhanced motor learning. Adapted from (Kos and Umek, 2018a).

2.1.3 IMUs in sports

For using IMUs for sports applications, several factors should be considered to perform effective measurements and reliable analysis. The inherent errors of the accelerometer and gyroscope caused by the imperfect physical properties of MEMS can lead to drift errors when integrated over time, which should be handled by signal processing approaches such as Kalman filter (Narasimhappa et al., 2019) or by motion-based techniques such as zero velocity update (Do and Tan, 2019). It should be noted that sensor positioning on athlete's body does not interfere with their actions or restrict their freedom of movement. Proper fixation of the sensor is an issue, as it can move due to external loads (e.g., water resistance in aquatic sports) and rapid movements, the effect of which is not investigated in the literature. In addition to this sensor wiggle, the use of IMUs as skin markers also raises the problem of soft tissue artifacts (Barré et al., 2015), which originates from the relative motion between the skin and the underlying bones. The motion magnitude of the sensor motion with respect to the bone can be in the order of a few centimeters, depending on the activity and placement of the sensor (Peters et al., 2010). Consequently, the ability of algorithms to accurately measure body motion depends on both sensor position and proper fixation.

Despite the technical limitations, IMUs are the most mobile systems that can be integrated into sports equipment, and they do not depend on a base station or external signals. They can detect very fast movements, which makes them even more attractive for individual sports. Athletes can accurately track their performance using IMU-based parameters not only during each training session, but also over weeks and seasons. The use of IMUs does not limit the coach in terms of capturing volume which is a big advantage for sports to record the athlete's actual performance.

As a result, IMUs can bring a lot of freedom to athletes and coaches in individual sports due to their availability, portability, and detailed technique analysis compared to other measurement systems. In general, the IMU systems used for athletes should be lightweight and small to minimize interference with their activity, and it should be quick to set up for daily use. It should function properly in the target environment in terms of temperature, shock and vibration, humidity or moisture. For long-term use, such as monitoring a marathon, an energy-efficient IMU should be used to avoid the risk of malfunction (Camomilla et al., 2018). Depending on the application, the sampling frequency should be high enough to capture all useful information from the motion, but at least two times the highest frequency of interest in the signal according to the Nyquist-Shannon sampling theorem (Woodman, 2007).

Parameters derived from IMU signals in sports can be divided into three categories: spatio-temporal, kinematic, and kinetic. Spatio-temporal parameters are usually extracted by detecting certain features in the signals that represent an event or phase of the athlete's activity. Some examples are the detection of moments related to the beginning or end of an activity, the identification of movement phases and important data segments, and the estimation of time intervals or dominant frequencies in cyclic movements. Kinematic parameters refer to the parameters obtained using the linear and angular forms of position, velocity, or acceleration derived respectively from the accelerometer and gyroscope of the IMUs. Estimation of the absolute orientation of the sensor is another important output of IMUs, which is used for orientation analysis of the sports equipment or the athlete's limbs. It is also necessary to separate gravity acceleration from motion acceleration, which is useful for estimating absolute kinematic parameters. Kinetic parameters such as forces, moments, power, or stiffness be estimated using the parameters obtained from IMUs along with relevant models of human body (Koning et al., 2015).

All of the three above categories can be used for technique analysis of athletes. Spatio-temporal parameters were used for technique analysis in both cyclic and non-cyclic tasks. Critical temporal events and task phases in ski jumping (Chardonnens et al., 2013), basketball (Straeten et al., 2019), baseball swing (Punchihewa et al., 2019), swimming tumble turn (Slawson et al., 2012) or soccer turning manoeuvers (Nedergaard et al., 2014) are examples of using IMUs to study non-cyclic activities. More studies are being conducted on cyclic tasks because extracting spatio-temporal parameters involves identifying a stride, step, or stroke event and then specifying the number, rate, and duration of each cycle, or a deeper analysis of the events within each cycle and dividing it into smaller phases (Camomilla et al., 2018). Stroke duration and number are extracted in canoeing (Galipeau, 2018), kayaking (Fernandes et al., 2021) and swimming on different positions and styles (Chakravorti et al., 2013; Fantozzi et al., 2022). The frequency of strides and steps are assessed in running (Gouttebarge et al., 2015), skating (Stetter et al., 2016), cycling (Fudickar et al., 2020) and cross-country skiing (Fasel et al., 2015)

IMU data can be used to track the athlete’s body center of mass (CoM) as a commonly used reference point for calculations in sport biomechanics. CoM kinematics can be determined by integrating the absolute acceleration after removing the sensor drift effect. The forward velocity of CoM is of great importance and has been studied with IMUs in sports such as alpine skiing (Fasel et al., 2016) or running based on step rate measurements (Neville et al., 2015). To reduce errors in instantaneous velocity estimation, average velocity during a cycle or phase can be estimated, e.g., for swimming stroke (Dadashi et al., 2015), swimming lap (Bächlin and Tröster, 2012), running cycle (Chew et al., 2018). The orientation of the body segment or sports equipment can usually be determined by data fusion of multiple sensors, as in the case of hip flexion during sprint (Nagahara et al., 2020), running on a track (Strohrmann et al., 2012), during a golf swing (Kim and Park, 2020), and snowboarding (Zihajehzadeh et al., 2015). Estimation of dynamic parameters with IMUs has been studied in specific cases in sports, such as hand force exerted on the javelin during the throw (Särkkä et al., 2016), strike force on a punching bag (Nakano et al., 2014), or IMU signals cross-correlation with in-sole pressure of skier (Yu et al., 2016), as it is difficult to evaluate the external forces and moments for validation (Camomilla et al., 2018).

Another application of IMUs in sports is identification and classification of athlete's activity in different contexts, e.g., standing walking, jumping and shuffling in netball (Smith and Bedford, 2020), swimming styles (Tarasevicius and Serackis, 2020), volleyball actions (Vales-Alonso et al., 2015) or skateboarding (Groh et al., 2016). To monitor the external training load of athletes, trunk acceleration is proposed as a relevant parameter. It is assumed that the mean square instantaneous rate of change of trunk acceleration is proportional to the external load studied with IMUs (Nedergaard et al., 2017). Because this parameter varies by sport, sport-specific validation is required, as has been done for volleyball (Jarning et al., 2015) or Gaelic football (O. Connor et al., 2016). Estimation of athletes' maximal velocity and strength is necessary to profile their motor capacity, which is then used to develop strength training programs. For this purpose, IMUs have been used because they can provide acceleration and velocity possible to be used for muscle strength determination (Gomez-Piriz et al., 2013; Jidovtseff and Laffaye, 2015).

As the data provided by IMUs has relatively low-volume and easy to transfer, these sensors have been incorporated into sport-specific feedback and coaching systems used for training analysis. After adding the proper user interface, IMUs can provide coaches and athletes with real-time visual, tactile, auditory or multi-modal information, specifically designed for the target sport. For example, IMU-based audio feedback systems have been developed for swimming (Schaffert et al., 2019), rowing (Schaffert et al., 2020) and canoeing (Wang et al., 2016b) during start and steady rowing conditions based on boat velocity and stroke rate. Aquatic sports like swimming are other promising sports for the use of feedback because of the high complexity of the activity and the difficulty of giving feedback during the activity. The kinematic parameters such as CoM velocity, stroke length, stroke rate, body rotations and balance are possible to extract from IMU data and transferred to the coach through a compatible interface (Bächlin and Tröster, 2012). The proof of concept for IMU-based feedback for coaching and training in other sports is demonstrated in tennis (Yang et al., 2017), skiing (Kos and Umek, 2018b), golf (Ghasemzadeh et al., 2009) and volleyball (Vales-Alonso et al., 2015).

2.2 IMUs in swimming

The aforementioned barriers to the quantitative use of cameras, as well as the requirements for an optimal analysis system, can be met with IMUs (Callaway et al., 2009). The use of this technology has attracted research attention, and commercially available devices have emerged to provide coaches with new insights into swimmer performance. A key element in the use of IMUs in swimming is minimizing the induced extra drag. Therefore, the use of miniature IMU and a minimal number of sensors with as little interaction with the water as possible is preferable. Although wrist is the most considered position for wearables in sport, arms are among the most dynamic limbs in swimming and generate greater drag. Furthermore, several factors influence swimmers' arm movements, such as swimming speed (Seifert et al., 2004), arm dominance (Figueiredo et al., 2012b), training intensity (Barden et al., 2011) and performance level (Nikodelis et al., 2005). There are a few studies comparing different sensor positions during swimming (Pansiot et al., 2010) to find the optimal position that extracts as much information as possible with acceptable accuracy for coaching. Despite all the advances in swimming analysis systems, the lack of a suitable system is still a major problem for the coaching community, and there is still a large gap between the needs of swim coaches for training sessions and the analysis systems available on the market (Mooney et al., 2016a). Therefore, a literature review of recent studies on swimming with IMUs and the technology available on the market is necessary to accurately identify the gaps.

2.2.1 Spatio-temporal parameters

Recording the lap time values of swimmer is regularly performed by coaches. Comparing with a stopwatch, Bächlin and Tröster estimated the lap time based on the acceleration from a single wrist IMU and reported an error of 0.3 s (Bächlin and Tröster, 2012). Callaway suggested a system of IMUs on different body locations (wrists, arms, lower and upper back) for extracting a group of kinematic parameters including the lap time (Callaway, 2015). The author used the lower back sensor data and reached an estimation error of 2.15 ± 1.93% (the absolute error values were not reported). Ganzevles et al. estimated the time between two consecutive push-off events as the lap time and used the acceleration signals of an IMU on the upper back for its estimation (Ganzevles et al., 2017). By thresholding the signal energy level, they managed to estimate the lap time with an error value of 0.74 ± 0.18 s compared to underwater cameras. Although lap time is a key metric related to the swimmer's performance, its extraction with IMUs highly depends on the sensor positions and it is not accurately investigated. A study over a head-mounted commercially available swimming analysis system shows that it can estimate lap time with a mean absolute percentage error under 5% for each stroke (Pla et al., 2021). However, most of the current commercially available swimming analysis systems did not report the accuracy of lap time detection (Mooney et al., 2016b). Therefore, it appears that accurate lap time estimation with IMUs is still an open area of research.

Swim start information that the coach tracks is generally limited to recording the time it takes the swimmer to be 15 m from the wall and possibly the reaction time (the time between the buzzer sounding and the swimmer leaving the block) (Cossor and Mason, 2001). Despite the performance of IMUs in tracking fast movements, less attention has been paid by researchers to the swimming start. Le Sage et al. developed a multi-sensor system that includes high-speed cameras above and below water, a force plate on start block, an IMU at the lower back, and a pressure pad with the ability to provide real-time audio and visual feedback to monitor elite swimmers (Le Sage et al., 2012). Using synchronized video images with the IMU data, the authors qualitatively analyzed the IMU acceleration signal during the start and separated the sub-phases (block and flight, entry and glide with stroke preparation) to extract key performance-related metrics (Figure 2.3). Using IMU as a stand-alone device to separate the sub-phases of start is challenging because the corresponding movements vary from place to place on the swimmer's body and have no immediate effect on the IMU data. For example, the exact moment at which the hand enters the water cannot be captured by the accelerometers based on what is known to date.

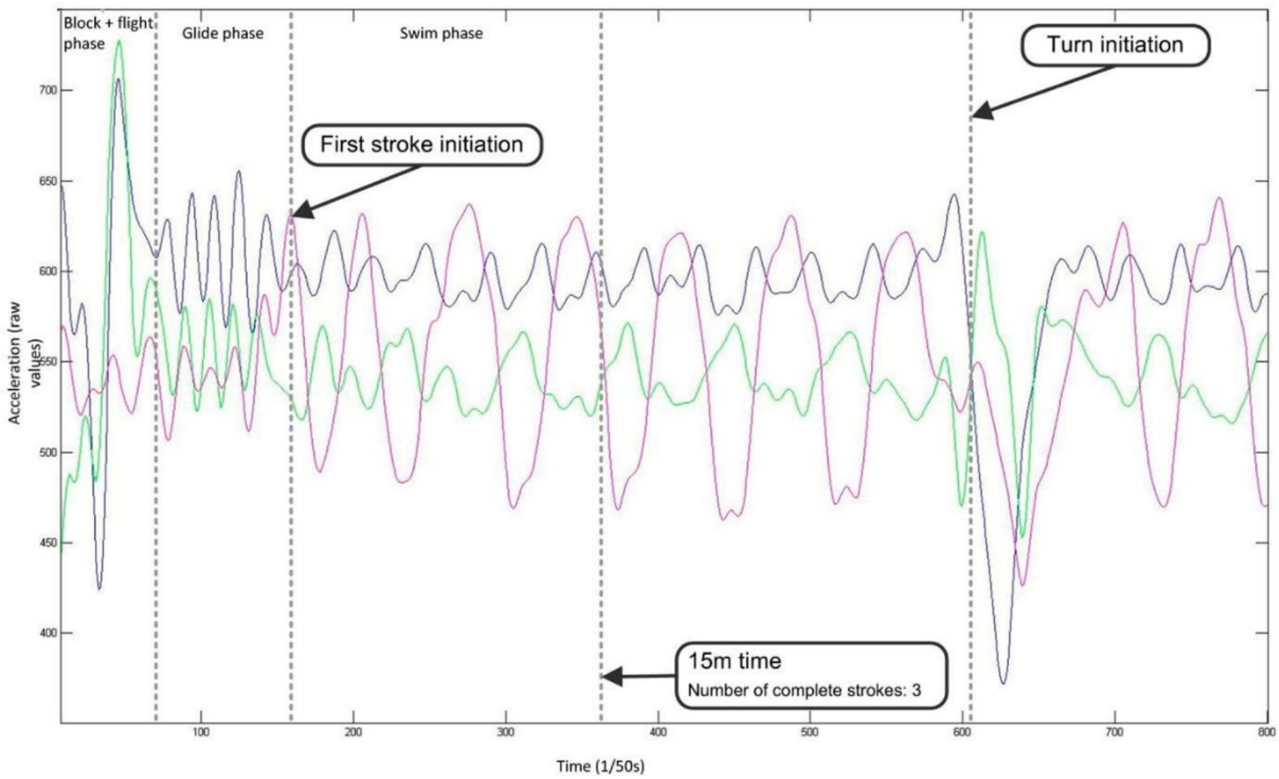

Figure 2.3 – Qualitative separation of swimming start on the acceleration signals from a back worn IMU with the aid of cameras. Adapted with permission from (Le Sage et al., 2012).

Despite its proven effect on overall swimmer performance in competitions (Sánchez et al., 2021), start has been barely studied using IMUs, mainly by estimating specific parameters during the sub-phases. Stamm et al. showed that push-off maximum velocity can be estimated as a performance-related metric by integrating the forward acceleration of a single IMU at the lower back (Stamm et al., 2013a). Compared to a velocity meter, the proposed method achieved a correlation coefficient of 0.94. Engel et al. also studied the underwater dolphin kicks during the sub-phase of stroke preparation and compared the duration of kick cycles estimated with IMUs and cameras over 110 cycles and found no significant difference between the two systems (Engel et al., 2020).

Analysis of the turn phase is usually performed qualitatively by coaches (e.g., the time between 5 m before the wall and 10 m after the wall) and has received less attention in IMU-based studies, although it makes a significant contribution to the final time of the race (Morais et al., 2018). Because the turn phase is easier to track at the body core, IMUs at the lower back were used in all studies, regardless of the type of turn (tumble of simple turn). The main findings were the qualitative segmentation of a full turn into more detailed sub-phases such as approach, rotation, push-off, and glide based on data from a few swimmers in tumble turn (Slawson et al., 2012). As a proof of concept, Lee et al. marked the differences between the tumble turns of two swimmers. Using the peak detection and zero crossing of the acceleration data, the authors were able to detect the temporal events of turn phase with an accuracy of 0.15 s (Lee et al., 2011). A recent study analysed the performance of a commercially available head-worn IMU that reports turn time, reaching a high coefficient of variation of 10.4% and 12.9% for tumble and simple turn respectively (Butterfield et al., 2021). Consequently, a deeper analysis of start and turn phases with more participants is needed to extract important performance-related kinematic parameters and arrive at more conclusive results in the application of IMU.

The counting of swimming laps and subsequent calculation of total swimming distance by IMUs is side result of studies (Brunner et al., 2019; Félix et al., 2019), as the detection of turns with a prior knowledge of pool length is sufficient for this purpose. The determination of swimming distance is of little importance for elite swimmers, as they always follow the plan set by the coach. However, open water training could benefit more from a swimming distance calculator as an alternative to GNSS tracking.

Most of the literature on the analysis of swimming with IMUs is essentially concerned with the free-swimming phase. The first application of IMUs to the analysis of swimming was the separation of stroke phases. Using three IMUs at the wrists and lower back, Dadashi et al. succeeded in measuring the changing angle between the sensors at the wrists and lower back and proposed a new approach for segmenting the stroke cycle (Dadashi et al., 2013c). This approach was further used to estimate the coordination index previously found to correspond to swimming skill level (Komar et al., 2012). The same concept was then followed for breaststroke using two IMUs at the wrist and lower leg within a hidden Markov model, resulting in an average correct phase detection of 93.5% for the arm stroke and 94.4% for the leg stroke (Dadashi et al., 2013b). Recent studies have attempted to more accurately identify the phases of the stroke cycle using the 3D trajectory of the wrist (Cortesi et al., 2019). They were able to obtain a low bias (0.8%, 0.6%, 0.5%, 1.4%) and a low root mean square error (2.9%, 2.8%, 2.3%, 3.5%) for the entry, pull, push and recovery phases, respectively.

Counting the number of strokes in a lap and the stroke rate are other representatives of swimmer's performance noticed by coaches (Maglischo, 2003). Since the effect of strokes is more visible on upper body, researchers used IMUs on wrists (Siirtola et al., 2011; Bächlin and Tröster, 2012) and back (Daukantas et al., 2008; Siirtola et al., 2011; Chakravorti et al., 2013) to calculate stroke count and rate. Depending on the style, researchers used peak detection techniques over acceleration signals to detect the strokes. A misdetection rate less than 1% was reported by Siirtola et al. for front crawl, breaststroke and backstroke styles based on wrist sensor. Beanland et al. used an IMU sensor on the head that worked well for counting the strokes in butterfly and breaststroke (correlations between 0.98 and 1.00 for manual and automatic stroke count detection). However, during front crawl and backstroke the swimmer tends to keep the head fixed and the stroke count algorithms did not work properly (Beanland et al., 2014).

Lower limb actions have been shown to contribute to streamlined positioning and propulsion of the body depending on the swimming style (Deschodt et al., 1999). The simplest approach to extracting the kick pattern is to use IMUs on the lower limbs, which resulted in a correlation coefficient of 0.96 with the reference values (Fulton et al., 2009). The same logic was used to determine the relationship between peak swimming speed and the kick rate in Paralympic front crawl swimmers (Fulton et al., 2011). Following a similar method and using zero-crossing of mediolateral angular velocity, Fantozzi et al. detected upward and downward leg motion by two IMUs on ankles. They were able to distinguish between propulsion and buoyancy kicks using a peak detection threshold of 100 °/s (Fantozzi et al., 2022). Since using wearables on lower limbs is uncomfortable and interferes with streamlining, it has been claimed that the front crawl kick pattern can be observed on the mediolateral axis of acceleration of a lower back IMU (Andreoni et al., 2015). However, the method of distinguishing between upper and lower limb actions via a lower back sensor is not explained by the authors.

2.2.2 Kinematic parameters

Although it is natural for coaches to track swimmers' performance in each style, it is necessary for an analysis system to identify the style type (i.e. front crawl, breaststroke, butterfly, and backstroke). For this purpose, signal processing of kinematic signals (e.g. acceleration) with minimal computational complexity were initially used, reaching overall recognition accuracy of 90.8%, 92.6%, and 88.8%, for classifying front crawl, breaststroke, and backstroke styles respectively (Siirtola et al., 2011). Ohgi et al. used descriptive statistics (e.g., mean, variance, skewness) from accelerometer data from a chest sensor and applied two methods: a multilayer neural network and a C4.5 decision tree for style identification. Both methods achieved similar accuracy of 91.1% in style classification (Ohgi et al., 2014). Kon et al. used acceleration signal features (mean, standard deviation and frequency-domain entropy) and classified the four styles with an accuracy greater than 95% (Kon et al., 2015).

More recent studies used machine learning or neural network classifiers as a more suitable and accurate solution for real-time analysis. Wang et al. used a single IMU sensor at lower back and extracted statistical parameters such as mean, mean absolute deviation, kurtosis, and energy of acceleration, angular velocity and magnetometer signals, which were inserted into a Hidden Markov model classifier to identify the style. The values for recall, precision, and F1 score for all four styles were higher than 0.91 (Wang et al., 2019). Considering the technique diversity between swimmers, style identification based on wrist motion is more difficult to handle when based only on signal processing approaches. Therefore, recent work has attempted to input acceleration and angular velocity signal features for a wrist-worn IMU into multilayer neural networks for a stronger, real-time algorithm (Brunner et al., 2019; Tarasevicius and Serackis, 2020), and in the best case Brunner et al. were able to achieve an F1 score of 97.4% for style identification. Since style identification is an initial step for deeper analysis of swimmer's performance, one should decide about the analysis approach based on the final goal parameters.

Another potential application of IMUs is to measure body alignment (roll and pitch) or the important angles of the swimmer's joints that contribute to performance such as knee, elbow, or shoulder, as the angles are important to monitor streamline shape and maximize propulsive forces (Toussaint and Truijens, 2005). The head and back have shown promise as locations for extracting pitch and roll angles, usually by representing the three-dimensional orientations and rotations of the swimmers' limbs using rotation matrices (Pansiot et al., 2010). Félix et al. proposed novel indicators based on trunk elevation, body balance and rotation for swimming performance evaluation (Félix et al., 2019), using an attitude and heading reference system (AHRS), and a gradient decent optimization algorithm (Madgwick et al., 2011). At least two IMUs should be used on the limbs attached to a joint to estimate the joint angle, since the angle is calculated based on the relative orientations for this purpose. Seifert et al. extracted knee and elbow angles during breaststroke and achieved an error between 0.09 rad and 0.15 rad from the reference system (Seifert et al., 2014). Elbow angle in front crawl strokes was estimated in a more recent study based on an artificial neural network trained by three minutes of ergometer swimming and then tested over 10 strokes during a second test. The root mean square difference of 7.75° was found between the estimated angle with two IMUs on the arm and the gold standard (Macaro et al., 2018). Guignard et al. compared the measured elbow angle based on two IMUs on upperarm and forearm with an optoelectronic system (Guignard et al., 2021), showing a median bias between the two systems lower than ±4° in the Bland-Altman analysis and a narrow limit of agreement (less than 15° amplitude between the 2.5^{th} and the 97.5^{th} percentiles).

As the most important parameter of performance, swimming velocity can reflect the final result of the swimmer's technique. The average velocity of the free-swimming phase (approximate stroke length divided by stroke rate) (Hagem et al., 2013b) or the entire lap (pool length divided by lap time) (Bächlin and Tröster, 2012) was estimated using the parameters explained so far. Thanks to recent advances in signal processing and machine learning, some studies have proposed new algorithms to remove the acceleration integration drift and extract the instantaneous velocity. Removing gravity acceleration using a Hamming window FIR filter from lower back IMU data was used by Stamm et al. for front crawl swimmers and resulted in an estimated instantaneous velocity within 4% of the reference values in the Bland-Altman plot (Stamm et al., 2013b). Similar results were reported by Dadashi et al. who used a geometric moving average change detection algorithm to account for integration drift (Dadashi et al., 2012). The same group then extended their research to a more comprehensive velocity estimation applicable in the real world using Gaussian (Dadashi et al., 2013d) and Bayesian (Dadashi et al., 2015) regression methods. The result was a relative error of 9.2% and 9.7% with respect to the reference, respectively. With the aim of extending the estimation of instantaneous velocity in swimming to Paralympic swimmers and to other swimming styles, Clément et al. used the driftless integration of forward acceleration of an IMU on lower back and validated it with a tethered speedometer (Clément et al., 2021). Considering the results of all trials, Bland-Altman analyses revealed a bias of 0.03-0.06 m/s with a 95% agreement limit of less than 0.31-0.80 m/s and a root mean square error range of 0.14-0.39 m/s between the two systems.

2.2.3 Kinetic parameters

Since the acceleration and deceleration of swimmer's body are directly related to the propulsive and drag forces, IMUs are likely to be an important tool for kinetic analysis of swimming. For example, propulsive force is shown to be a determinant of swimming velocity (Morouço et al., 2011). The extraction of kinetic parameters with IMUs has not been studied as much in swimming as in other sports due to the complicated nature of propulsive and drag forces in water (Mooney et al., 2016b). Dadashi et al. used a linear Bayesian model to estimate the energy expenditure of front crawl swimmers based on biomechanically interpretable descriptors extracted from four IMUs worn on the swimmers' forearms, sacrum, and right shank. High agreement was shown between the model output based on IMU and validation (correlation coefficient of 0.93) with a relative estimation error of 0.8 ± 9.4% (Dadashi et al., 2014).

Hand propulsive force is another important kinetic parameter studied mainly with pressure sensors and marker-based motion capture (Tsunokawa et al., 2018), which is mainly affected by limitations such as reduced visibility of attached reflective markers due to light scattering around the hand caused by bubbles or limited measurement range. Lanotte et al. used two instrumented paddles that measure the pressure difference between the palm and the back of the hand, and an IMU, which only displays the effects of these forces on hand acceleration (Lanotte et al., 2018). A recent study by Kadi et al. used a single IMU on the back of the hand to estimate hand propulsive force and compared it to a combination of pressure sensors and an underwater motion capture system (Kadi et al., 2022). The two systems showed good agreement in estimated force (19.59 ± 7.66 N and 19.36 ± 7.86 N for the reference system and IMU, respectively) and an intraclass correlation coefficient of 0.966. This study also showed that the additional drag force caused by the use of IMUs on hand is proportional to hand angle and velocity with respect to the direction of water flow and is significant at angles less than 30°. This is the main reason why IMUs are still limited for estimating propulsive forces in water, and further technological advances are needed to make them smaller and more reliable for swimming kinetics analysis.

Comparably, spatio-temporal and kinematic parameters are more investigated than kinetic parameters in swimming mainly due to the complicacy of force estimation under water and the extra drag force induced by IMUs. Given the parameters extracted for IMU data in these two categories, coaches can benefit from them in two main levels: **(i)** increasing the estimation accuracy of useful parameters in an organized manner and **(ii)** gaining new insights into the details of the swimmer's performance. General information such as lap time or swim distance in each swimming style can be recorded and tracked throughout the season for each swimmer. At the second level, coaches receive quantified analysis of parameters that were not measurable (e.g., duration of start and turn sub-phases, instantaneous velocity) or were only observed and measured qualitatively using traditional approaches (e.g., stroke count and rate). However, the review shows that researchers have focused on the free-swimming phase in front crawl style and neglected other phases and styles. Therefore, we plan to develop a comprehensive and reliable approach for swimming analysis that will provide coaches with performance-related spatio-temporal and kinematic parameters in all swimming phases, regardless of the style.

2.2.4 Performance evaluation

As the end goal of a swimmer, swimming faster is the focus of all coaching strategies and training procedures in swimming. Theoretically, the swimmer should: **(i)** produce the highest mechanical power to generate the maximum propulsive forces, **(ii)** avoid water resistance through proper body posture, and **(iii)** maintain the highest mechanical efficiency to achieve peak performance (Toussaint and Truijens, 2005). To assess the contribution of IMUs to performance evaluation, the extracted parameters should be examined for their relevance to swimming performance. Based on the parameters described in previous sections, lap time is the only parameter that reflects the swimmer's overall performance. The start and turn parameters extracted by the IMUs are limited to the detection of the events corresponding to the sub-phases of each phase and require a more detailed analysis to relate to the swimmer's performance.

For the free-swimming phase, researchers have claimed that some parameters are related to the swimmer's performance, while they do not provide evidence to relate them to the propulsion generated, the swimmer's posture, or the swimming efficiency. For example, stroke count and rate are used as indicators of swimmer performance and are often used in training sessions, while swimming at a high stroke rate does not guarantee higher propulsion or higher efficiency or less drag. The same is true for stroke cycle sub-phases or kick count and rate as they are not independently related to the performance factors and must be optimized based on the swimmer's profile. The coordination index is defined with three modalities of opposition, catch-up and superposition depending on the delay between arms or arms and legs, each modality being suitable for a different purpose (Seifert and Carmigniani, 2021). Opposition is more suitable for high-level swimmers, while superposition is a more economical modality appropriate for long-distance swimming (Chollet et al., 2000). Two new coordination indices are introduced recently between arms and legs as index of synchronization between arm and leg actions and inter-limb coordination as the relative foot position during successive arm stroke phases (Mezêncio et al., 2020). However the coordination index is relevant to the swimming efficiency, it needs to be considered along with other parameters (e.g., cycle velocity variation and stroke rate) to be used as a reliable performance predictor and assist the coach (Dadashi et al., 2016).

Head and trunk pitch angles both have crucial effects on the streamline shape of the body. The trunk roll angle can represent body rotation, which should have an average value of zero for symmetrical styles (Félix et al., 2019). Head rotation angle is another useful parameter that shows the effect of breathing on body alignment during front crawl (Pansiot et al., 2010). Developing an algorithm based on head pitch and roll angles in front crawl to detect breathing pattern, is another attempt towards providing posture information to the coach (Jeng, 2021). These angles are easily recorded with a single IMU, which is integrated into the swim cap or swim suit. The angles of the body joints can be interpreted as the orientation of the arms and legs, which are related to drag and propulsion. The major limitation in estimating body joint angles with IMUs is the high number of sensors needed on arms and legs as they move quickly and increase drag.

Velocity is one of the most important parameters that directly reflects swimming performance and can be used as a reliable measure in different swimming phases (Dadashi, 2014). Due to the drift problem that occurs when integrating acceleration, researchers have tried a variety of techniques to accurately estimate the swimmer's velocity during the free-swimming phase. However, velocity during start and turn sub-phases has not been specifically studied with IMUs, and researchers have focused primarily on the swimming styles of front crawl and breaststroke (Clément et al., 2021). Stroke length, or distance per stroke, is also a parameter relevant to the velocity that reflects stroke efficiency. This metric is approximated by multiplying the average velocity of the lap by the time per stroke (Bächlin and Tröster, 2012), ignoring the start and turn phases. As can be seen from the review, the estimation of metrics related to swimming performance with IMUs remains to be explored, as acceleration and angular velocity data are directly or indirectly related to propulsion and body posture. This data can also reflect swimming efficiency by comparing the acceleration generated in different axes with respect to the forward direction.

2.2.5 IMU-based feedback

According to a survey of third-level swim coaches in the United States, feedback is among the coaches' top four priorities in an analysis system beside ease of use, accessibility, easy-to-understand results (Mooney et al., 2016a). Converting hydrodynamic pressure on swimmer's palm to sound was the first type of concurrent feedback for swimmers that helped the swimmer maintain stroke velocity, and improve movement stability (Chollet et al., 1992). The same opinion was more recently expressed by Cesarini et al. using a set of piezo probes integrated into a pair of gloves for front crawl and breaststroke swimmers (Cesarini et al., 2016). Although IMUs have lot of potentials to provide feedback thanks to its portability and low-volume and easy to transfer data, few studies have used them for this purpose.

Using accelerometers on the wrist, lower back, and upper back, Bächlin proposed visual, tactile, and auditory feedback on average swim velocity, stroke time, and body orientation (Bächlin et al., 2009). ISwimCoach is a recently developed swim analysis system that detects and transmits correct hand movement (correct recovery, high elbow and exit compared to predefined trajectories) to the coach based on a wrist IMU, achieving 91% classification accuracy of incorrect strokes (Ehab et al., 2020). IMUs have been used in combination with other measurement systems such as a heart rate monitor and a temperature sensor to provide a range of kinematic and physiological information to the coach as more comprehensive feedback (Rocha and Correia, 2006). In a pilot study, tactile feedback from an IMU on lower back helped swimmers maintain the body rotation within a range of 40° to 50° (Li et al., 2016). Although only four swimmers participated in this study, two swimmers performed more balanced when they received feedback. Despite the existing studies on the use of IMUs for feedback, researchers have rarely reached the field test and only observed a few swimmers over a short period of time to show the effect of feedback on their performance. In addition, there are other types of feedback based on swimmer performance that have not yet been studied. Examples of useful types of feedback in swimming include feedback on the swimmer's performance progress during each training session or at the end of each lap.

2.2.6 Commercialized IMU-based systems

Regarding the use of IMUs for swimming analysis, several commercial measurement devices are now available. For ease of interaction with the device, most companies have opted for a wrist-worn design. Considering the patent applications that have surfaced in recent years, there is a growing interest in IMU-based solutions in sports and specifically swimming. However, few of these systems have validated their accuracy against gold standard (Mooney et al., 2016b) and researchers have recently begun to conduct studies on the validity of these systems

Mooney et al. compared the results of two commercially available swim activity monitors (Finis Swimsense® and Garmin Swim™) for identifying swimming style and calculating swim distance, lap time, stroke count, stroke rate, stroke length, and average speed with video recordings. Both devices identified the four swimming styles (overall sensitivity rate of 95.4% for Garmin and 96.4% for Finis) and there was no significant difference between the swim distance and video recording results. However, lap time and stroke count values were significantly different from the gold standard ($p < 0.05$), resulting in lower accuracy of stroke rate, stroke length, and average speed values (Mooney et al., 2017).

Lee et al. evaluated the accuracy of lap count, stroke count, and energy expenditure from two wrist-based monitors (Apple Watch S2, and Garmin Finex 3HR) with a total of 78 swimmers (Lee et al., 2018). Energy expenditure was compared with a portable respiratory gas analyzer (K4b2, Cosmed, Italy) and a swimming snorkel (Aqua Trainer Snorkel, Cosmed, Italy). The mean absolute percentage error of lap and stroke count measurements was less than 10% for Apple and about 20% for Garmin. However, the error in energy expenditure was high for both (ranging from 17.1% to 151.7% for Apple and 17.9% to 32.7% for Garmin), showing the poor performance of the two devices for this purpose. In another study, the VO2 Max reliability of Garmin Forerunner Fitness Watch 935 synchronised with a heart rate chest strap was evaluated by Muthusamy et al. in a study of 10 university swimmers in two trials. The results showed an intra-class correlation coefficient of 0.87 and a standard error of 0.231 ml/kg/min (Muthusamy et al., 2021). This indicates that improving swimming performance by targeting heart rate and VO2 Max is a viable option for wearables.

The validity and reliability of a head-worn device for analysing swimming performance (TritonWear, TritonWear Inc.®) was evaluated by Pla et al. in front crawl swimmers using a group of spatio-temporal parameters: Average speed, lap time, stroke count, stroke length, stroke rate, and stroke index (average speed × distance per stroke × cycle multiplier-2 for front crawl and backstroke and 1 for breaststroke and butterfly). The mean absolute percentage error in estimating lap time was less than 5% for each style. The accuracy of stroke count was higher for symmetrical swimming styles (mean absolute percentage error of 0, 2.4, 7.1 & 4.9% for butterfly, breaststroke, backstroke and freestyle respectively). The error value for stroke length, stroke rate, and stroke index was less than 5% for all styles (Pla et al., 2021).

Butterfield et al. evaluated more parameters (split time, stroke count and rate, average speed, distance per stroke, turn time, and time underwater) offered by the same device (TritonWear) in front crawl and breaststroke and compared them with three cameras above and below water (Butterfield et al., 2021). They observed a systematic bias for breaststroke distance per stroke ($p < 0.05$) and the coefficient of variation was lower than 10.4%, except for distance per stroke (14.64%) and time underwater (18.15%). The study suggests that the device can be used for basic metrics such as split- time, but the error in more complex measurements such as time underwater or turn- times makes them unreliable for detecting changes in performance.

An overview of the currently available products for swimming analysis based on IMUs provides valuable information about the favorable sensor position and the most common parameters offered (Table 2.2). It can be shown that they are mostly capable of measuring basic metrics such as stroke count and rate or average speed. Although useful for recreational swimmers, competitive swimmers need more accurate and comprehensive evaluation of different swimming phases, swimming styles and performance aspects to improve.

Most of the available systems used the wrist-worn design because it is more used in sports and easier for the swimmer to handle. Although the upper limbs are commonly used by researchers, they were able to extract basic parameters from wrist motion signals, which can also be seen in Table 2.2. Products based on the wrist provide general parameters that are more interesting for recreational swimmers rather than professionals. In addition, the wrist position is the least appropriate position in terms of changing the body profile and increasing the resistance force, which is an important factor in swimming. Head positioning has recently received more attention due to several advantages such as easier integration with swimwear (goggles or swimming cap) and proximity to eyes and ears for visual and auditory feedback. Furthermore, similar to the literature discussed, start and turn parameters are still massively ignored by commercial products, especially in the wrist-worn design. Feedback is mostly in the form of reports available during or shortly after the training session. Providing real-time feedback directly to the swimmer or coach has gained more attention with the introduction of head-worn systems (Table 2.2).

Table 2.2 – Commercially available swimming analysis systems based on IMUs.

			Swimmo	Swimovate Poolmate	Garmin fēnix® 5S Plus	Fitbit Charge 3 / flex 2	Speedo Misfit shine 2	MOOV Now	SUUNTO AMBIT3	Polar V800	Finis Swimsense	TritonWear	Phlex Swim	Incus Nova	Firebelly	FORM smart goggles	SwimBETTER	Swimtraxx
Sensor position		Head										•	•		•	•		•
		Back												•				
		Wrist	•	•	•	•	•	•	•	•	•						•	
Parameters categories	General	Style identification			•			•	•	•		•	•	•				•
		Drill detection^Δ			•				•			•	•					
		Lap count	•	•			•	•	•		•	•	•	•	•			•
		Lap time	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•
		SWOLF†		•	•				•	•	•	•	•					
		Swim distance	•	•	•	•	•	•	•	•	•	•	•	•	•	•		•
	Start-specific parameters*											•						•
	Free-swimming	Breath Count										•			•			•
		Swimming time										•					•	•
		Stroke Count		•	•							•	•	•	•	•	•	•
		Pitch/roll symmetry												•				
		Hand trajectory															•	
		Distance per stroke		•	•			•			•	•	•	•		•		
		Stroke rate		•	•				•	•	•	•	•	•	•	•	•	•
		Average speed		•	•				•	•		•						
	Turn-specific parameters**											•						•
Feedback modality		Visual (real-time)														•		
		Tactile (real-time)	•										•					
		Audio (real-time)													•			
		Report	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•

Δ Exercises done to help swimmer's technique, usually a modified version of one of the four main swimming styles

† SWOLF is a value used as a metric of efficiency used by coaches, which is equal to the sum of stroke count and lap time values

***** Start-specific parameters: push-off velocity, underwater time and percent, maximum depth, start average speed, push depth, push maximum acceleration

****** Turn-specific parameters: turn type, turn time and turn rate

2.3 Concluding remarks

In this chapter, we began our review with the duties of a coach in sports training to determine the contribution of technological tools to the coaching community. Subsequently, the benefits of IMUs in different sports were highlighted, especially in the motion analysis of swimmers. We took a closer look at the studies and research groups that have used IMUs to analyze swimmers in main swimming styles and phases. Spatio-temporal, kinematic and kinetic parameter extraction, performance evaluation, and feedback were the three aspects of swimming that have been studied with IMUs. A brief look at commercial swimming analysis systems shows that the true potential of IMUs in training sessions has yet to be realized in practice. In the following, the main outcomes of this review are outlined:

- A coach performs several analyses to determine the athlete's target and then guide them efficiently during training sessions. Based on the duties defined for a coach, it seems that technique analysis and feedback are the two tasks to which motion analysis has contributed the most.
- Motion analysis is used in sports because it can give the coach an objective and much deeper understanding of the athlete's performance. New technologies give the coach feedback based on detailed quantitative technique analysis that was not possible with traditional coaching methods.
- Among the various technologies used for motion analysis, IMU is of particular interest for in-field applications because they are easier to use despite technical limitations such sensor wobbling as soft tissue artifact or signals bias that might lead to drift in the results. For the motion analysis of indoor sports with large capture volumes, such as swimming, IMUs are one of the best options.
- IMUs have been successfully used in swimming to extract mostly spatio-temporal and kinematic parameters, evaluate swimming performance, and provide feedback to swimmers and coaches. However, given the gaps in the literature, further research is needed to develop an analysis system that meets the needs of coaches:
    - The extraction of IMU-based parameters mostly refers to general information about a training session. In addition, research groups mostly focused on kinematic parameters of front crawl style in free-swimming phase. The sensor positions used also depend on the target parameters and there is no comparison to find an optimal sensor position that works for parameter extraction in all styles and phases. Therefore, in Chapter 3 of this thesis, a novel approach for swimming analysis is proposed using IMUs at different viable positions on swimmer's body for comparison, covering all swimming phases in four main styles to provide a comprehensive evaluation of the swimmer's performance throughout the training session

- Performance-related parameters such as velocity in various swimming phases have received less attention in the literature, and researchers have only attempted to show that IMU data can provide detailed information about swimmer's motion. There is a gap between the extracted parameters and the performance of a swimmer. In Chapter 4, we use the algorithms developed in Chapter 3 beside a feature selection method to select the most relevant parameters related to swimming propulsion, posture, or efficiency as the three aspects of performance. The selected features are then used to estimate a set of goal metrics based on a regression model to quantify the swimmer's performance at each phase of all swimming styles.

- Researchers have claimed that giving the extracted parameters to the coach and the swimmer can lead to more efficient training sessions and better progress. However, few of them have achieved practical application or analysed the effects of the given feedback on the swimmer's training routine and performance. Therefore, we first evaluated the sensitivity of the estimated phase-based goal metrics in relation to swimmers' progress in chapter 5 and then provided them as feedback for the coach of a swimming team. The results of the feedback-assisted training are discussed in Chapter 6.

PART II – PHASE-BASED TECHNIQUE ANALYSIS WITH IMU

Chapter 3 A novel IMU-based swimming analysis approach

Publication Note: this chapter is adapted from the following journal paper:

Hamidi Rad, Mahdi, et al. "A Novel Macro-Micro Approach for Swimming Analysis in Main Swimming Techniques Using IMU Sensors." Frontiers in bioengineering and biotechnology (2021): 1511.

Supplementary materials:
https://www.frontiersin.org/articles/10.3389/fbioe.2020.597738/full#supplementary-material

Following the gaps introduced in the previous chapter, this chapter presents the second part of the investigation on a comprehensive solution for swimming analysis with IMUs. To provide a comprehensive view of swimmers' performance, a new macro-micro analysis approach is described in this chapter that is thorough enough to cover a complete training session, regardless of swimming style. Seventeen national-level swimmers (5 females, 12 males, 19.6 ± 2.1 years) were equipped with six IMUs and asked to swim 4×50m in each swimming style (i.e. frontcrawl, breaststroke, butterfly, and backstroke) in a 25m pool in front of five 2D cameras (four underwater and one above water) for validation. The proposed approach detects swimming bouts, laps, and swimming styles at the macro level and swimming phases at the micro level at all sensor positions for comparison. The swimming phases are the phases that the swimmer goes through from wall to wall (wall push-off, glide, stroke preparation, free-swimming and turn), and the micro analysis detects the beginning of each phase. In macro analysis, an overall accuracy of 0.83-0.98, 0.80-1.00, and 0.83-0.99 was achieved for swimming bouts detection, lap detection and swimming style identification on selected sensor positions, respectively, with the highest accuracy at the sacrum. In micro analysis, the lowest mean and standard deviation were obtained at the sacrum for the onset of wall push-off, glide and turn (-20 ± 89 ms, 4 ± 100 ms, and 23 ± 97 ms, respectively), on shank for the beginning of stroke preparation (0 ± 88 ms), and at the wrist for the onset of swimming (-42 ± 72 ms). Considering all swimming styles, sacrum sensor achieved the smallest range of error mean and standard deviation in the micro analysis. By using the same macro-micro approach for different swimming styles, this study shows how efficient it is in detecting the main events and phases of a training session. Comparing the results of the macro and micro analysis, it can be seen that the sacrum has a relatively higher accuracy and a lower mean and standard deviation of error for all swimming styles.

***Keywords**: Sports biomechanics, Wearable sensor, Swimming, Macro-micro analysis, Lap segmentation.*

3.1 Introduction

As a competitive sport, swimming is one of the most popular disciplines for world-class athletes who want to optimize their performance. Among the most important tasks of coaches is to constantly monitor swimmers, evaluate their performance, and provide feedback for improvement (Nathan and Scobell, 2012; Marinho et al., 2020). To help coaches with these tasks, research has examined swimming from different perspectives, such as physiology (Pendergast et al., 1980; Lavoie and Montpetit, 1986; Zamparo et al., 2005), motor control (Seifert et al., 2011a; Morais et al., 2020), and biomechanics (Payton and Bartlett, 1995; Morais et al., 2012). Although all these aspects have their own importance, studies show the dominance of biomechanical factors over the other aspects (Figueiredo et al., 2013). Moreover, swimming coaches also consider biomechanics as the most important area for swimmers' improvement (Mooney et al., 2016a).

Using video-based systems is a common tool for motion analysis, which is still considered as the most accurate method and gold standard (Mooney et al., 2015; Seifert et al., 2015). However, as a result of its limitations in aquatic environments (Callaway et al., 2010), the number of studies on swimming with inertial measurement units (IMUs) has been increased (Guignard et al., 2017b). There is a multitude of research on measuring the swimming kinematic parameters using IMUs in different swimming phases, such as start (Stamm et al., 2013a; Vantorre et al., 2014), swimming (Ohgi et al., 2003; Davey et al., 2008), or turn (Slawson et al., 2012; Nicol et al., 2018). To evaluate the swimmer’s performance, many studies focused on extracting specific parameters such as stroke rate (Siirtola et al., 2011; Beanland et al., 2014), distance per stroke (Bächlin et al., 2008), velocity (Wright and Stager, 2013; Dadashi et al., 2015), lower limbs actions rate (Fulton et al., 2009) or body coordination (Osborough et al., 2010; Silva et al., 2019).

The general approach of most studies is limited to a specific swimming style or phase. As the most prevalent swimming style, front crawl has been more investigated in the literature (Mooney et al., 2016b) and development of swimming style specific algorithms is proposed as a future application for IMUs (Magalhaes et al., 2015). Swimming phases are the phases swimmers pass from wall to wall (wall push-off, glide, stroke preparation, swimming and turn). Among different phases, swimming phase has been noticed the most, while start or turn have not captured enough attention. It is well established that these phases are of utmost importance for coaches (Mooney et al., 2016b). Another downside is focusing only on a small number of swimmers, lacking variety of technique among subjects (Slawson et al., 2012; Hagem et al., 2013; Seifert et al., 2014). Using the least number of IMUs is another challenge for a wearable analysis system, as they induce drag unlike video-based systems. By reducing the number of sensors and providing adequate fixation or integrating the wearable sensor into the suit, goggles or watch, swimmers face less drag. Only one study performed a qualitative comparison for possibility of direct or indirect extraction of kinematic parameters with IMU on lower and upper limbs (Pansiot et al., 2010).

Therefore, a comprehensive study of different swimming styles and phases with IMUs at different sensor positions during a training session is necessary to obtain a complete overview of the swimmer's performance from the macro to the micro level. All four main swimming styles, i.e., crawl, breaststroke, butterfly, and backstroke, can be decomposed into different locomotion phases from wall to wall. There is an analogy between swimming and gait analysis in terms of how to progress from the big picture to the detailed parameters, also known as the macro-micro approach (Lord et al., 2013). Using body-worn sensors, such as accelerometers, this approach first captures the amount and variability of ambulatory activity (lying, sitting, or standing and gait) as the macro level and then moves on to gait phases and spatio-temporal parameters as the micro level. Similarly, in the analysis of swimming, the acquisition of the amount of swimming (swimming bouts and laps) with different swimming styles in each lap forms the macro level, while the micro level aims to capture the swimming phases in each lap and finally extract parameters within each swimming phase.

Following this approach, the main objective of this study was to develop an IMU-based wearable system for the analysis of swimming during training sessions, including the four main swimming styles. As shown in Figure 3.1, a macro-micro approach was followed, where swimming laps and techniques were identified at the macro level and individual phases within each lap were identified at the micro level. More detailed parameter extraction within each phase (e.g. detecting stroke cycle sub-phases) is the next step of the micro analysis, which is outside the scope of this study (Figure 3.1). This approach aims to provide the coach with a comprehensive overview of the swimmer's performance during each training session.

We hypothesized that movement and postural changes alter the kinematic profile of the wrists, sacrum, head, and shanks, which could be detected by appropriate IMU-based algorithms to recognize swimming bouts, laps, swimming styles, and later swimming phases. The accuracy and precision of the detection algorithms for each sensor position will be estimated and compared to find the most suitable location for monitoring swimmers' training using this approach. All abbreviations used in this study are explained in a glossary table at the end of this chapter.

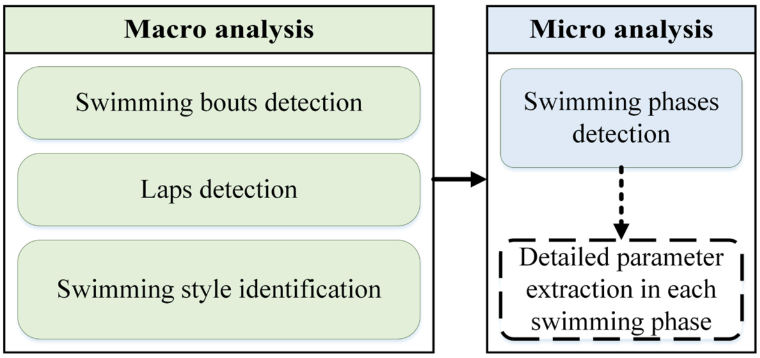

Figure 3.1 – Macro-micro analysis approach diagram to show the scope of this study.

3.2 Materials and methods

3.2.1 Measurement setup

Seventeen national-level swimmers (with attributes listed in Table 3.1) were asked to perform four 50-m trials in each swimming style in a 25-m indoor pool at 80% of their best speed. Since the analysis of swimming during training sessions is the main objective of this study, 80% is considered a moderate pace that is close to the pace used during training sessions and allows a balance between speed and accuracy of movement (Schmidt and Lee, 2019). The moderate pace helps swimmers maintain efficient performance while avoiding fatigue during a long training session. In addition, the wearable sensors induce more drag on the swimmer's body, especially at high pace, and it is necessary to compensate for this effect by reducing the pace (Magalhaes et al., 2015; Guignard et al., 2017b). Trials were interrupted with a short rest, resulting in several swimming bouts and the total duration of the measurement was one hour per swimmer. During the test, the coach observed and evaluated the pace qualitatively and asked the swimmers to correct it if it was too fast or too slow. The swimmers were selected from national swimming clubs and train more than five times a week for competitions. Each swimmer was informed of the procedure and gave written consent before participating. This study was approved by the EPFL Human Research Ethics Committee (HREC, No. 050/2018).

Table 3.1 – Statistics of the measurement population. All variables are presented as mean ± standard deviation. $Record_{50m}$, and $FINA_{50m}$ are the average and standard deviation of 50m record and FINA points (for 2019) of the swimmers separately for each swimming style.

Male	Female	Age (yrs)	Height (cm)	Weight (kg)	$\mathbf{Record_{50m}}$ (s)		$\boldsymbol{FINA_{50m}}$
12	5	19.6 ± 2.1	179.5 ± 6.7	74.5 ± 7.1	Front crawl	24.56 ± 1.26	725 ± 53
					Breaststroke	32.13 ± 1.52	631 ± 42
					Butterfly	26.86 ± 1.68	652 ± 83
					Backstroke	28.63 ± 1.41	612 ± 95

A wearable measurement system with six IMUs (Physilog® IV, GaitUp, CH.) was used. The IMUs were attached with waterproof tapes (Tegaderm, 3M Co., USA) to the right and left shanks (R/ LS), right and left wrist (R/LW), sacrum (SA), and head (HE). Swimmers were asked to wear two swim caps to fix the head sensor to the back of the head as best as possible. The remaining sensors were taped directly to the swimmer's skin. Each unit contained a 3D gyroscope (±2000 °/s) and a 3D accelerometer (±16 g) with a sampling rate of 500 Hz (Figure 3.2). Five 2D cameras (GoPro Hero 7 Black, GoPro Inc., US) were used for validation, four of which were underwater (attached to the pool wall, distributed along the length of the pool) to capture all lap events, and one camera above water that moved with the swimmer (Figure 3.3), all capturing at a rate of 60 Hz. A push button used to start data acquisition by the IMUs also provided a flashlight in front of the cameras to synchronize the two systems. The rising edge of the signal on the IMU was matched with the frame the light turned on from the videos. This procedure is performed at the beginning and end of each measurement to ensure that the systems remain synchronized throughout the measurement.

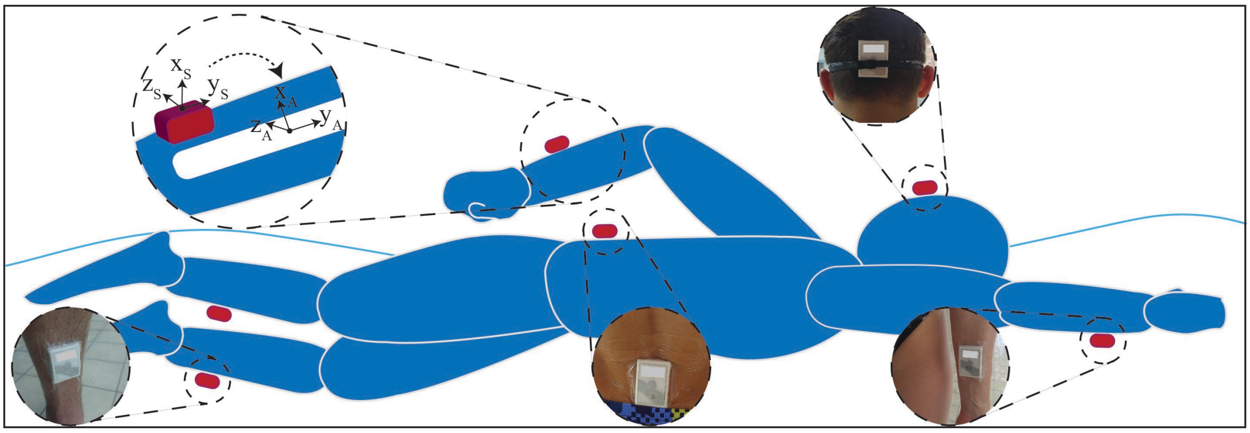

Figure 3.3 – IMU-based measurement setup. Six IMUs were attached to shanks, wrists, sacrum and head using waterproof tapes. During functional calibration, for each segment, the data will be transformed from sensor frame ($\mathbf{xyz_S}$) to anatomical frame ($\mathbf{xyz_A}$).

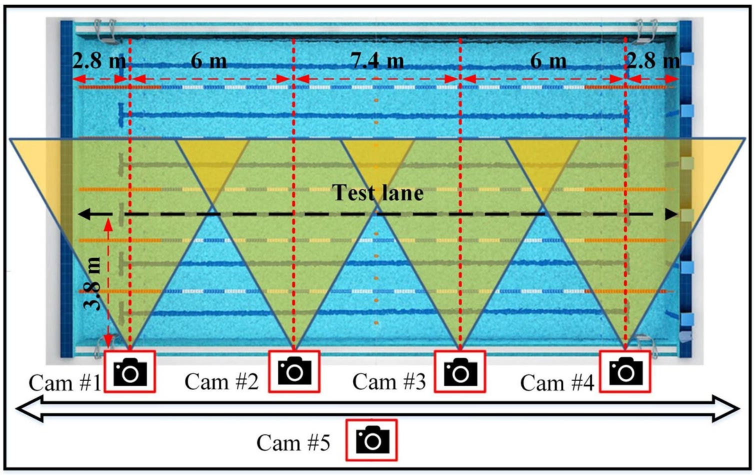

Figure 3.2 – Validation system including four cameras (Cam#1 - Cam#4) distributed along the pool in the same depth (0.5 m) underwater and one camera (Cam#5) moving with swimmer in land to capture the events over water

In order to make the data from IMU independent of the exact placement of the sensors on the swimmers' bodies, a functional calibration was performed after the sensors were installed. The result of this calibration is that the data represents the actual movement of the limbs, regardless of the exact location of the sensors, and that the different placement of the sensors on different swimmers or limbs does not affect the data. The purpose of this calibration is to find the transformation matrix that connects the sensor frame $(x_S, y_S, z_S)_i$ of each sensor i (i=1,...,6) with the corresponding anatomical frame of the body segment $(x_A, y_A, z_A)_i$ (Figure 3.2). The functional calibration procedure is explained in (Dadashi et al., 2014) and involves simple movements (upright standing, squatting, and arm rotation) on land. Based on the alignment of the vertical axis of the sensor and gravity during the static postures and the dominance of a mediolateral angular velocity during the squats, the data is transferred from sensor frame to the functional frame. According to this calibration, each sensor coordinate system has a y-axis along the longitudinal limb axis pointing upward (y), an x-axis along the anterior-posterior axis pointing forward (x), and a z-axis along the mediolateral axis (z) pointing to the right (Figure 3.2). The pitch and roll motions of the trunk during swimming are defined as rotation about the medial-lateral and inferior-superior axes of the body, respectively.

3.2.2 Analysis approach

During a training session, there are several swimming bouts in different swimming styles (front crawl, breaststroke, butterfly, backstroke), each one consisting of one or more laps. Within each lap, from one pool wall to the other, swimmers pass five main phases: wall push-off (*Push*), glide (*Glid*), stroke preparation (*StPr*), free-swimming (*Swim*) and turn (*Turn*).

1. Wall push-off phase starts on the frame with forward motion of swimmer's trunk and finishes upon swimmer's feet leaving the wall (Slawson et al., 2010; Stamm et al., 2013b). This phase is the same for all swimming styles except it happens in supine posture during backstroke.

2. Glide phase continues as long as swimmer's body glides under water without upper or lower limb movement. This phase ends with butterfly lower limbs action (for front crawl, butterfly and backstroke) or one upper limbs cycle and then a lower limb action under water (for breaststroke) (Stamm, 2013; Vantorre et al., 2014). Although it is allowed to do one butterfly lower limbs action for breaststroke, the swimmers were trained to follow the traditional method.

3. Stroke preparation is the phase after glide, which continues up to the first upper limbs cycle (Silveira et al., 2011; Vantorre et al., 2014).

4. Free-swimming phase is usually the longest phase, which lasts as long as the swimmer performs upper limbs cycles. During tumble turn, swimming phase ends with the last upper limbs cycle and head downward motion for rolling, while during simple turn, it finishes by touching the wall (Pereira et al., 2015; Mooney et al., 2016b).

5. Turn phase happens after free-swimming phase and ends on the frame of the next wall push-off phase start (Le Sage et al., 2010; Vannozzi et al., 2010).

The training session can be conceptualized at a macro level by estimating the training volume, i.e., the number and duration of swimming bouts and laps with a given swimming style, and at a micro level, which includes the different phases of each lap and the spatio-temporal features of swimming within each phase (number, duration, or distance per stroke). Here, the macro-analysis consists of the detection of swimming bouts detection, the recognition of laps, and the identification of swimming style, while the micro-analysis is limited to phase detection within each lap (Figure 3.4) and more detailed parameters in each phase are not considered in this study. Since these phases occur sequentially, we focused on finding the beginning of each phase for lap segmentation. The beginning and end of each phase triggers a specific change in the profile of the acceleration and angular velocity of the body segment and requires specific rules for their detection, the details of which are explained in the appendix (Table 3.7 and Table 3.8). These rules are based on common processing functions, which are described in the following section.

3.2.3 Common processing functions

Despite the differences between the movement patterns of body segments, there are common function that are used frequently in macro-micro analysis algorithms. These functions are explained in Table 3.2 and applied on acceleration (Acc_x, Acc_y, Acc_z) and angular velocity (Gyr_x, Gyr_y, Gyr_z) or their norms ($|Acc|$ and $|Gyr|$) expressed in the bone anatomical frame after noise removal with low-pass filtering (second order Butterworth filter, $f_c = 10$Hz). These methods are thresholding (Cronin and Rumpf, 2014), extremum detection (Chardonnens et al., 2012), sharp change detection (Dadashi et al., 2013a), principle component analysis (Jollife and Cadima, 2016), frequency analysis (Aung et al., 2013), empirical mode decomposition and Hilbert-Huang transform (Ge et al., 2018). For macro-micro analysis algorithms, a mixture of these methods are used for all sensor positions. As most of the motions are symmetric, always the sensor on the right wrist and shank are used in algorithms unless mentioned otherwise. The details of macro and micro algorithms are explained in Table 3.7 and Table 3.8 in the appendix.

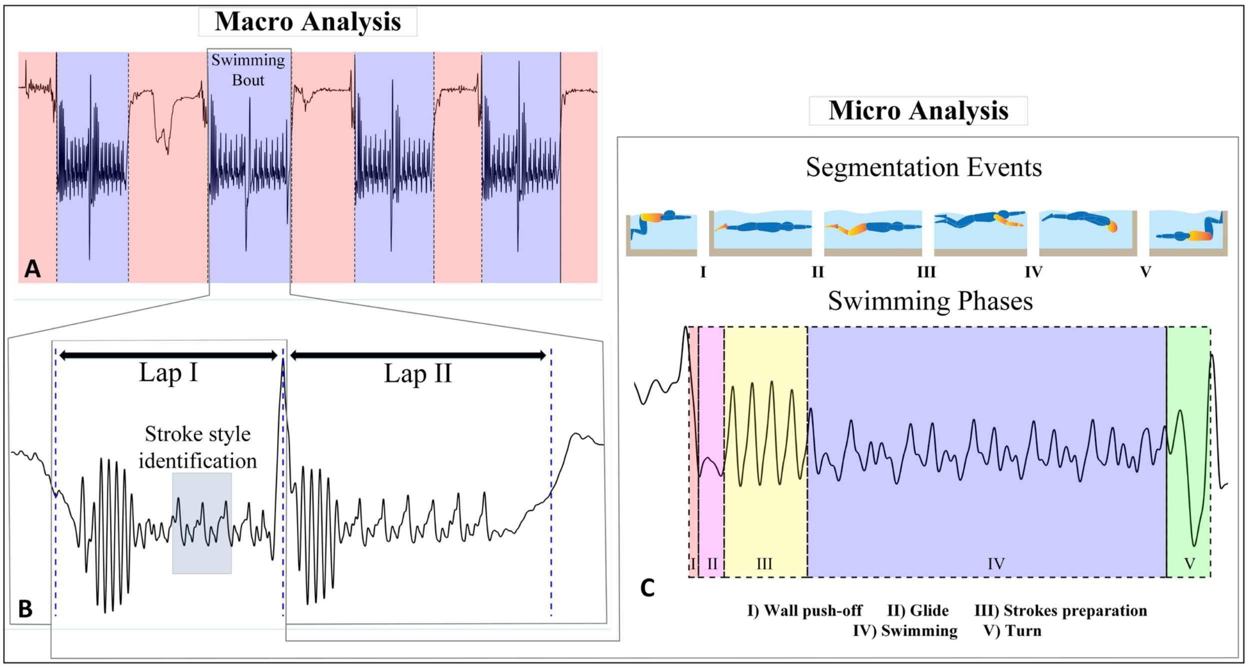

Figure 3.4 – Analysis approach and segmentation events considered in this study (sacrum acceleration signal during front crawl is used as an example). The steps of the approach are: **(A)** detection of swimming bouts in a training session, **(B)** separation of laps and identification of swimming style using a short period of upper limb cycles, **(C)** segmentation of the lap into the five swimming phases of wall push-off (*Push*), glide (*Glid*), stroke preparation (*StPr*), free-swimming (*Swim*), and turn (*Turn*) using the segmentation events.

Table 3.2 – Common processing methods used for macro-micro analysis

Method	Description	Example
Thresholding ($\mathbf{TH}$)	When the signal goes higher or lower than a threshold (TH) due to an event, thresholding can detect it.	Acceleration amplitude change for swimming bouts detection on wrist
Extremum detection $[\mathbf{A}, \mathbf{t}] = \mathbf{EXT}(\mathbf{s}, \mathbf{TH})$	Local increase or decrease of the signal (s) generates peaks or troughs comparable with a threshold (TH). Extremum detection finds the magnitude (A) and time (t) of extremums	Peak on sacrum forward acceleration at the beginning of wall push-off phase
Sharp change detection $\mathbf{t} = \mathbf{SC}(\mathbf{s}, \mathbf{TH})$	The occurrence time (t) of some events are abrupt, easier to detect on the derivative of the signal (s) by comparing it with a threshold (TH)	Swimming bout start and end detection with sacrum
PCA Analysis $[\mathbf{PC_1}, \mathbf{PC_2}, \mathbf{PC_3}] = \mathbf{PCA}(\mathbf{v})$	Finding the principle components (PC_1, PC_2, PC_3) of a vector (v) is useful for decreasing dimensionality to identify the type of movement	Swimming style identification with head
Frequency analysis $\mathbf{FFT}(\mathbf{s})$	The single-sided power density spectrum of the signal (s) and its analysis reveals the behavior of the signal in frequency domain	Differentiating between breaststroke and butterfly techniques with sacrum
Empirical mode decomposition $\mathbf{IMF} = \mathbf{EMD}(\mathbf{s})$	It decomposes the signal (s) into its intrinsic modes to facilitate the change detection in time domain	Detecting the beginning of upper limbs cycles on sacrum
Hilbert-Huang transform $\mathbf{inse} = \mathbf{HHT}(\mathbf{s})$	It extracts many features of a signal (s) such as instantaneous energy, which is useful to find the change start	Detecting the beginning of upper limbs cycles on head

3.2.4 Macro analysis algorithms

Swimming bouts detection. Each swimming bout starts and ends with an abrupt change in swimmer's body posture between upright and supine or prone postures. This change is observed either after (for swimming bout start) or before (for swimming bout end) a rest period. The detection method on all sensor positions except right wrist is to use $SC(Acc_y, TH_B)$, where TH_B = ± 0.3 × EXT(low pass filtered $\dot{Acc_y}$), and $\dot{Acc_y}$ denotes the derivative of Acc_y (equation 3.1). Negative and positive threshold is used for detecting troughs (corresponding to approximate start) and peaks (corresponding to approximate end) respectively (equations 3.2 and 3.3).

$$t = SC\left(Acc_y, 0.3 \times EXT\left(\text{Low pass filtered } \dot{Acc_y}\right)\right) \tag{3.1}$$

$$\text{Approximate start} = \text{t}\left(\text{negative peaks on } \dot{Acc_y}\right) \tag{3.2}$$

$$\text{Approximate end} = \text{t}\left(\text{positive peaks on } \dot{Acc_y}\right) \tag{3.3}$$

For the right wrist sensor, while it has a clear cyclic pattern during swimming phase in all swimming styles, its motion is erratic before upper limbs actions. Despite the inter-individual variability in swimmer's wrist motion during swimming phase (Martens et al., 2016), the swimming bout was detected as the period where the envelope of $|Acc|$ is higher than an empirical threshold (TH_{BW} = 1.6 g). This period starts with the upper limbs cycles in the first lap, until the end of the swimming bout.

Lap detection. In our measurement protocol, each swimming bout consisted of two laps, separated by a turn. Therefore, lap detection requires finding the approximate turn. The detection algorithm for sacrum, head and right shank finds the highest peak during the swimming bout on Acc_x and $|Acc_{y,z}|$. For right shank the peak is detected using a threshold with the function $EXT(Acc_z$ or Gyr_z (the one happens earlier), TH_{LS} = highest peak in a two-second period during swimming phase). As wrist's angular velocity amplitude decreases during turns (compared to swimming phase), the algorithm detects a decrease of $|Gyr|$ where low pass filtered $|Gyr|$ is less than the threshold (TH_{LW} = 200 °/s).

Swimming style identification. For head and sacrum, a two-upper-limbs-cycle period was chosen. The $PCA(Gyr_{x,y,z})$ to separate swimming styles with dominant trunk pitching motion (breaststroke/butterfly) from the techniques with trunk rolling motion (front crawl/backstroke), gravity effect (positive versus negative sign of Acc_x average to distinguish backstroke) and threshold-based Fast Fourier Transform (FFT) of Acc_x for sacrum and $|Acc_{x,y}|$ for head (to distinguish between butterfly and breaststroke) were used for swimming style identification ($TH_{StyleHE}$ = 0.2 g, $TH_{StyleSA}$ = 0.16 g). Equation 3.4 explains the use of FFT analysis for technique identification on sacrum and head.

$$\begin{gathered} EXT(\text{power density spectrum magnitude}, TH_{StyleHE} \text{ or } TH_{StyleSA}) \rightarrow \\ \text{Butterfly technique} \end{gathered} \tag{3.4}$$

A period including five lower limbs actions is chosen during swimming phase for swimming style identification with right shank, which was not a limit, as all swimmers did more than five lower limbs actions in every lap. Gravity effect (same as head and sacrum to distinguish backstroke) and PCA analysis of angular velocity vector are used for swimming style identification on right shank. For right wrist, the PCA of acceleration separates backstroke from other techniques and the mean and variation of $|Acc|$ are compared with two thresholds ($TH_{StyleWmean}$ = 1.7 g, $TH_{StyleWvar}$ = 0.01g) to identify butterfly and front crawl respectively.

3.2.5 Micro analysis algorithms

The results achieved from macro analysis (approximate start, approximate end, approximate turn, and swimming style) were used for further detailed lap components detection. These approximate events are enough to find the exact locations of the events for phase detection in micro level.

Beginning of Wall Push-Off ($Push_B$). Wall push-off accompanies a forward acceleration increase close to approximate start. For sacrum and head during backstroke, the detection is done with $EXT(Acc_y)$ for both sensor positions, while for other techniques with sacrum, concavity change of Acc_y is used to find a negative trough, close to $Push_B$. For head during other swimming styles,

$EXT(|Acc|)$ estimates the answer. Right wrist has a downward motion during wall push-off causing a negative trough on Acc_y and right shank represents a peak on $|Gyr|$ close to $Push_B$.

Beginning of Glide ($Glid_B$). As the glide phase starts, the whole body glides in water with no propulsion. The first trough after $Push_B$ detected by EXT(-Acc_y) for sacrum and head or the first peak found by $EXT(|Gyr|)$ for right shank is considered as $Glid_B$. On the right wrist, Acc_y gets close to zero and shows a peak right after beginning of wall push-off, which is $Glid_B$.

Beginning of Stroke Preparation ($StPr_B$). Stroke preparation phase includes underwater lower limbs actions (except for breaststroke, which includes one lower limb action and one upper limb cycle). Detection method for sacrum, head and right wrist is threshold-based and the idea is using thresholds on peak magnitude, peak prominence or signal variation depending on sensor position (for sacrum; $EXT(|Acc_x|, TH_{SPSA} =$ g, $TH_{SPSAvar} = 0.06$ g), for head; $EXT(|Acc_y|$, TH_{SPHE} =-0.5 g, $TH_{SPHEprom}$ = 0.1 g), for right wrist; $EXT(|Acc|, TH_{SPRW}$ = -0.9 g). On right shank, the first positive peak of Acc_y is $StPr_B$ for backstroke, while for other swimming styles, the peak is detected with $EXT(|Acc_x|, TH_{SPRS}$ =1.3 g) and then the next sample on $|Acc|$ passing from g is $StPr_B$.

Beginning of Swimming ($Swim_B$). In swimming phase, swimmer's body starts the rolling (for front crawl and backstroke techniques) or pitching motion (for breaststroke and butterfly techniques). On sacrum, the detection for front crawl and backstroke is done using $EXT(|Gyr_y|$, $TH_{SSA-FCBaS}$ =200 °/s). For breaststroke and butterfly, the second intrinsic mode of low pass filtered Gyr_z and Acc_y were obtained. For breaststroke, instantaneous energy of Gyr_z increases more than $TH_{SSA-BrS}$ =550 °/s² at $Swim_B$. For butterfly, EXT(second intrinsic mode of Acc_y, TH_{SSA-BF} = 0.1 g) detects a peak close to $Swim_B$. On head, instantaneous energy of Gyr_y (for front crawl) and Gyr_z (for breaststroke, butterfly and backstroke) are used. The decrease (for backstroke) or increase (for front crawl, breaststroke and butterfly) of instantaneous energy is taken as the criterion for $Swim_B$ detection by thresholds $TH_{SHE-FC} = 5000$ °/s², $TH_{SHE-BFBrS}$ =12000 °/s² and $TH_{SHE-BaS}$ =1000 °/s².

For wrists during front crawl and backstroke, both wrists are used to find $Swim_B$ because upper limbs cycles can start on either one. The detection method is to find the trough before the first peak on right and left wrists. It is performed over Acc_y for front crawl and butterfly and over Acc_x for backstroke. The same is done over Gyr_y for breaststroke to find an approximation of $Swim_B$. On right shank, the lower limbs action pattern changes after $Swim_B$, which is noticeable on the second intrinsic mode of Acc_x (for front crawl , butterfly and backstroke) or Acc_y (for breaststroke). The trough before the first peak found with EXT(second intrinsic mode of Acc_x or Acc_y, TH_{T-RS} =1.7 g) is considered as $Swim_B$.

Beginning of Turn ($Turn_B$). Regardless of the turn type (simple or tumble turn), the algorithms use approximate turn to find the beginning of turn. During backstroke, approximate turn fits greatly as $Turn_B$. For the rest of the techniques, $Turn_B$ on sacrum is the first trough before the large peak on Acc_x close to approximate turn. On head, $EXT(|Acc|)$ and $EXT(Gyr_x)$ were used shortly before approximate turn for tumble turn and simple turn respectively to find $Turn_B$. On right wrist, EXT(low pass filtered Acc_y) and $EXT(Acc_y)$ are used for tumble turn and simple turn respectively to find $Turn_B$. Right shank motion also shows a peak detectable respectively by $EXT(Gyr_z)$ and $EXT(Acc_z)$ for tumble turn and simple turn.

3.2.6 Validation and error analysis

For validating the temporal macro and micro events described above, cameras were used as ground truth. To validate the macro events the camera over water was used as the main reference, while the detection of swimming phases start during micro analysis was done by underwater cameras by one observer. For validation of swimming bouts and laps detection, the accuracy, sensitivity and precision are defined based on the number of true or false detections (equations 3.5 to 3.7). Accuracy shows how much the algorithms work correctly and the results match the true values. Precision represents how much the algorithm results are correct when it claims the detection of an event (if it is truly happened or not), and sensitivity displays how much the algorithm is sensitive to occurrence of an event (if it is correctly detected or not).

$$\text{Accuracy} = \frac{\sum \text{True positive} + \sum \text{True negative}}{\sum \text{Total}} \tag{3.5}$$

$$\text{Sensitivity} = \frac{\sum \text{True positive}}{\sum \text{True positive} + \sum \text{False negative}} \tag{3.6}$$

$$\text{Precision} = \frac{\sum \text{True positive}}{\sum \text{True positive} + \sum \text{False positive}} \tag{3.7}$$

For example, the results are checked if the beginning and end of a swimming bout or turns are correct (true positive), missed (false negative) or mixed with other motions (false positive). Total parameter includes all the cases (e.g. the number of all the turns) and true negative is zero for our algorithms, as the purpose is to detect the happening of the event. The same logic holds true for swimming style identification, if the technique is correctly identified or mixed with another technique.

Synched with the IMUs, the cameras were used to mark the frames when each phase started and finished. The detected event using IMUs was then compared to the corresponding frame on the cameras and the mean and standard deviation of the errors were calculated. This method is used for validation in swimming for comparing IMUs and cameras in similar studies (Dadashi et al., 2013c). To assess the reliability of the validation process, two observers detected the events on cameras and compared with each other using Bland-Altman plots for the beginning of each phase. For each event, mean and standard deviation of the difference between the event observed on camera and IMU were calculated.

For phase duration (denoted by Δ of the phase name, e.g. $\Delta Push$ for wall push-off phase duration) confined with its starting and ending event, the absolute and relative error of phase duration are calculated. This error is the difference of estimated duration and the true duration (obtained from validation system). The relative phase duration error is then calculated by dividing it to the true phase duration. Equations 3.9 and 3.10 are examples for $Push$ phase duration error and relative error. $\Delta Push$ denotes the duration of $Push$ phase, $\Delta Push_{IMU}$ signifies the duration of $Push$ phase estimated by IMUs and $\Delta Push_{True}$ is the duration of $Push$ phase estimated by cameras. Then mean and standard deviation of phase duration error and phase duration relative error was calculated.

$$\Delta Push \ = Glid_B - Push_B \tag{3.8}$$

$$\text{Phase duration error} = \ \Delta Push_{IMU} - \ \Delta Push_{True} \tag{3.9}$$

$$\text{Phase duration realive error, \%} = \frac{\Delta Push_{IMU} - \ \Delta Push_{True}}{\Delta Push_{True}} \tag{3.10}$$

Three swimmers were chosen randomly from the dataset (one female and two males, making 20% of the dataset) who were trained with different coaches and tested in different pools. These swimmers were from the same technique level as others and trained regularly as planned by coaches. To make the algorithms and the thresholds more generalizable, they were developed and adjusted using the data from these three swimmers and then tested over the other fourteen swimmers to include as much diversity as possible in the algorithms.

All the algorithms that use threshold have been analyzed in terms of their results sensitivity to the change of threshold values. The results are the accuracy and precision for macro analysis algorithms and the error mean and standard deviation for micro analysis algorithms. The information about the exact values is presented in Table 3.9 of the appendix. Each threshold is changed at least 10% in both directions and the corresponding effect on algorithm results have been explored.

3.3 Results

To generate the results, the data of all laps are used for swimming style identification and the phases are investigated from the beginning of each swimming bout up to the end of the turn to have all the phases completely.

3.3.1 Macro analysis results

Figure 3.5 shows a typical example of macro analysis using sacrum sensor. As described in 3.2.4, posture changes at the beginning and end of swimming bout were detected by the filtered $\dot{Acc_y}$ (Figure 3.5, I-A and I-B). The approximate turn within each swimming bout are detected for separating laps (Figure 3.5, III-A). Swimming styles were identified based on $PCA(Gyr_{x,y,z})$, gravity effect of Acc_x and dominant frequency during a period of swimming phase (Figure 3.5, II-A to II-F). It is worth mentioning that the frequency resolution of fast Fourier transform analysis was at least 0.35 Hz considering all swimmers and swimming styles, small enough to capture the dominant frequency.

According to Figure 3.6, sacrum shows the most promising results in terms of both accuracy and precision for swimming bouts and lap detection. After lap detection, the swimming style is identified with each sensor separately (Table 3.3). Sacrum represents the best results for all swimming styles. It is possible to identify all front crawl and backstroke laps correctly and differentiate between breaststroke and butterfly with precision and accuracy higher than 0.97.

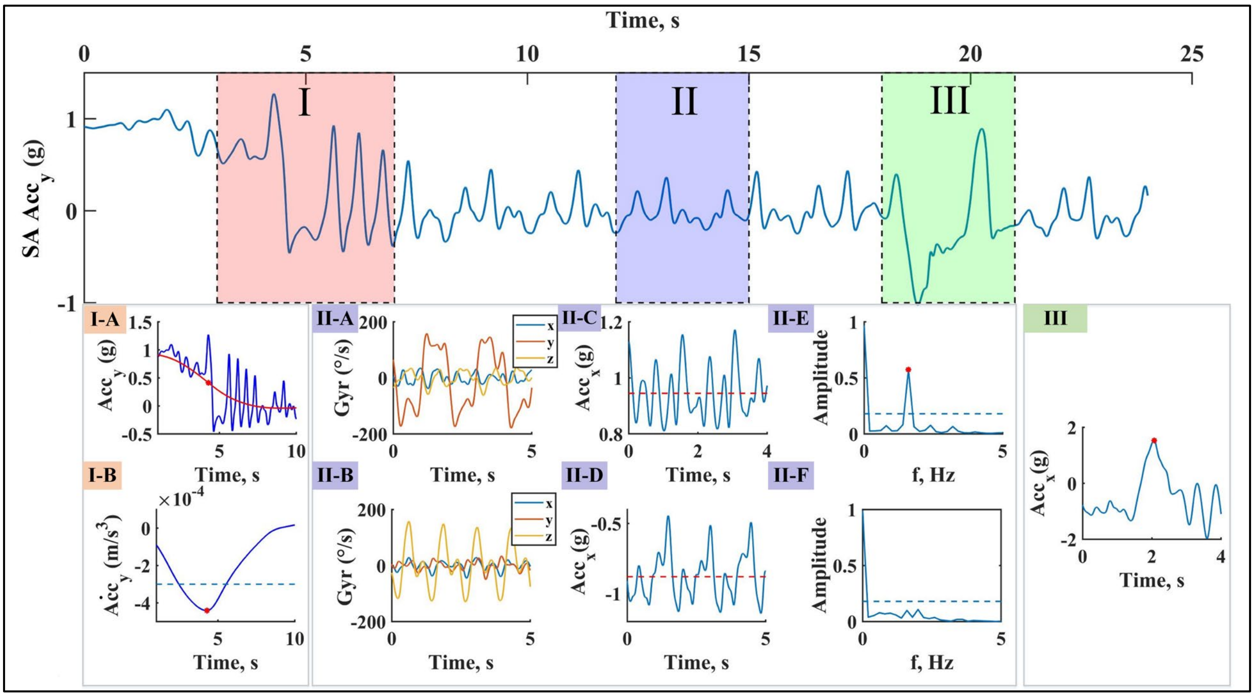

Figure 3.5 – Example of macro analysis with sacrum $\boldsymbol{Acc_y}$ data. I) Swimming bouts detection: swimming bout start causes a change in filtered $\boldsymbol{Acc_y}$ amplitude level (I-A), detected using its derivative (I-B) which corresponds to $\boldsymbol{start_{app}}$ (the rule is the same for swimming bout end). II) Swimming style identification: a short period of upper limbs cycles is selected for swimming style identification. Principal component of angular velocity (II-A for front crawl or backstroke, II-B for breaststroke or butterfly), gravity effect on $\boldsymbol{Acc_x}$ (II-C for front crawl, breaststroke or butterfly, II-D for backstroke) and FFT of the data (II-E for butterfly, II-F for breaststroke) are mainly the tools used for this purpose. III) Lap detection: at the end of each lap turning accompnies with a peak on $\boldsymbol{Acc_x}$ detected as $\boldsymbol{turn_{app}}$.

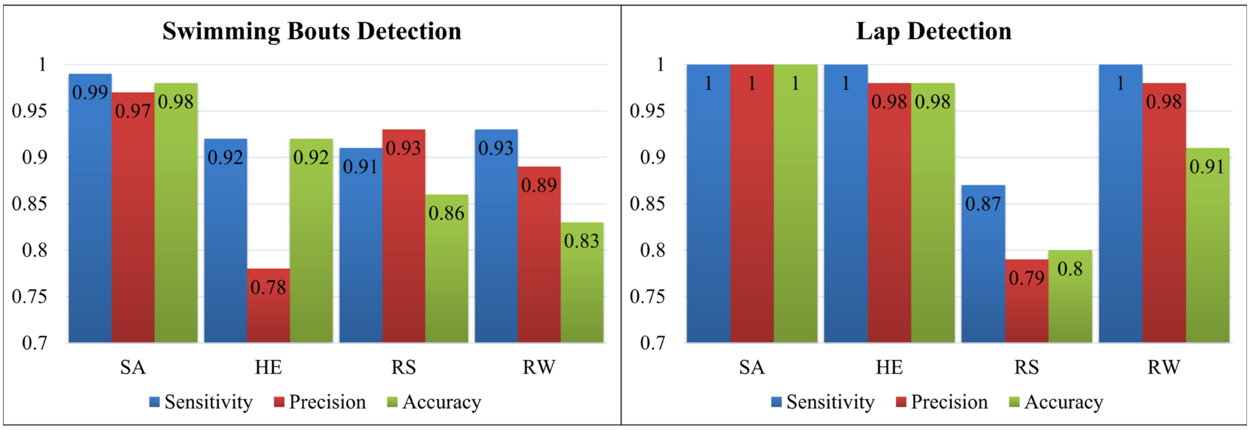

Figure 3.6 – Sensitivity, precision and accuracy achieved for swimming bouts and laps detection on all sensor positions (SA, HE, RS, RW)

Table 3.3 – Accuracy and precision for swimming style identification of four swimming styles over different sensor positions (SA, HE, RS and RW)

Sensor position	**SA**				**HE**			
Swimming style	Front crawl	Breaststroke	Butterfly	Backstroke	Front crawl	Breaststroke	Butterfly	Backstroke
Precision	1.00	0.98	0.97	1.00	1.00	0.86	0.83	1.00
Accuracy	1.00	0.97	0.98	1.00	0.99	0.82	0.86	0.97
Sensor position	**RS**				**RW**			
Swimming style	Front crawl	Breaststroke	Butterfly	Backstroke	Front crawl	Breaststroke	Butterfly	Backstroke
Precision	0.80	0.86	0.93	1.00	0.77	0.76	0.91	0.79
Accuracy	0.91	0.81	0.82	1.00	0.81	0.73	0.90	0.86

3.3.2 Micro analysis results

Figure 3.7 and Figure 3.8 show one example of detecting the beginning of these events on corresponding locations and signals. The examples show the estimated values on different locations (red dots) are close to each other and to the true value (the black dashed line), such as beginning of wall push-off, whereas estimations are more diverse for some other events, such as swimming start. The main challenge is whether the phase starts at the same time on all sensor positions and which limb is used to define the beginning of the phase. The mean and standard deviation of error for the beginning of each phase on all sensor positions are displayed in Table 3.4.

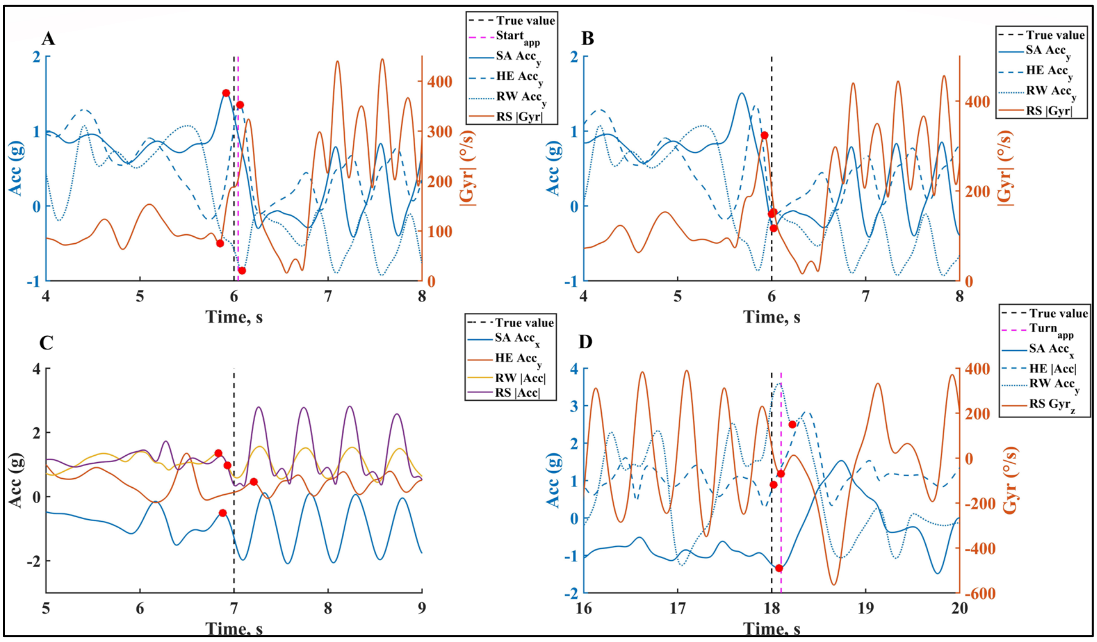

Figure 3.7 – An example of the swimming phases beginning event detection, **(A)** $Push_B$, **(B)** $Glid_B$, **(C)** $StPr_B$, **(D)** $Turn_B$, on all sensor positions during front crawl. The estimated values are represented on the corresponding signal with red dots and the true value is shown as a vertical dashed line.

Table 3.4 – Phases starting event detection error in ms by comparing IMU and camera results on all sensor positions (SA, HE, RS, RW). The events are $Push_B$, $Glid_B$, $StPr_B$, $Swim_B$ and $Turn_B$ and the next $Push_B$, which completes the lap segmentation

Phase event	$Push_B$	$Glid_B$	$StPr_B$	$Swim_B$	$Turn_B$	$Push_B$
SA	-20 ± 89	4 ± 100	-32 ± 107	136 ± 226	23 ± 97	-1 ± 65
HE	-35 ± 76	-35 ± 58	87 ± 214	58 ± 563	53 ± 195	-1 ± 70
RS	-118 ± 77	76 ± 77	0 ± 88	342 ± 473	-47 ± 390	-64 ± 89
RW	40 ± 71	49 ± 51	-151 ± 124	-42 ± 72*	118 ± 151	44 ± 82

*** Obtained using both right and left wrists**

The accuracy of detecting each event changes with the sensor position and type of event. Based on the results, right shank has the highest error mean at the beginning of the lap (for beginning of wall push-off and beginning of glide) where the motion is the same for all swimming styles. However, right shank provides an estimation with lowest error mean and standard deviation for beginning of stroke preparation, while it is detected with negative (on right wrist and sacrum) or positive (on head) error mean on other sensor positions. Beginning of swimming seems to be the most challenging event since the mean and standard deviation of error is high on all locations other than right wrist, where the swimming phase starts. Although beginning of turn results depend on turn type, sacrum and head both estimate it with low error mean and standard deviation.

Although the results depend on swimming style, they match with the detected events displayed in Figure 3.7 and Figure 3.8. The mean and standard deviation of absolute and relative error for each phase duration ($\Delta Push$, $\Delta Glid$, $\Delta StPr$, $\Delta Swim$, $\Delta Turn$) over all sensor positions are displayed in Table 3.5. Depending on the duration of each phase, error percentage vary based on the sensor position. For short phases (such as wall push-off), the relative error is higher than long phases, since even a small error will cause a high relative error in phase duration estimation. To provide a comparison between four swimming styles in terms of micro analysis results, the range of micro analysis error is reported in Table 3.6. The table represents the range of both error mean (mean range) and standard deviation (standard deviation range) for four techniques.

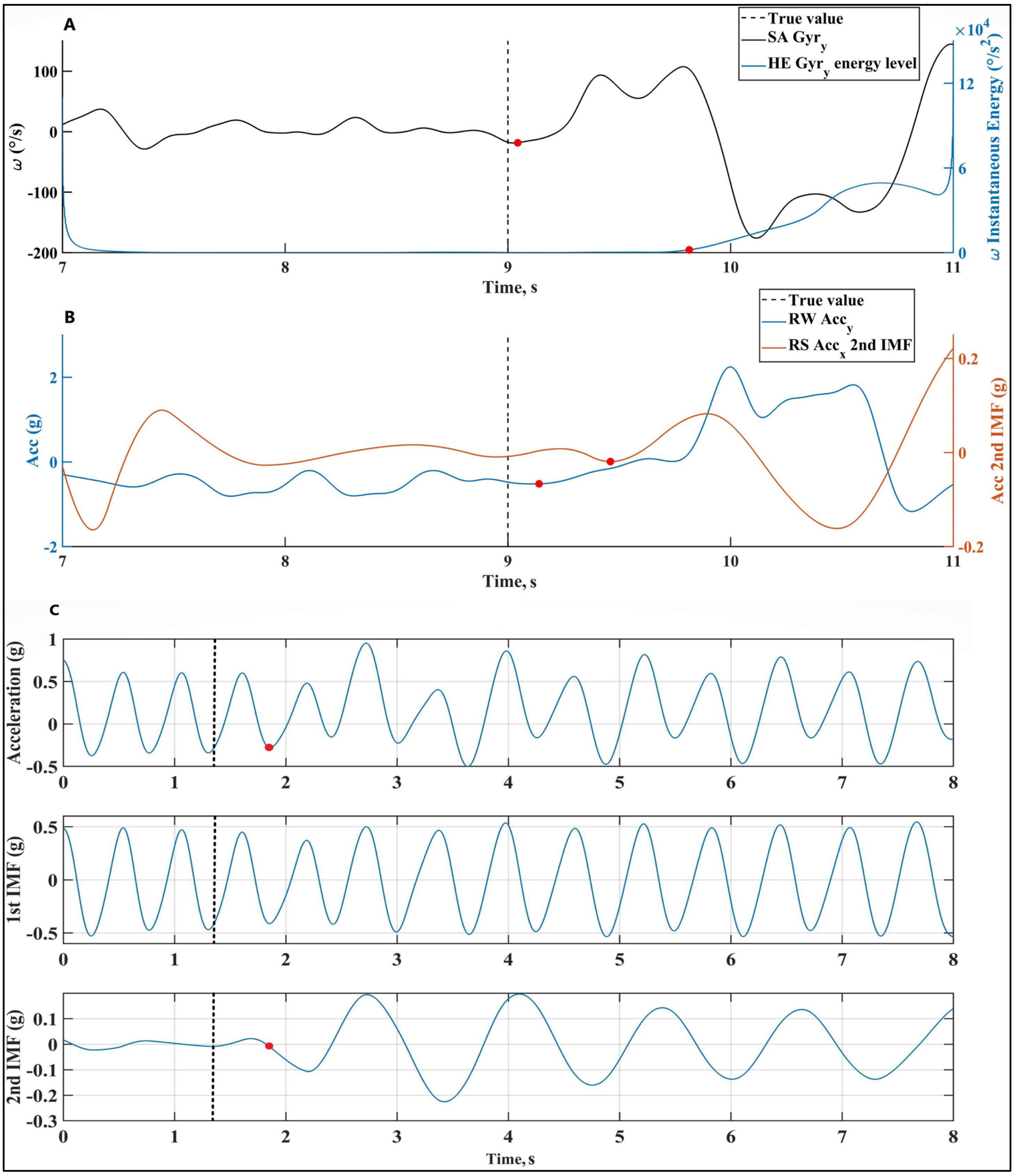

Figure 3.8 – An example of $\boldsymbol{Swim_B}$ event detection on all sensor positions. **(A)** $Swim_B$ detection on SA and HE during front crawl, **(B)** $Swim_B$ detection on RW and RS during front crawl, **(C)** an example of the process of using EMD technique for $Swim_B$ detection during butterfly technique. It is shown that the second intrinsic mode function (IMF) separates the motion after $Swim_B$. The estimated values are represented on the corresponding signal with red dots.

Table 3.5 – Estimated phase duration (with IMU), its phase duration error and phase duration relative error compared to the true phase duration (with camera) for each sensor position (SA, HE, RS and RW). All value are expressed in ms except for relative error expressed in percent.

	Phase duration	*ΔPush*	*ΔGlid*	*ΔStPr*	*ΔSwim*	*ΔTurn*
True values (validation data)		218 ± 29	880 ± 476	2673 ± 1268	12423 ± 1905	1223 ± 166
SA	Estimated (mean±SD)	242 ± 37	991 ± 560	2732 ± 1439	12241 ± 1754	1180 ± 170
	Error (mean±SD)	22 ± 51	10 ± 218	152 ± 300	-100 ± 286	-26 ± 69
	Relative Error (mean±SD)	12 ± 24	-1 ± 24	4 ± 12	-0.8 ± 2	-2 ± 5
HE	Estimated (mean±SD)	211 ± 52	936 ± 442	2424 ± 1185	12263 ± 2700	1069 ± 355
	Error (mean±SD)	-7 ± 53	121 ± 218	-27 ± 1124	-14 ± 1255	-149 ± 334
	Relative Error (mean±SD)	-2 ± 25	8 ± 27	-1 ± 42	0.6 ± 9	-11 ± 26
RS	Estimated (mean±SD)	415 ± 70	815 ± 470	3093 ± 1127	10812 ± 2873	1198 ± 390
	Error (mean±SD)	199 ± 80	-82 ± 113	479 ± 737	-767 ± 1096	-2 ± 393
	Relative Error (mean±SD)	96 ± 46	-7 ± 15	21 ± 35	-6 ± 8	-3 ± 29
RW	Estimated (mean±SD)	204 ± 43	775 ± 460	2730 ± 1234*	12358 ± 1732*	1082 ± 225
	Error (mean±SD)	1 ± 46	-188 ± 184	118 ± 147*	154 ± 190*	-122 ± 170
	Relative Error (mean±SD)	2 ± 22	-21 ± 19	5 ± 6*	1 ± 1*	-10 ± 17

*** Obtained using both right and left wrists**

Table 3.6 – The range of error mean (Mean range) and standard deviation (SD range) during micro analysis using four sensor positions (SA, HE, RW, RS) in four swimming styles. The values are in millisecond.

	SA		**HE**		**RW**		**RS**	
	Mean range	**SD range**	**Mean range**	**SD range**	**Mean range**	**SD range**	**Mean range**	**SD range**
Front crawl	78	123	421	346	234	106	427	322
Breaststroke	314	63	516	306	427	88	358	595
Butterfly	287	109	152	384	411	37	569	390
Backstroke	154	186	413	503	455	180	723	306

In order to check the reliability of the validation method, the true frames on cameras are detected with a second expert observer and compared with the first observer using Bland-Altman plots. Figure 3.9 show the agreement between two observers with a 95% limit of agreement (LoA). The plots show that the limit of agreement is higher for swimming start (225 ms), turn start (115 ms) and stroke preparation start (100 ms), while it is lower than 65 ms for other phases. All of the thresholds have been modified at least 10% depending on their values, while the results changed less than 5% for all of them except for TH_{SPHE} and $TH_{SPHEprom}$, which changed the estimated beginning of stroke preparation with head result more than 10%, meaning that they should be chosen more carefully.

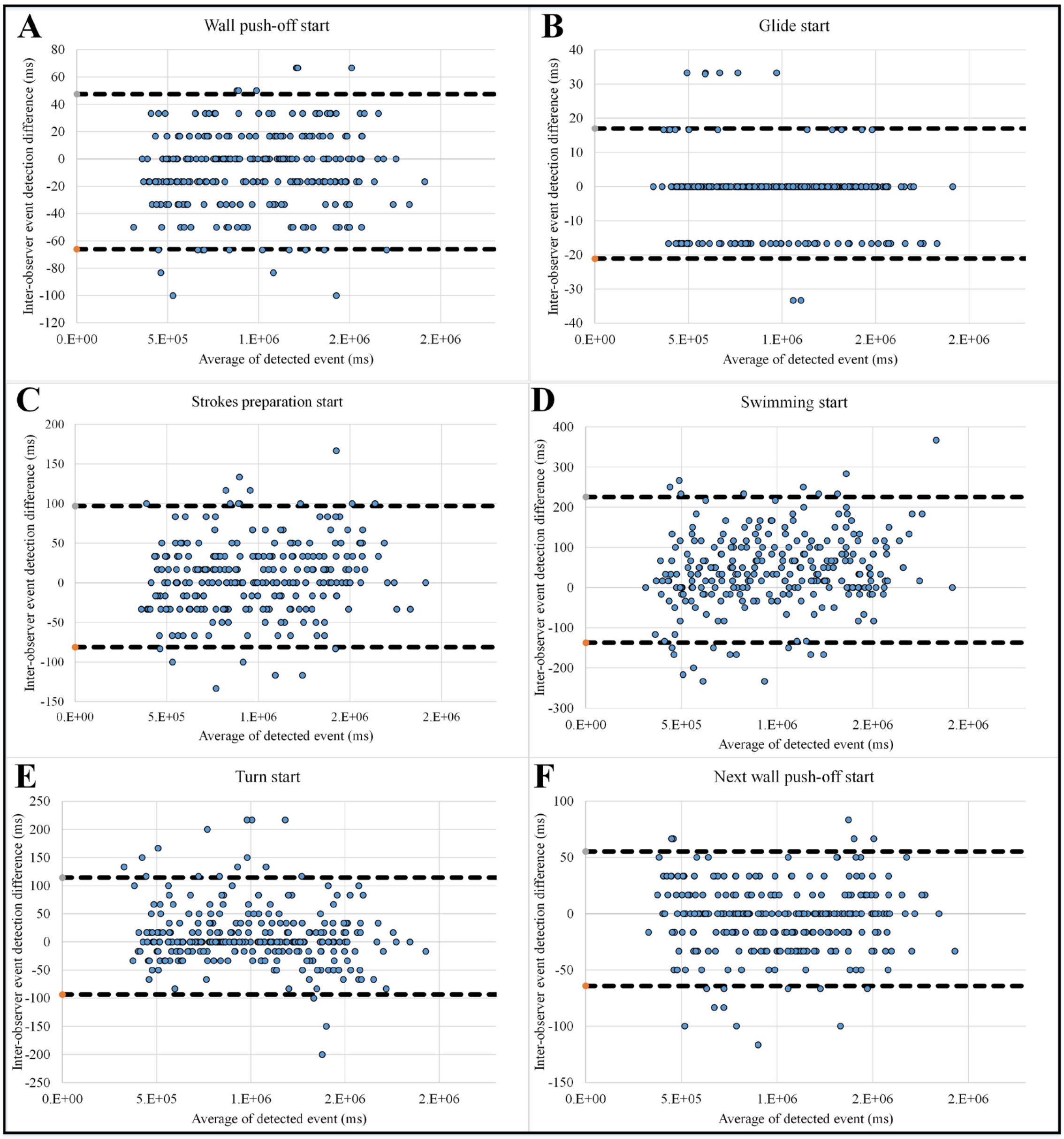

Figure 3.9 – Bland-Altman plot for inter-observer agreement for micro analysis event detection, including wall push-off start **(A)**, glide start **(B)**, stroke preparation start **(C)**, swimming start **(D)**, turn start **(E)** and next wall push-off start **(F)**, which completes the lap.

3.4 Discussion

In this study, we proposed a novel swimming analysis method with a macro-micro approach that applies the same unified analysis to all main techniques. Our hypothesis was that suitable IMU-based algorithms can analyze a training session at both macro and micro levels, which was confirmed by the results obtained. These results were presented in terms of accuracy and precision to find the most suitable sensor position for this approach. To obtain a larger sample size, we did not distinguish between male and female swimmers. Although only the right shank or wrist was used in the algorithms, the same results can likely be obtained with the left shank or wrist due to the similarity of the movements. The range of swimming velocity during the tests for front crawl, breaststroke, butterfly, and backstroke is [1.5-1.9], [1.0-1.4], [1.3-1.7], and [1.3-1.7] m/s, respectively. Therefore, the algorithms and discussion are valid for these paces.

3.4.1 Macro Analysis

Beginning with macro analysis to detect swimming bouts, the sacrum has the best results among all positions (sensitivity = 0.99, precision = 0.97, accuracy = 0.98). Because the sacrum is closer to the body's center of mass, the movements of the sacrum and head are more distinguishable in macro analysis and more robust in detecting swimming bouts with our analysis method. In some cases, our algorithm cannot distinguish between head motion during simple turns and the onset of swim bout, which decreases the precision of the algorithm (precision = 0.78).

The sacrum and head achieve the best results in lap detection. Right shank achieves worse results in lap detection (sensitivity = 0.87, precision = 0.89, accuracy = 0.80) than the sacrum or head because it is less affected by the sudden change in acceleration pattern due to the fast dynamics of the turn. Lap detection with the right wrist works during the swimming bouts starting from the first lap swimming phase, which is a disadvantage for this position. As a result, the lap detection algorithm worked with the right wrist for a shorter period of time and obtained better results (sensitivity = 1.00, precision = 0.98, accuracy = 0.91) than with the right shank. Previous studies focused only on detecting laps at the sacrum (Le Sage et al., 2011) and head (Jensen et al., 2013) and achieved lower accuracies than ours.

The swimming style identification results show that the sacrum is the most reliable sensor position, correctly identifying the front crawl and backstroke, with accuracy and precision greater than 0.95 for breaststroke and butterfly. Right wrist motion is the most variant among swimmers and produced the worst results. It is well known that hand movement patterns show significant variation due to various factors, including individual anthropometric and technique differences or performance level (Seifert et al., 2011b). In addition, inter-cyclic variation is another important factor (Barbosa et al., 2005; Figueiredo et al., 2012a) that can lead to errors in technique identification, which was not investigated in this study. However, our method has a higher accuracy compared to results reported in the literature based on sacrum sensor (Davey et al., 2008; Omae et al., 2017). Some studies use a network of IMUs (Wang et al., 2016a) or a smartphone (Pan et al., 2016) to identify swimming style, while we focus on each sensor position individually.

3.4.2 Micro Analysis

Performing a Wilcoxon rank sum test on the segmentation error of male and female swimmers showed that there is no significant difference (p-value > 0.05) between them and the results can be mixed. The results of lap segmentation are shown in Table 3.4. Starting from $Push_B$, the algorithms developed for the sacrum and head achieved lower error means and standard deviations. Since $Push_B$ is defined as the beginning of the forward motion of the trunk, these two positions are better suited to capture it. The mean value of the error is negative and higher on the right shank for both the first (-118 ms) and second (-64 ms) wall push-off (the $Push_B$ after the turn). This is because during the wall push-off phase, the swimmer begins to extend the shank for push-off, while the body posture changes from vertical to horizontal before moving the sacrum forward.

$Glid_B$ is detected with the lowest and highest error mean at the sacrum (4 ms) and the right shank (76 ms), respectively. Since the sacrum, right wrist, and head are located above the right shank, the transition from the wall push-off to the glide phase is more abrupt at these locations, whereas the change in angular velocity of the right shank is smoother at the start of the glide (the peak of $|Gyr|$ is difficult to observe in some cases).

$StPr_B$ is detected earlier at the right wrist (-151 ms) and the error standard deviation is high for the head (214 ms) and right wrist (124 ms), while the right shank has the lowest error mean and standard deviation. Stroke preparation phase accompanies with the generation of a wave throughout the body after glide phase. This wave begins on the right shank with the first action of the lower limbs, but in many swimmers the wrist movement occurs earlier to generate the reaction force during the lower limb actions, resulting in a high negative error for the right wrist. When the wave starts in the lower or upper limbs, the standard deviation increases for the sensor attached to the upper limbs (right wrist and head). The sacrum, located in the middle of this wave, detects motion with a moderate error mean and standard deviation (-32 ± 107 ms).

Since $Swim_B$ is defined as upper limbs cycle start on hand, wrists obtain the best result (-42 ± 72 ms). During front crawl or backstroke, sacrum is delayed (136 ms), sometimes two or three upper limbs cycles, in receiving the rolling motion during swimming phase, which is used for $Swim_B$ detection. Right shank is also delayed (342 ms) mostly during butterfly or breaststroke techniques since lower limb action starts always after the upper limbs cycle on hand. High standard deviation for swimming start detection on sacrum (226 ms), head (563 ms) and right shank (473 ms) are the result of high variation between swimmers and motion transfer delay to these sensor positions. For example, the lower limbs action might start after or before upper limbs cycle during front crawl and backstroke as it is not dependent on upper limbs.

Although the detection of $Turn_B$ relies mainly on turn type (simple or tumble turn), sacrum is the best location for it (23 ± 97 ms), as the turn motion reaches sacrum right after it starts on head (tumble turn) or wrist (simple turn). Right wrist has a late response during tumble turn, which causes high positive error mean (118 ms) since the swimmer tries to keep wrists backward and right wrist does not necessarily follow the turn quick motion. The wall reaching speed also affects the standard deviation of $Turn_B$ detection with right shank (390 ms) and head (195 ms). The swimmer should estimate the wall distance at the right time before turn and adapt their speed. When the swimmer touches the wall with low or high speed in simple turn, the algorithms detect $Turn_B$ on head and right shank earlier or later than the true value.

To understand better the event detection error, the estimated phase duration and its absolute and relative error compared to the true value are shown in Table 3.5. Detecting the phase duration for short phases accompanies with higher relative error. For example, this value for $\Delta Push$

detection on sacrum is 12 ± 24 %, while the same value for $\Delta Swim$ on sacrum is -0.8 ± 2 %. Hence, the detection of long phases duration such as swimming phase is more reliable than short phases. The absolute value of each phase duration error is affected by both phase start and end detection error. As shown in Table 3.5, right wrist has the highest amount of error for $\Delta Swim$ estimation, while it was the best location for $Swim_B$ detection, the reason of which is its poor performance for $Turn_B$ detection. Although the short phases duration estimation has higher relative error, the parameters within these phases are possible to extract. Interesting parameters, such as maximum push-off velocity (Stamm et al., 2013a) during wall push-off lies between wall push-off start and end.

The superiority of sacrum for micro analysis over other sensor positions is pointed out by the results displayed in Table 3.6. The smallest range of error mean (78 ms for front crawl, 314 ms for breaststroke, 287 ms for butterfly and 154 ms for backstroke) and standard deviation (123 ms for front crawl, 63 ms for breaststroke, 109 ms for butterfly and 186 ms for backstroke) for all swimming styles are achieved with sacrum. In conclusion, this location is the best for micro analysis in all swimming styles. Since sacrum also worked better in macro level, this is the best candidate for a single sensor analysis system. In macro scale, sacrum data can provide reliable results, and in micro level, it captures the events starting from upper limbs and lower limbs with less delay than other sensor positions, as it is located in the middle of the body. As shown by Bland-Altman plots (Figure 3.9), the inter-observer limit of agreement is 225 ms, 115 ms, and 100 ms for beginning of swimming, beginning of turn and beginning of stroke preparation detection respectively. Since the mean and standard deviation of error for detecting these events were higher than others in most cases (e.g. for sacrum and head), part of the error is due to observer error in validation.

In terms of usability, sacrum, head and right wrist are suitable locations, as they can easily fit into the swimming suit and goggles or be used as a watch. It is observed that head is capable of macro level analysis with lower standard deviation and higher accuracy than wrist or shank. Other than its performance for $Swim_B$ detection, head seems to be the second promising location for micro analysis. Right wrist or right shank both suffer from high error in both macro and micro levels, which might be the result of intra-swimmer variability. As a biomechanically driven approach, macro-micro analysis can provide a detailed view about the nature of movements but its downside is being prone to error caused by technique diversity or being more sensitive to thresholds. Wrist and shank did not perform well with our algorithms and they need further investigation for dealing with their pattern variability.

We included both male and female swimmers, as there was no significant difference between them in the results. Comparing the swimmers due to their individual differences is out of the scope of this study. Since the measurements started from in-water situation, the algorithms cannot cover the dive at the beginning, but it is possible to add to our method. The main influence is replacing the wall push-off phase with dive phase. Since we included a moderate pace in our measurements (80% of the best speed), the algorithms are not generalizable to all competitive paces and are valid only within the range of paces included in the measurements. However, improving technique at a moderate pace and then increasing speed is used in training. The use of the highest speed during training is generally required as competitions approach. Therefore, our system can be used in most training sessions where the pace is moderate. Although the validity of our system is not demonstrated by the highest pace, it nevertheless covers a wide range of paces for main swimming styles. Another limit of this study is the observer error while using the validation system (cameras), showing itself in lap segmentation into swimming phases. Moreover, using camera from the side view, the detection of some events is difficult to observe such as swimming phase start during breaststroke or butterfly, as they are easier to detect in front view.

3.5 Conclusion

The analysis approach proposed in this study recognized important temporal events during a training session. It started by identifying swimming bouts and laps during a training session. Then, the swimming style in each lap is identified, which is useful in micro analysis to find lap components. Then, each lap is divided into five phases: Wall push-off, glide, stroke preparation, swimming and turn for all techniques. This study showed that the macro-micro approach with the developed algorithms can cover all movement phases during a training session. The sacrum was found to provide equally good or more promising results than other sensor positions in both levels (except for a few cases such as the start of swimming or stroke preparation). At the macro level, the sacrum achieved the highest accuracy within a range of 0.83-0.98 for swimming bout detection and a range of 0.73-0.97 and 0.82-0.98 for breaststroke and butterfly technique identification, respectively. The mean and standard deviation for swimming lap segmentation were also relatively low in most cases. All these results demonstrate that the sacrum is the most suitable sensor position for an analysis system with one sensor designed to cover both macro and micro level parameters. To improve the algorithms, we are considering investigating machine learning methods that can better handle the inter- and intra-variability of swimmers' technique. Future studies focusing on the detailed parameters in each swimming phase will be the next step of the current analysis approach.

3.6 Appendix

3.6.1 Rules of algorithms

Table 3.7 and Table 3.8 represent a summary of rules developed for macro and micro swimming analysis and related biomechanics hypothesis. Refer to section 2.1 in the main text for definition of anatomical axes.

Table 3.7 – Table of rules for macro analysis. The table includes the hypothesis, rule, involved signals and functions for each algorithm developed to find macro parameters on all sensor positions.

Macro Analysis				
Parameter	**Location**	**Hypothesis**	**Signal(s)**	**Rule**
Swimming bouts	SA	The change in trunk posture between standing and prone (for front crawl, butterfly and breaststroke techniques) or supine (for backstroke technique) posture at the beginning and end of each swimming bout will affect sacrum acceleration in sagittal plane.	Acc_y	The derivative of the low pass filtered Acc_y (f_c = 0.1Hz) shows obvious peaks or troughs at the beginning and end of each bout (trough for start and peak for end) because of inclination changes (detectable by a threshold (TH_B)).
	HE	The head posture changes along with trunk between upright and prone or supine posture during each swimming bout start and end which is observable on Acc_y.	Acc_y	The derivative of the low pass filtered Acc_y (f_c = 0.1Hz) shows obvious peaks or troughs at the beginning and end of each bout (trough for start and peak for end) because of inclination changes (detectable by threshold (TH_B)).
	RW	High variability of wrist motion during upper limbs cycles makes this period significant in a full training session. Beginning of a swimming bout is not observable on wrist because no special change was observed before starting the upper limbs cycles.	$\|Acc\|$	The envelope of $\|Acc\|$ increases with the start of upper limbs cycles and stays high until the end of swimming bout, which is detectable using an empirical threshold (TH_{BW}).
	RS	Swimmers bend their knee and change their shank inclination for wall push-off before	Acc_y	The derivative of the low pass filtered Acc_y (f_c = 0.1Hz) shows obvious peaks or troughs (detectable by threshold (TH_B)) because of

		start or at the end of a swimming bout, which is observable on Acc_y.		inclination changes (troughs for start and peaks for end).
	SA	Sudden change in moving direction during simple or tumble turn affects sacrum acceleration. This change happens in all axes but more obviously on Acc_x and Acc_y. However, Acc_x is better than Acc_y because it has a relatively lower amplitude during swimming bout, while it shows the same change in turns	Acc_x	The highest peak of Acc_x during a full swimming bout represent turns (simple or tumble turn).
	HE	Tumble turn and simple turn have different effects on head but during both, there is a quick head motion in one direction (downward for tumble turn (in sagittal plane) and sideways (z axis) for simple turn).	$\lvert Acc_{y,z} \rvert$	The highest peak that exists in $\lvert Acc_{y,z} \rvert$ during a full swimming bout representing the turn (simple or tumble turn).
Swimming lap	RW	During turns, wrist motion has lower magnitude than other part of a swimming bout. Using this decrease in angular velocity level is the key to detecting turns on wrist.	$\lvert Gyr \rvert$	The low pass filtered (f_c = 3Hz) moving average (window size: 1s) of $\lvert Gyr \rvert$ is used for finding a period with relatively lower level of angular velocity. Detection is done by locating approximate turn with a threshold (TH_{LW}).
	RS	During simple turn, shanks move sideways (z axis) quickly to start pushing the wall, while during tumble turn, shanks rotate along with the whole body (in sagittal plane).	Acc_z Gyr_z	Relatively large peaks (detectable by threshold (TH_{LS})) appear on Acc_z during simple turn and on Gyr_z during tumble turn.
Swimming style	SA	In four swimming styles, sacrum motion is different in terms of angular velocity, gravity direction and	Acc_x $Gyr_{x,y,z}$	A two-upper-limb-cycle period is located by peak detection on Acc_x in each lap. Front crawl/backstroke category separates from butterfly/breaststroke category using

		motion patterns. Angular velocity is mainly around y axis for front crawl and backstroke, while it is around z axis for breaststroke and butterfly. Supine posture of swimmer during backstroke causes gravity to be in the opposite direction compared to other techniques. Sacrum motion is different in breaststroke and butterfly in terms of motion frequency.		the axis with maximum value of PCA analysis of sacrum $Gyr_{x,y,z}$. In front crawl, the trunk is downward while in backstroke, the trunk is upward (the sign of Acc_x mean is positive for backstroke). Butterfly and breaststroke are different in terms of dominant frequency of Acc_x, detected with a threshold ($TH_{StyleSA}$).
	HE	Head motion is different in terms of angular velocity, gravity effect and motion patterns. Angular velocity is mainly around y axis for front crawl and backstroke, while it is around z axis for breaststroke and butterfly. Supine posture of swimmer during backstroke causes gravity to have opposite effect compared to other techniques. Head motion is different in breaststroke and butterfly in terms of motion frequency.	$\|Acc_{x,y}\|$ $Gyr_{x,y,z}$	A two-upper-limb-cycle period is located by peak detection on $\|Acc_{x,y}\|$ in each lap. Front crawl and backstroke are different in terms of gravity effect on $\|Acc_{x,y}\|$ (the sign of $\|Acc_{x,y}\|$ mean is positive for backstroke). Front crawl/backstroke techniques separates from butterfly/breaststroke techniques using PCA analysis of head $Gyr_{x,y,z}$. Butterfly/breaststroke are different in terms of dominant frequency of $\|Acc_{x,y}\|$ detectable with a threshold ($TH_{StyleHE}$).
	RW	Wrists motion depends on swimmers' learning and technique. The principal component of acceleration shows its highest value on x axis for backstroke technique. Average of acceleration norm is used to identify butterfly since hands	$Acc_{x,y,z}$ $\|Acc\|$	A two-upper-limb-cycle period is located by peak detection on $\|Acc\|$ in each lap. During backstroke, the principal component of acceleration is in x direction. The mean and variation of $\|Acc\|$ is higher that a threshold ($TH_{StyleWmean}$) for butterfly and front crawl ($TH_{StyleWvar}$) respectively.

		motion has the highest average acceleration in butterfly. Between breaststroke and front crawl, the variation of acceleration norm is higher for front crawl.		
	RS	From technique to technique, shank motion is different in terms of principal component of angular velocity and gravity effect. Similar to head and sacrum, gravity effect on shank during backstroke is in opposite compared to other techniques. Breaststroke is the only technique, in which shank motion goes out of sagittal plane. Symmetrical kicks during butterfly is the last clue for separating this technique from front crawl because it causes a specific rotation in shanks during butterfly.	Acc_x $Gyr_{x,y,z}$	During a five-kick period, gravity effect on Acc_x separated backstroke from other techniques (the sign of Acc_x mean is positive for backstroke). Using a PCA analysis, breaststroke shows its minimum component in y direction because the motion is mainly in shank transverse plane. During butterfly, second component of shank principal angular velocity is positive for right shank (or negative for left shank) due to outward motion of shanks, while it does not necessarily happen for front crawl.

Table 3.8 – Table of rules for micro analysis. The table includes the hypothesis, rule, involved signals and functions for each algorithm developed to find micro parameters on all sensor positions.

Micro Analysis				
Parameter	**Location**	**Hypothesis**	**Signal**	**Rule**
Wall push-off start ($Push_B$)	SA	Sacrum has a motion with high forward acceleration (y axis) at the beginning of wall push-off. This motion leaves a peak in Acc_y, After which the acceleration decreases due to water drag.	Acc_y	Backstroke: The maximum of Acc_y in a 2-second window after swimming bout start is the closest point to push-off start. The result is not sensitive to the length of this window. Other: it is easier to find the trough after push-off start and use it to detect the push-off start. In a 2-second window after swimming bout start, Acc_y concavity changes which is detectable on its derivative. If this sample is followed by a trough lower than zero on Acc_y, then the peak before this trough is the closest point to push-

				off start. The result is not sensitive to the length of the window.
	HE	Head has a motion with high forward acceleration (y axis) at the beginning of wall push-off. This motion leaves a peak in Acc_y and $\|Acc\|$, After which the acceleration decreases due to water drag.	Acc_y $\|Acc\|$	Backstroke: The maximum of Acc_y in a 2-second window after swimming bout start is the closest point to push-off start. The result is not sensitive to the length of the window. Other: in a 2-second window after swimming bout start, the maximum of $\|Acc\|$ provides a rough approximation which will be finetuned with a close peak on Acc_y. The result is not sensitive to the length of the window.
	RW	The swimmer wrists goes down in water for push-off, which causes an acceleration against gravity on axis y. As the swimmer is raising and stretching the arms forward, this acceleration increases.	Acc_y	As Acc_y decreases below zero due to wrist downward motion, it increases afterwards when the swimmer raises their wrists for push-off. The trough before this increase in Acc_y is detected as the closest to push-off start.
	RS	Swimmer's knees extend during push-off after an almost motionless period, so this sharp increase in $\|Gyr\|$ is a sign of push-off start.	$\|Gyr\|$	As knees starts to extend at the beginning of push-off, $\|Gyr\|$ increases and shows a peak. The first minimum before this peak is the closest point to push-off start.
Glide start ($Glid_B$)	SA	Sacrum forward acceleration (y axis) gets closer and closer to zero due to the end of push-off period and deceleration start.	Acc_y	The first negative trough on Acc_y after push-off start shows the beginning of glide period that the swimmer's body starts to decelerate.
	HE	Head forward acceleration (y axis) should get close to zero due to the end of push-off period.	Acc_y	The first negative trough on Acc_y after push-off start shows the beginning of glide period that the swimmer's body decelerates.
	RW	As the arms are fully stretched, Acc_y at glide start will be a sample closest to zero after push-off start.	Acc_y	As push-off start on wrist was a negative trough, after which the acceleration started increasing towards zero, the first peak on Acc_y after push-off start is the closest to glide start. It is close to zero.
	RS	$\|Gyr\|$ of Shank decreases close to zero due to the end of push-off period.	$\|Gyr\|$	The first trough of $\|Gyr\|$ after push-off start, where angular velocity is almost zero.

	SA	The wave generated in swimmer's body due to stroke preparation kicks causes a periodic change in sacrum acceleration after a motionless glide. The change is clear on sacrum Acc_x because of its upward and downward motion.	$\|Acc_x\|$	Start of this phase is detectable by using two thresholds on peaks of $\|Acc_x\|$ (TH_{SPSA}) and its variation ($TH_{SPSAvar}$) obtained with moving standard deviation (100 samples window size). As soon as they get higher than the thresholds, stroke preparation phase is started. The first peak or trough (the ones happening earlier) of this period is considered as stroke preparation start.
	HE	The thrust caused by stroke preparation kicks will show a periodic change on head Acc_y. This change happens after the motionless period of glide.	$\|Acc_y\|$	The first peak of this periodic change in $\|Acc_y\|$ is considered as stroke preparation start. It is detected using thresholds on peak magnitude (TH_{SPHE}) and prominence ($TH_{SPHEprom}$).
Stroke preparation start ($StPr_B$)	RW	As wrist is almost motionless before stroke preparation start, its $\|Acc\|$ remains equal to g. Stroke preparation kicks causes a wave motion on wrists too.	$\|Acc\|$	The first peak on $\|Acc\|$, detected by a threshold (TH_{SPRW}) after motionless glide phase is considered as stroke preparation start.
	RS	Upward and downward motion of shanks during the dolphin kicks after a motionless period is the clue to find stroke preparation start. It is observable on all axes of shank acceleration.	Acc_y $\|Acc_x\|$ $\|Acc\|$	Backstroke: The first positive peak on Acc_y after glide start caused by kicking thrust is the start of stroke preparation phase. Other: The first peak on $\|Acc_x\|$ bigger than a threshold (TH_{SPRS}) is close to the answer. The first sample before this peak where $\|Acc\|$ passes g is the start of stroke preparation phase because the shanks are motionless and $\|Acc\| = g$ before stroke preparation start
Swimming start ($Swim_B$)	SA	Sacrum motion changes with the start of upper limbs cycles. For front crawl and backstroke, the sacrum angular velocity is in sagittal plane (XY plane) during stroke preparation phase while it changes to frontal plane (XZ plane) during upper limbs cycles. For	Gyr_y $\|Gyr_y\|$ Gyr_z Acc_y	Front crawl & backstroke: Gyr_y becomes prominent after the first upper limbs cycle start because of body rolling motion. It is detected with a threshold ($TH_{SSA-FCBaS}$) on $\|Gyr_y\|$ and then finetuned with the closest peak of Gyr_y before this sample. Breaststroke: Using Empirical Mode Decomposition (EMD) and Hilbert-Huang transform, abrupt increase in instantaneous energy level of second mode of filtered Gyr_z (f_c = 2 Hz) happens in free-swimming phase. The

	breaststroke and butterfly the motion changes in terms of energy increment of Gyr_z and Acc_y with start of free-swimming phase.		sample is detected using a threshold ($TH_{SSA-BrS}$) and the previous peak on Gyr_z is close to free-swimming phase start. Butterfly: Acc_y is decomposed into several components using EMD method. The second component starts a periodic change after free-swimming phase start and the first peak on it is detected with a threshold (TH_{SSA-BF}). The trough before this peak is close to free-swimming phase start.
HE	Head motion changes due to free-swimming phase start varies from technique to technique. In front crawl, head starts to roll, causing an increase in Gyr_y energy level. For butterfly and breaststroke, head upward and downward motion intensifies, which causes an increase in Gyr_z energy level. In backstroke, head become steadier after upper limbs cycles start, which means less energy level of Gyr_z .	Gyr_y Gyr_z	Front crawl: Threshold-based detection (TH_{SHE-FC}) of Gyr_y energy level (obtained with HHT(Gyr_y)) increase is used to find the vicinity of upper limbs cycle start. The first trough before this increment is chosen as swimming start. Butterfly & breaststroke: Threshold-based detection ($TH_{SHE-BFBrS}$) of Gyr_z energy level increase (obtained with HHT(Gyr_z)) is used to find the vicinity of swimming start. The first trough before this increment is chosen as swimming start. Backstroke: Threshold-based detection ($TH_{SHE-BaS}$) of Gyr_z energy level decrease (obtained with HHT(Gyr_z)) is used to find the vicinity of swimming start. The first peak before this decrement is chosen as swimming start.
R&LW	Wrists start to move at the beginning of free-swimming phase, which is observable on acceleration and angular velocity. For front crawl and butterfly, Acc_y change is easier to detect because of hands downward motion right from the swimming start. For breaststroke, hand rotation at the free-swimming phase start	Acc_x Acc_y Gyr_y	For front crawl and backstroke, the algorithm is implemented on both wrists and the earlier result was chosen as the answer. Front crawl & butterfly: The trough before the first peak on Acc_y caused by upper limbs cycles after stroke preparation start is swimming start. Breaststroke: Gyr_y first peak after stroke preparation start an approximate period for the answer. The trough before the first peak of filtered Acc_x (f_c = 5 Hz) happening in this period is the closest to swimming start. Backstroke: The trough before the first peak on Acc_x caused by upper limbs

		causes a change in Gyr_y and Acc_x .		cycles after stroke preparation start is swimming start.
	RS	Start of upper limbs cycles on shanks causes a change in the kicking method depending on swimming style. Except for breaststroke, kicking happens in sagittal plane and Acc_x is the signal that changes more obviously. The same happens on Acc_y for breaststroke. This change in kicking is possible to detect as the beginning of free-swimming phase.	Acc_x Acc_y	Using EMD method on Acc_y for breaststroke and Acc_x for the rest techniques, the second mode separates the fluctuations after swimming start on shanks. Threshold-based peak detection (TH_{SRS}) finds the first peak of this mode and the trough before it is considered as swimming start.
Turn start ($\boldsymbol{Turn_B}$)	SA	During tumble and simple turn, sacrum motion is mainly in sagittal and frontal plane respectively. In both cases, Acc_x is affected by the motion and shows a sudden change. Approximate turn, which is a sample during turn phase is already detected with lap detection algorithm and is used here.	Acc_x	Backstroke: it happens at a peak caused by the rolling before turn. This peak is the same as approximate turn already detected on Acc_x. Other: in a period before approximate turn, the turn causes a large peak in Acc_x, the trough before which is close to turn start.
	HE	For tumble turn, head starts the downward motion, which can be observed as a big peak on head $\lvert Acc\rvert$. Before turning, head rests for a short period where $\lvert Acc\rvert$ should be close to g. For simple turn, the motion is basically in frontal plane which is detectable on head Gyr_x.	$\lvert Acc\rvert$ Gyr_x	Front crawl & backstroke: $\lvert Acc\rvert$ shows a peak which is close to approximate turn. The sample before this peak where acceleration is equal to g is close to turn start. Butterfly & breaststroke: Gyr_x has a peak close to approximate turn. Turn start is the trough before this peak
	RW	During tumble turn, wrists undergo a	Acc_y	Front crawl & backstroke: wrist Acc_y shows a peak close to approximate

		complete turn from prone to supine along with the whole body. This change is clear on Acc_y. During simple turn, forearm orientation changes from horizontal before turn to vertical (or close to vertical) and again to horizontal after turn. This change is observable on wrist Acc_y.		turn, clear on high-filtered Acc_y (f_c = 2 Hz). The trough before this peak is close to turn start. Breaststroke & butterfly: Acc_y shows a peak close to approximate turn. The trough before this peak is close to turn start.
	RS	During tumble turn, shanks rotate with the whole body, causing a clear change on Gyr_z, while during simple turn, they move sideways (z axis) to reach the wall for push-off.	Gyr_z Acc_z	Front crawl & backstroke: shank Gyr_z increases abruptly during rotation, close to approximate turn. The trough before this change is turn start. Breaststroke & butterfly: Acc_z increases because of the shank sideway motion, close to approximate turn. The trough before this increase is turn start.

3.6.2 Sensitivity analysis of thresholds

The thresholds are changed in both directions according to the percent declared and the total change in algorithm result (accuracy and precision of swimming bouts and lap detection and swimming style identification in macro analysis and the estimated values for phase starts in micro analysis) is reported. The percent of change depends on how the results changed with a least amount of 10% (Table 3.9).

Table 3.9 – Table of thresholds sensitivity analysis

Threshold	Description	Threshold change (%)	Results change (%)
TH_B	The thresholds used for swimming bouts detection on SA, HE and RS	30	0
TH_{BW}	The threshold used for swimming bouts detection on RW	15	5
TH_{LW}	The threshold used for swimming lap detection on RW	30	0
TH_{LS}	The threshold used for swimming lap detection on RS	15	5
$TH_{StyleSA}$	The threshold used for swimming style identification on SA	30	Less than 1
$TH_{StyleHE}$	The threshold used for swimming style identification on HE	30	Less than 1
$TH_{StyleWmean}$	The first threshold used for swimming style identification on W	10	5
$TH_{StyleWvar}$	The second threshold used for swimming style identification on W	50	1

$\boldsymbol{TH_{SPSA}}$	The first threshold used for $StPr_B$ detection on SA	This threshold is 1g and can be justified biomechanically	
$\boldsymbol{TH_{SPSAvar}}$	The second threshold used for $StPr_B$ detection on SA	30	0
$\boldsymbol{TH_{SPHE}}$	The first threshold used for $StPr_B$ detection on HE	20	12
$\boldsymbol{TH_{SPHEprom}}$	The second threshold used for $StPr_B$ detection on HE	10	15
$\boldsymbol{TH_{SPRW}}$	The first threshold used for $StPr_B$ detection on RW	10	5
$\boldsymbol{TH_{SPRS}}$	The first threshold used for $StPr_B$ detection on RS	15	5
$\boldsymbol{TH_{SSA-FCBaS}}$	The threshold used for $Swim_B$ detection on SA for front crawl and backstroke	15	5
$\boldsymbol{TH_{SSA-BrS}}$	The threshold used for $Swim_B$ detection on SA for breaststroke	20	Less than 1
$\boldsymbol{TH_{SSA-BF}}$	The threshold used for $Swim_B$ detection on SA for butterfly	15	Less than 1
$\boldsymbol{TH_{SHE-FC}}$	The threshold used for $Swim_B$ detection on HE for front crawl	20	Less than 1
$\boldsymbol{TH_{SHE-BFBrS}}$	The threshold used for $Swim_B$ detection on HE for butterfly and breaststroke	10	5
$\boldsymbol{TH_{SHE-BaS}}$	The threshold used for $Swim_B$ detection on HE for backstroke	15	9
$\boldsymbol{TH_{SRS}}$	The threshold used for $Swim_B$ detection on RS	10	5

3.6.3 Glossary of terms

Here if the table of glossary of all the terms used for macro/micro approach of swimming analysis.

Table 3.10 – Table of glossary for Chapter 3

Term	Definition
IMU	Inertial measurement unit
Acc	Acceleration data (g)
Gyr	Gyroscope data ($°/s$)
$\boldsymbol{\lvert Acc_{y,z} \rvert}$	Sum of the acceleration on y and z axes
$\boldsymbol{Gyr_{x,y,z}}$	All three axes of gyroscope
|Gyr|	Norm of angular velocity
$\boldsymbol{\dot{Acc}_y}$	Derivative of Acc_y
SA	Sacrum
HE	Head
RW	Right wrist
RS	Right shank
Swimming bout	The swimming parts (in any swimming style) during a training session that includes one or more laps.
Swimming lap	The wall-to-wall period of swimming
Simple turn	The turn at the end a the swimming lap during breaststroke and butterfly styles
Tumble turn	The turn at the end a the swimming lap during front crawl and back swimming styles
Swimming style	The style of swimming which is one among this list: Front crawl, Breaststroke, Butterfly, Backstroke
Swimming phase	Each swimming lap is divided in five swimming phases (wall push-off, glide, stroke preparation, swimming and turn)

$Push_B$	Beginning of wall push-off phase
$Glid_B$	Beginning of glide phase
$StPr_B$	Beginning of stroke preparation phase
$Swim_B$	Beginning of free-swimming phase
$Turn_B$	Beginning of turn phase
Δ-	Stands for the duration of each phase
$\mathbf{TH_{B}}$	The thresholds used for swimming bouts detection on SA, HE and RS
$\mathbf{TH_{BW}}$	The threshold used for swimming bouts detection on RW
$\mathbf{TH_{LW}}$	The threshold used for swimming lap detection on RW
$\mathbf{TH_{LS}}$	The threshold used for swimming lap detection on RS
$\mathbf{TH_{StyleSA}}$	The threshold used for swimming style identification on SA
$\mathbf{TH_{StyleHE}}$	The threshold used for swimming style identification on HE
$\mathbf{TH_{StyleWmean}}$	The first threshold used for swimming style identification on W
$\mathbf{TH_{StyleWvar}}$	The second threshold used for swimming style identification on W
$\mathbf{TH_{SPSA}}$	The first threshold used for $StPr_B$detection on SA
$\mathbf{TH_{SPSAvar}}$	The second threshold used for $StPr_B$detection on SA
$\mathbf{TH_{SPHE}}$	The first threshold used for $StPr_B$detection on HE
$\mathbf{TH_{SPHEprom}}$	The second threshold used for $StPr_B$detection on HE
$\mathbf{TH_{SPRW}}$	The first threshold used for $StPr_B$detection on RW
$\mathbf{TH_{SPRS}}$	The first threshold used for $StPr_B$detection on RS
$\mathbf{TH_{SSA-FCBaS}}$	The threshold used for $Swim_B$detection on SA for front crawl and backstroke
$\mathbf{TH_{SSA-BrS}}$	The threshold used for $Swim_B$detection on SA for breaststroke
$\mathbf{TH_{SSA-BF}}$	The threshold used for $Swim_B$detection on SA for butterfly
$\mathbf{TH_{SHE-FC}}$	The threshold used for $Swim_B$detection on HE for front crawl
$\mathbf{TH_{SHE-BFBrS}}$	The threshold used for $Swim_B$detection on HE for butterfly and breaststroke
$\mathbf{TH_{SHE-BaS}}$	The threshold used for $Swim_B$detection on HE for backstroke

Chapter 4 Phase-based performance evaluation with IMU

Publication Note: this chapter is adapted from the following journal paper:

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Supplementary materials:
https://www.frontiersin.org/articles/10.3389/fbioe.2021.793302/full#supplementary-material

This chapter presents a phase-based performance evaluation of swimming based on the macro-micro approach developed in the previous chapter. Regardless of the swimming style, the swimmer passes various swimming phases from wall to wall, including a dive into the water or wall push-off, then glide and stroke preparation and finally, swimming up to the turn. The coach focuses on improving the performance of the swimmer in each of these phases. The purpose of this chapter was to assess the potential of using a sacrum-worn IMU for performance evaluation in each swimming phase (wall push-off, glide, stroke preparation and swimming) of elite swimmers in four main swimming styles (i.e. front crawl, breaststroke, butterfly and backstroke). Nineteen swimmers were asked to wear a sacrum IMU and swim four one-way 25-m trials in each technique, attached to a tethered speedometer and filmed by cameras in the whole lap as reference systems. Based on the literature, several goal metrics were extracted from the instantaneous velocity (e.g. average velocity per stroke cycle) and displacement (e.g. time to reach 15m from the wall) data from a tethered speedometer for the swimming phases, each one representing the goodness of swimmer's performance. Following a novel approach, that starts from swimming bout detection and continues until detecting the swimming phases, the IMU kinematic parameters in each swimming phase were extracted. The highly associated parameters with the corresponding goal metrics were detected by LASSO (least absolute shrinkage and selection operator) parameter selection and used for estimating the goal metrics with a linear regression model. The selected kinematic parameters were relevant to the motion characteristics of each phase (e.g. selection of propulsion-related parameters in wall push-off phase), providing more interpretability to the model. The estimation reached a determination coefficient (R^2) value more than 0.75 and a relative RMSE less than 10% for most goal metrics in all swimming styles. The results show that a single sacrum IMU can provide a wide range of performance-related swimming kinematic parameters, useful for performance evaluation in four main swimming styles.

Keywords: *Sports biomechanics, swimming, wearable sensor, performance evaluation, parameter selection.*

4.1 Introduction

Swimming coaches seek comprehensive monitoring of performance to develop and refine a competition model for their top athletes. During a competition, the swimmer goes through several swimming phases from wall to wall, including a dive into the water or wall push-off, then glide and stroke preparation and finally swimming up to the turn at the end of the lap and repeating the same sequence in the next lap. Therefore, to have a comprehensive performance evaluation, studies have focused on various swimming phases, since the swimmers aim to master all of them (Mooney et al., 2016b). As the principal goal of a swimmer is to reduce the swimming time by increasing the velocity, performance evaluation goal metrics in different phases are based on time records and velocity. Flight distance (Ruschel et al., 2007), time to 15 meters (Vantorre et al., 2010), average velocity per stroke (Dadashi et al., 2015), swimming phase average velocity (Mason and Cossor, 2000), turn time (5m before to 10m after the wall) (Mooney et al., 2016b) or lap time are examples of common goal metrics.

Recently, wearable IMUs (inertial measurement unit) have been used more for swimming motion analysis in all competitive swimming styles (Guignard et al., 2017b), because of the challenges of video-based systems application in aquatic environments (Callaway et al., 2010). They are used in a multitude of studies for parameter extraction in various swimming phases, such as start (Vantorre et al., 2014), swimming (Davey et al., 2008), and turn (Slawson et al., 2012). Novel orientation analysis algorithms made it possible to estimate the 3-dimensional orientation of IMU with high accuracy by fusing accelerometer, gyroscope and magnetometer data (Madgwick et al., 2011). This approach is implemented in swimming for inter-segmental coordination assessment (Guignard et al., 2017a), posture recognition (Wang et al., 2019) and intra-stroke velocity (Worsey et al., 2018). In another study, a new analysis approach is proposed and trunk elevation, body balance, and body rotation are used as new indices for swimming analysis (Félix et al., 2019; Morouço et al., 2020). Considering the significance of phase related kinematic parameters, we have recently proposed a macro-micro approach for swimming analysis using IMUs (Hamidi Rad et al., 2021b). In our approach, swimming bouts, laps and swimming style are detected in macro analysis. Afterwards in micro level, each lap is segmented into swimming phases of wall push-off (*Push*), glide (*Glid*), stroke preparation (*StPr*), swimming (*Swim*) and turn (*Turn*) from wall to wall. In the next level of micro analysis, the kinematic parameters within each swimming phase (micro parameters) are extracted from IMU data.

These studies show there is still a substantial undiscovered potential for kinematic parameter extraction with IMUs in swimming analysis. However, the association between the swimming kinematic parameters extracted by IMU and the above-mentioned goal metrics is still unclear. Furthermore, as the parameters provided by the IMU are claimed to be associated with the swimmers' performance, they can be used for estimating the goal metrics of performance evaluation. As a result, the relationship between IMU kinematic parameters and goal metrics is yet to be studied to prove IMU potential not only for swimming kinematic parameter extraction, but also for performance evaluation and training optimization.

The main objective of this study is to find the association between swimming kinematics extracted using a sacrum-worn IMU and goal metrics in different swimming phases. We hypothesized that the micro parameters extracted from IMU data are associated with the goal metrics used for performance evaluation, regardless of the swimming style. Following the macro-micro approach for swimming analysis (Hamidi Rad et al., 2021b), within each swimming phase ($Push$, $Glid$, $StPr$ and $Swim$), we selected the kinematic parameters that are highly associated with goal metrics. We then used the selected kinematics to estimate the goal metrics. Using the underlying model, we can explains how kinematics determine the performance.

4.2 Materials and methods

4.2.1 Measurement setup

Nineteen elite swimmers took part in this study, whose attributes are shown in Table 4.1. They were informed of the procedure and gave their written consent prior to participation. This study was approved by the EPFL human research ethics committee (HREC, No: 050/2018). One IMU (Physilog® IV, GaitUp, CH.) was attached to swimmer's sacrum, using waterproof band (Tegaderm, 3M Co., USA). The sensor contained a 3D gyroscope (±2000 °/s) and 3D accelerometer (±16 g), with a sampling rate of 500 Hz (Figure 4.1). A functional calibration was performed after sensor installation with simple movements in land (upright standing and squats) before the measurement to make the data independent of sensor placement on swimmer's body (Dadashi et al., 2013c). The possibility of removing functional calibration and its effect on phase-based performance evaluation results will be investigated in section 5.6.2. During the measurements, the swimmers were asked to perform four one-way trials in each swimming style (i.e. front crawl, breaststroke, butterfly, backstroke) with a progressive velocity (70%-100%) in a 25m indoor pool, starting with wall push-off inside water. The trials were separated with one-minute rests, and the total duration of the measurement was around one hour per swimmer.

Table 4.1 – Statistics of the study participants. All parameters are presented as mean ± standard deviation. $Record_{50m}$ is the average and standard deviation of 50m record of the swimmers separately for each swimming style

Male	Female	Age (years)	Height (cm)	Weight (kg)	$\mathbf{Record_{50m}}$ (s)	
9	10	19.5 ± 2.7	177.5 ± 7.5	67.9 ± 8.3	Front crawl	25.85 ± 1.65
					Breaststroke	34.76 ± 3.87
					Butterfly	28.55 ± 2.47
					Backstroke	30.19 ± 1.88

Two systems were used as references in our study to validate the goal metrics estimated by the IMU. The first one was a set of four 2D cameras (GoPro Hero 7 Black, GoPro Inc., US) used for detecting the swimming phases. The cameras synchronized with the IMU, using the LED light of a push-button (Hamidi Rad et al., 2021b) were attached to the pool wall (distributed along the length of the pool) to videotape all the lap from wall to wall underwater with a 60 Hz rate (Figure 4.1). The second reference system was a tethered speedometer (SpeedRT®, ApLab, Rome, Italy), attached with a belt to the waist of the swimmer. The speedometer calculated the displacement and velocity of the swimmer at a rate of 100 Hz and was used for finding the reference values of goal metrics in different swimming phases. As the speedometer was installed on the starting block above the swimmer's level, it caused a parallax problem (Le Sage et al., 2011). Since the device level difference with respect to the still pool water was known (62 ± 1 cm), the velocity projection along the swimming direction was separated as the forward velocity of the swimmer.

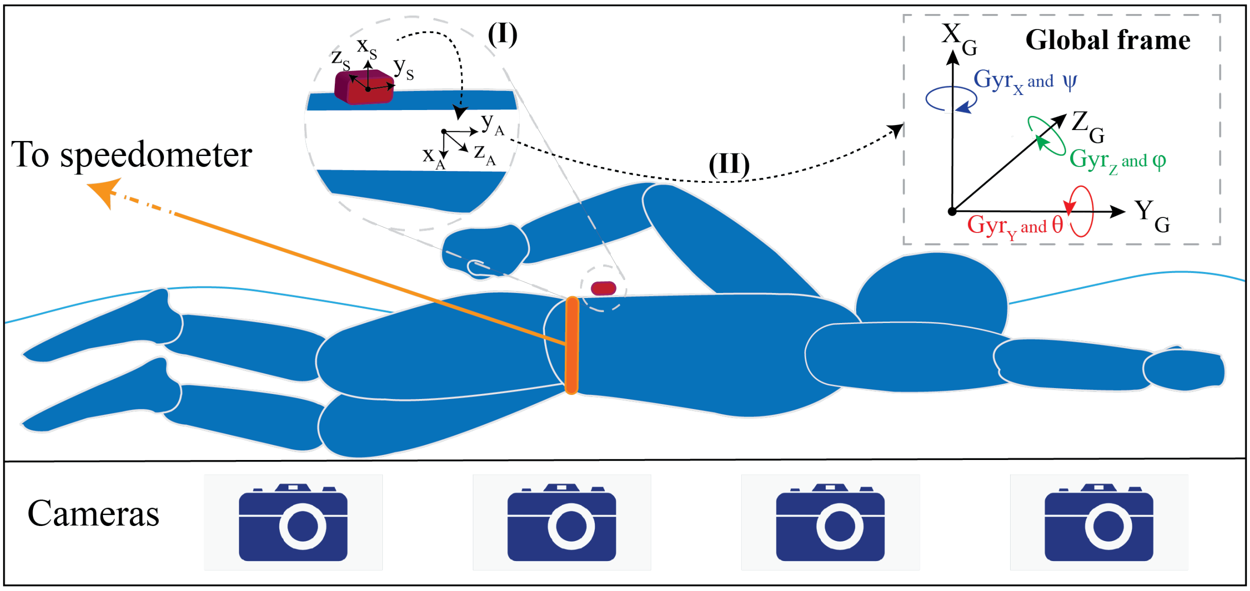

Figure 4.1 – Measurement setup, including one IMU attached to the sacrum, four cameras to capture the whole lap and tethered speedometer to record swimmer's displacement and velocity. IMU data is transferred from sensor frame $(x,y,z)_S$,first to anatomical frame $(x,y,z)_A$ using functional calibration (I), and then to the global frame $(X,Y,Z)_G$ using the gradient-descend based optimization algorithm (II) .The global axes of acceleration, angular velocity and angles are displayed in the figure.

4.2.2 Performance evaluation

The general flowchart for performance evaluation is outlined in Figure 4.2. The algorithm includes three parts: **(i)** IMU data preparation **(ii)** phase detection and phase-based micro parameters extraction, **(iii)** kinematic parameter selection and goal metrics estimation. IMU data preparation aims to transfer the data to the global frame to achieve the true motion data of swimmer's sacrum. Then we divided each lap into four phases of Push, Glid, StPr and Swim by camera or IMU (Hamidi Rad et al., 2021b). To observe the error induced by IMU-based phase detection, the rest of the analysis was done once with swimming phases detected by cameras and once by the IMU for comparison, the results of which are illustrated in appendix (Table 4.5). Using the data in global frame (acceleration (Acc_X, Acc_Y, Acc_Z), angular velocity (Gyr_X, Gyr_Y, Gyr_Z) and orientation (Roll, Pitch, Yaw)) within the detected phases, we extracted the micro parameters of each phase.

In the third part of this approach, we used the extracted phase-based micro parameters to estimate the goal metrics. First, LASSO (least absolute shrinkage and selection operator) parameter selection is used to rank and select the micro parameters with higher importance (Fonti and Belitser, 2017). Using the speedometer and camera data, several goal metrics are extracted on the velocity and displacement of the swimmer in different swimming phases. These goal metrics are representatives of how well the swimmer performed in the corresponding phase. Finally, we used the selected micro parameters to estimate the goal metrics. The principal outputs of this analysis are the selected parameters and the error of using them for goal metrics estimation.

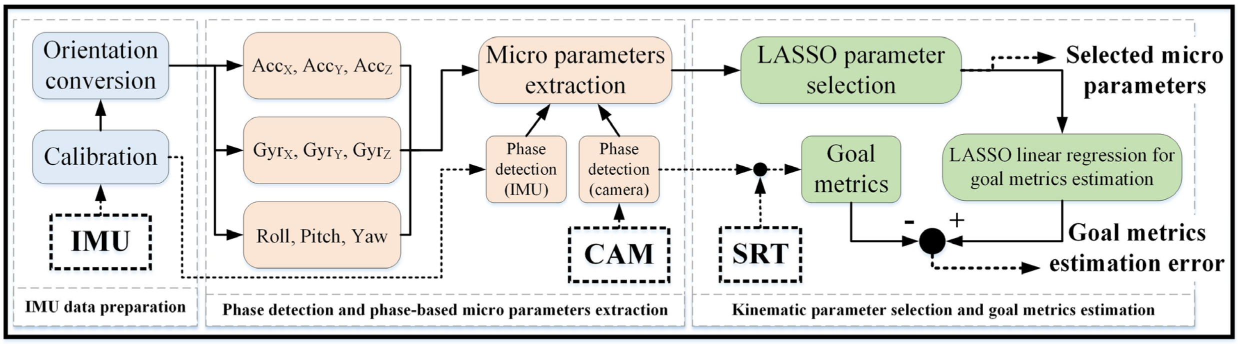

Figure 4.2 – Flowchart of the performance evaluation algorithm. IMU data preparation including IMU calibration and expressing data in the global frame (left), phase detection by cameras (CAM) or IMU calibrated data and micro parameter extraction from IMU data in global frame (middle) and parameter selection from micro parameters and the goal metrics estimation (right). The actual goal metrics are defined and extracted from the velocity and displacement data by tethered speedometer (SRT) during swimming phases separated by the cameras (CAM).

4.2.3 IMU data preparation

First, the data was calibrated for offset, scale and non-orthogonality (Ferraris et al., 1995). As explained in section 4.2, a functional calibration is also performed before each measurement trial. The goal of this calibration is to transform the data from sensor frame $(x, y, z)_S$ to anatomical frame $(x, y, z)_A$ (Figure 4.1 - I). Following that, the data is ready to be expressed in the global frame. The swimmers were asked to hold an upright posture in water before lap start for five seconds to find the initial orientation of the sacrum with respect to the pool. The changes from the initial orientation are estimated by angular velocity integration from gyroscope data and corrected with acceleration using a gradient-descend based optimization algorithm (Madgwick et al., 2011). The algorithm provides the orientation changes in quaternion q (represented by four elements (q_1, q_2, q_3, q_4)) and use them to convert the accelerometer and gyroscope data from anatomical frame ($(x, y, z)_A$) to global frame ($(X, Y, Z)_G$) (Figure 4.1 - II), expressed in equations 4.1 and 4.2.

$$Acc_G = q \otimes [0 \; Acc_A] \otimes q^T \tag{4.1}$$

$$Gyr_G = q \otimes [0 \; Gyr_A] \otimes q^T \tag{4.2}$$

Where Acc_A and Acc_G are the acceleration in anatomical and global frame respectively, $\otimes$ represents quaternion multiplication and q^T is the transpose of the quaternion q. The same notation holds true for gyroscope data in equation 4.2. Moreover, by changing quaternions into Euler angles, roll (θ), pitch (φ) and yaw (ψ) angles could be found (equation 4.3). The angles θ, φ and ψ are defined respectively around the longitudinal, mediolateral, and anterior-posterior axes of swimmer's sacrum.

$$\begin{cases} \psi \ = Atan2(\, 2q_2q_3 - 2q_1q_4, 2{q_1}^2 + 2{q_2}^2 - 1) \\ \theta \ = \ -sin^{-1}(\, 2q_2q_4 + 2q_1q_3) \\ \varphi \ = \ Atan2(\, 2q_3q_4 - 2q_1q_2, 2{q_1}^2 + 2{q_4}^2 - 1) \end{cases} \tag{4.3}$$

4.2.4 Phase-based micro parameters

For IMU-based detection of swimming phases, we used a macro-micro approach in our previous study, started from swimming bouts detection down to lap segmentation into swimming phases (Hamidi Rad et al., 2021b). Using the acceleration, angular velocity and orientation data in global frame, various kinematic parameters based on motion biomechanics in every swimming phase are defined. As frequently discussed in the literature, fast swimming depends on **(i)** the ability to generate high propulsive forces, **(ii)** the ability to keep the correct posture for reducing the drag, while **(iii)** swimming with the highest efficiency (Toussaint and Truijens, 2005). Therefore, knowledge of the propulsion, posture and efficiency is relevant to optimize swimming performance. We related the extracted micro parameters to one of these three categories (Table 4.2). We also added a fourth group for the parameters related to the durations and rates of motion, which did not fit into the previous three categories. For example stroke rate in *Swim* phase which is not necessarily a sign of high or low propulsion, good or bad posture and high or low efficiency but it is widely used for performance evaluation (Siirtola et al., 2011; Beanland et al., 2014).

We extracted the micro parameters by extremum detection, integration or calculation of the average, range, and standard deviation of the signal. The parameters defined per stroke in *Swim* phase need a cycle separation algorithm. For front crawl and backstroke, the duration between the two successive positive peaks on the longitudinal angular velocity in anatomical frame (Gyr_y) is one cycle (Dadashi et al., 2013c). The same method is used with mediolateral angular velocity in anatomical frame (Gyr_z) for cycle separation of breaststroke and butterfly techniques.

Table 4.2 – Categories and description of the phase-based micro parameter defined on IMU data in global frame. The name of the functions used for micro parameters extraction are abbreviated in parentheses.

Category	Description	Micro parameters
Propulsion	Parameters related to the amount of propulsion generated by the swimmer	Mean (*Mean*), range (*Range*) and standard deviation (*SD*) of Acc_X, Acc_Y and Acc_Z. Maximum (*Max*), integral (*Int*), and momentum change (*Momentum*) of Acc_X, Acc_Y and Acc_Z.
Posture	Parameters related to the body posture and drag effects on swimmer' body	*Mean*, *Range* and *SD* of θ and φ
Efficiency	Parameters related to the efficiency of motion which can reflect in acceleration	Ratio of positive Acc_Y to $\lvert Acc \rvert$ (*Eff_dir*) or to negative Acc_Y (*Eff*), distance per stroke (*DPS*) in *Swim* phase
Duration/ rate	Parameters related to the duration of a phase or the rate of movement	*Mean*, *Range* and *SD* of Gyr_X, Gyr_Y and Gyr_Z. phases and cycles duration. Kick rate and count in *StPr* phase. Stroke rate and count in *Swim* phase.

4.2.5 Goal metrics

We extracted eight goal metrics from the tethered speedometer data i.e. the velocity and displacement of the swimmer, from wall to wall within the swimming phases detected on the cameras (Figure 4.3).

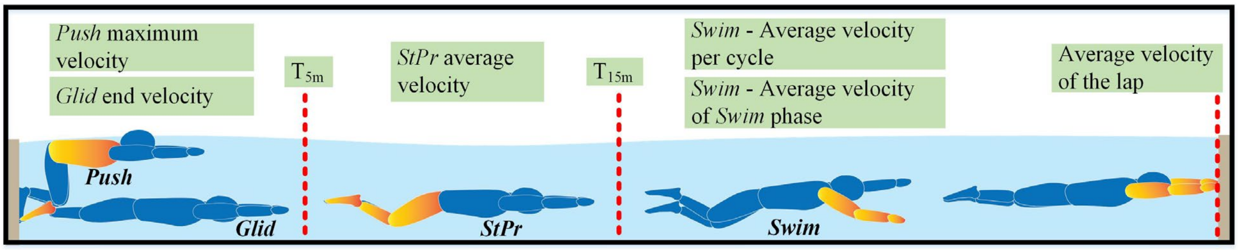

Figure 4.3 – The defined goal metrics for different swimming phases from wall to wall

1. ***Push*** **maximum velocity**: the highest velocity during the lap is generated at start, as the swimmer can reach a velocity much greater than other swimming phases (Shimadzu et al., 2008). During *Push* phase, the maximum velocity reached is used to assess wall push-off (Stamm et al., 2013a). We use this value as the goal metric for *Push* phase.

2. ***Glid*** **end velocity**: the velocity decreases during *Glid* phase because of water drag. The swimmer should keep the streamlined horizontal posture and start *StPr* phase at the right time before losing too much velocity (Vantorre et al., 2014). So, we considered the velocity of the swimmer at the end of *Glid* phase as the goal metric for this phase.

3. ***StPr*** **average velocity**: the average velocity of the swimmer during *StPr* lower limbs actions is shown to have a negative correlation with 15-meter time of the swimmer (Cossor and Mason, 2001). We used it as the goal metric for *StPr* phase.

During *Swim* phase, the performance of the swimmer can be studied per cycle or in the whole phase. Thus, two goal metrics are defined in this phase:

4. ***Swim* - average velocity per cycle**: the average velocity of the swimmer per cycle provides valuable information of swimmer's performance in every cycle (Dadashi et al., 2015).

5. ***Swim* - average velocity of *Swim* phase:** for looking at all the cycles together, the average velocity of the whole *Swim* phase is used as the second goal metric for this phase.

We also used three more goal metrics based on the literature, which include more than one phase.

6. $\boldsymbol{T_{5m}}$: normally *Glid* phase finishes before reaching five meters from the wall when the swimmer starts by wall push-off in all swimming styles. The time it takes the swimmer to reach five meters from the wall is a goal metric (Zatsiorsky et al., 1979), which shows the combination of swimmer's performance during *Push* and *Glid* phases.

7. $\boldsymbol{T_{15m}}$: 15 meters is the limit for the swimmer to re-surface (except for breaststroke technique) according to FINA (Federation International de Natation) rules. So the time it takes to reach 15 meters from the wall is a goal metric referring to underwater phases (*Push*, *Glid* and *StPr*) (Vantorre et al., 2010).

8. **Lap average velocity**: considering all the phases together, average velocity of the lap (determined by lap time) is the final goal metric, displaying the overall performance of the swimmer in all phases (Davey et al., 2008; Mooney et al., 2016b).

Among the defined goal metrics, *Push* maximum velocity is calculated with a peak detection algorithm in *Push* phase. The rest of the goal metrics only rely on the beginning or end of swimming phases, which are already obtained by phase detection.

4.2.6 Association between micro parameters and goal metrics

After extracting the micro parameters from IMU and goal metrics from speedometer and camera data, we look for association between every goal metric with the micro parameters of its corresponding phase or phases. For example, *Push* maximum velocity is associated with *Push* phase micro parameters. For goal metrics involving more than one phase, such as T_{5m}, T_{15m} and lap average velocity related to *Push*/*Glid*, *Push*/*Glid*/*StPr* and all phases respectively, the micro parameters from the relevant phases were used.

To identify the parameters with higher significance, we ran a parameter selection algorithm. In the first step, we normalized each parameter and removed the multicollinearity between them using variance inflation factors (VIF) (Mansfield and Helms, 1982). LASSO parameter selection is then applied over the parameters related to each goal metric, to select the ones of higher importance. LASSO is a forward-looking parameter selectin method for regression, which improves both the estimation accuracy and the interpretability of the model (Muthukrishnan and Rohini, 2017). It ranks the parameters and allocates a weight to each one based on their significance in the regression model. Among the selected parameters, we neglected the ones with a relative weight less than 5% because of their less important role. Moreover, to quantify the contribution of each category to the regression model, we summed the relative weights of parameters from each category (propulsion, posture, efficiency, and duration/rate).

Once the significant parameters were identified, we utilized them to estimate the goal metrics by a LASSO regression model with leave-one-out cross-validation to avoid overfitting (Berrar, 2018). The cross validated determination coefficient (R^2) is reported as a metric of association between true values (reference values from speedometer) and the estimated value (output of the models). The error between the true and estimated values of goal metrics is analyzed using the root mean square of error (*RMSE*) and its relative value in percent.

4.3 Results

A sample size analysis based on a previous study (Dadashi et al., 2012) that used the same speedometer and measurement protocol for velocity estimation is performed. Considering a power of 80% (β = 0.2) and 95% (α = 0.05) confidence interval, we reached a sample size of 64 for this study. Since the models are generated using the data from all swimmers pooled together, the number of observations used to estimate all goal metrics, except for average velocity of the cycle in Swim phase was 76 samples. The overall number of cycles used for estimating the average velocity per cycle in Swim phase was 1166, 627, 695 and 1052 for front crawl, breaststroke, butterfly and backstroke respectively.

4.3.1 Goal metrics estimation

The cross-validated values (R^2, RMSE and the relative RMSE in percent) of LASSO regression model used for estimating the corresponding goal metric are reported in Table 4.3 for each goal metric. Table 4.3 shows that LASSO regression model fits the data with an R^2 value more than 0.75 for most goal metrics in all swimming styles. The RMSE of the regression are less than 0.15 $m/_{s}$ (11%) for all goal metrics defined over velocity and less than 0.21 s (7%) and 0.52 s (5%) for T_{5m} and T_{15m} respectively. The highest value of relative RMSE belongs to *Glid* end velocity with 11.1%, while the relative error is less than 10% in all other cases. The results are also calculated with swimming phases found by cameras for comparison in appendix (Table 4.5) and showed a maximum decrease of 0.05 in R^2 when using the true phases detected by IMU.

Table 4.3 – The results of evaluating LASSO regression for goal metrics estimation. The determination coefficient (R^2) and root mean square of error (RMSE) and the relative RMSE (in %) of regression are reported for each swimming style.

Goal metric	Front crawl		Breaststroke	
	R^2	RMSE (%)	R^2	RMSE (%)
Push maximum velocity (m/s)	0.74	0.140 (5.7)	0.75	0.131 (5.3)
Glid end velocity (m/s)	0.76	0.123 (10.1)	0.64	0.139 (11.1)
StPr average velocity (m/s)	0.72	0.075 (4.4)	0.58	0.058 (5.9)
Swim – average velocity per cycle (m/s)	0.89	0.050 (8.3)	0.84	0.044 (5.7)
Average velocity of *Swim* phase (m/s)	0.90	0.044 (2.7)	0.71	0.061 (5.3)
$\boldsymbol{T_{5m}}$ (s)	0.64	0.158 (7.6)	0.74	0.209 (6.9)
$\boldsymbol{T_{15m}}$ (s)	0.75	0.369 (4.3)	0.81	0.430 (6.7)
Lap average velocity (m/s)	0.95	0.032 (2.4)	0.85	0.038 (3.4)
	Butterfly		**Backstroke**	
Push maximum velocity (m/s)	0.71	0.149 (5.9)	0.72	0.107 (4.9)
Glid end velocity (m/s)	0.80	0.111 (9.1)	0.84	0.104 (6.4)
StPr average velocity (m/s)	0.75	0.152 (6.7)	0.75	0.079 (5.3)
Swim – average velocity per cycle (m/s)	0.88	0.067 (4.9)	0.89	0.076 (5.7)
Average velocity of *Swim* phase (m/s)	0.79	0.049 (3.3)	0.73	0.056 (4.3)
$\boldsymbol{T_{5m}}$ (s)	0.63	0.209 (7.0)	0.71	0.202 (6.4)
$\boldsymbol{T_{15m}}$ (s)	0.79	0.344 (4.6)	0.77	0.521 (5.0)
Lap average velocity (m/s)	0.86	0.049 (3.3)	0.80	0.063 (4.6)

4.3.2 Micro-parameters selection

The selected parameters for each goal metric estimation during front crawl technique are listed in Table 4.4. Same tables for other swimming styles are brought in appendix (Table 4.6 to Table 4.8). The parameters were the same for the phases selected by the IMU and cameras. Among acceleration axes, Acc_Y and its related parameters (e.g. Mean (Acc_Y), Max (Acc_Y), Int (Acc_Y)) are more selected for different goal metrics. Gyr_Z and φ related parameters seem to be more associated with the defined goal metrics than other axes of orientation in front crawl technique. For T_{5m}, T_{15m} and lap average velocity, a mixture of parameters from corresponding phases are selected, some of which were already selected for the specific goal metric of these phases.

The overall contribution of each category in estimating the goal metrics is illustrated in Figure 4.4 for all four swimming styles. It is observable that propulsion category plays an important role in Push phase, while posture-related parameters are more selected in Glid phase. StPr phase is less affected by efficiency compared to other categories. Efficiency and propulsion categories are both significant in determining the average velocity per cycle in Swim phase. Duration/rate category is dominant in estimating average velocity of Swim phase and lap average velocity. T_{5m} and T_{15m} are affected mainly by a mixture of propulsion, posture and duration/rate categories depending on the swimming style.

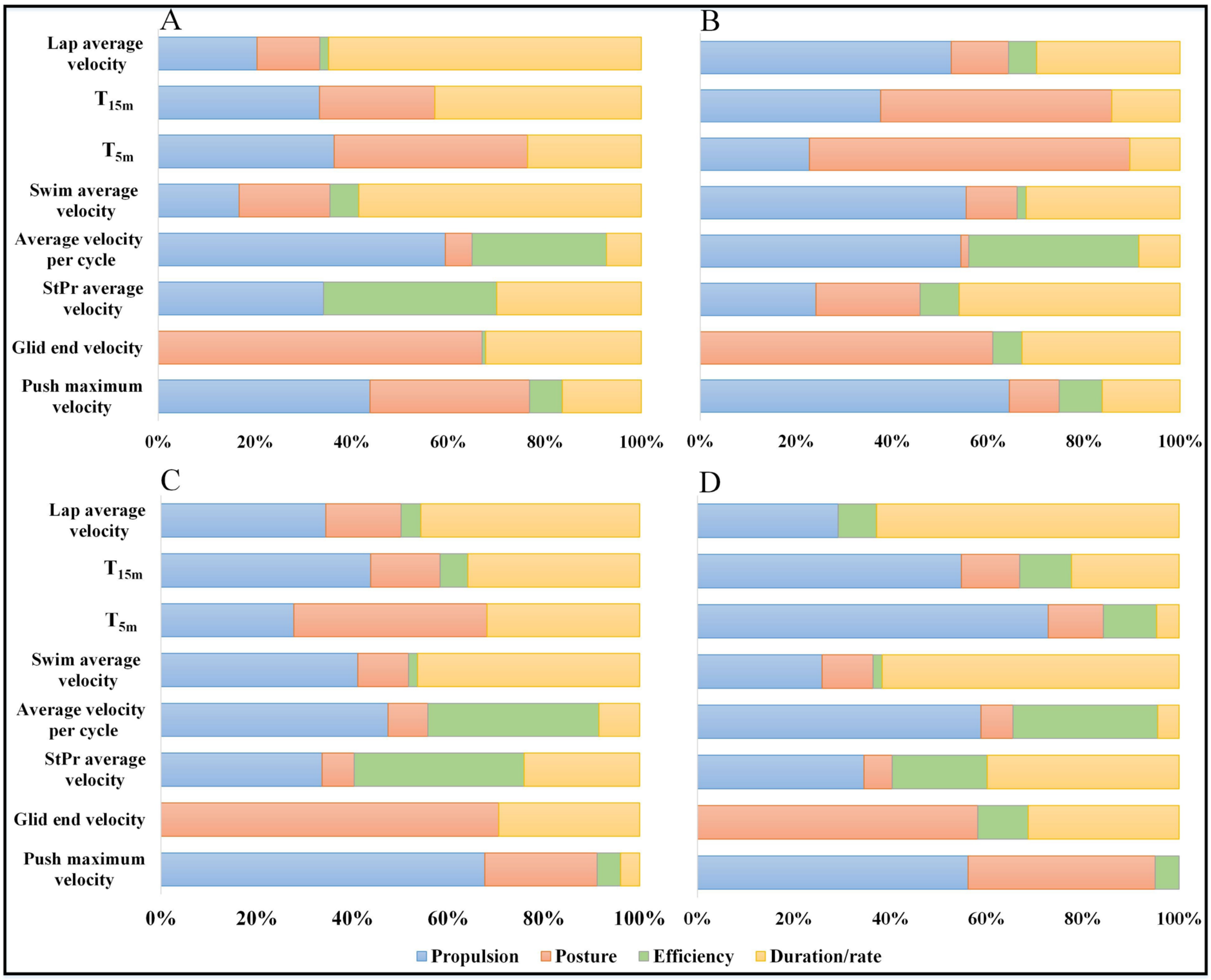

Figure 4.4 – Parameter categories contribution to goal metrics estimation for front crawl **(A)**, breaststroke **(B)**, butterfly **(C)** and backstroke **(D)**. The contribution of each category (propulsion: blue, posture: orange, efficiency: green, duration/rate: yellow) is represented in percent for estimating the corresponding goal metric. The results are based on the parameters with higher than 5% relative weight in LASSO parameter selection.

Table 4.4 – The selected parameters for estimating each goal metric for front crawl technique, written in the order of relative weights. The parameters are written in the order of their relative weights. For the abbreviated name of functions, see Table 4.2.

Goal metric	Selected parameters
Push maximum velocity	*Range* (φ), *SD* (φ), *Int* (Acc_Y), *Momentum* (Acc_Y), *Range* (Acc_Y), *Max* (Acc_Y), *Mean* (Gyr_Z), *Eff* (Acc_Y)
Glid end velocity	*Glid* duration, *Momentum* (Acc_Y), *Int* (Acc_Y), *Range* (Acc_Y), *Range* (φ), *Mean* (φ)
StPr average velocity	*Mean* (Acc_Y), *Eff* (Acc_Y) , *Eff_dir* (Acc_Y), *SD* (Acc_Y), number of kicks, *StPr* duration
Swim – average velocity per cycle	Cycle duration, DPS, *Mean* (φ) per cycle
Average velocity of *Swim* phase	Stroke rate, Mean (φ), number of strokes, *SD* (Acc_Y), *Range* (θ)

$\boldsymbol{T_{5m}}$	*Momentum* (Acc_Y) in *Glid*, *Max* (Gyr_Z) in *Push*, *SD* (φ) in *Glid*, *Range* (φ) in *Push*, *Max* (Gyr_Z) in *Glid*
$\boldsymbol{T_{15m}}$	*Glid* duration, *Range* (φ) in *StPr*, *SD* (Gyr_Z) in *StPr*, *SD* (Acc_Y) in *Push*, *StPr* kick rate, *Momentum* (Acc_Y) in *Push*
Lap average velocity	Stroke rate, number of strokes, *Max* (Acc_Y) in *Push*, *Mean* (Acc_Y) in *Glid*, *Mean* (φ) in *Swim*, number of kicks in *StPr*

4.4 Discussion

In this research, we studied the association between IMU micro parameters and the performance evaluation goal metrics found by camera and speedometer during the swimming phases from wall to wall in four main swimming styles. The obtained results confirmed our hypothesis that micro parameters extracted from a single IMU placed at sacrum within each phase are associated with the corresponding goal metrics used generally for performance evaluation. As a result, using a single IMU would be enough for performance evaluation in main swimming styles. Micro parameters, showing strong association with the goal metrics, were identified thanks to LASSO parameter selection, and used for predicting the goal metrics.

4.4.1 Goal metrics estimation

The selected kinematic parameters within each swimming phase were used for estimating the corresponding goal metrics (Table 4.3). Estimating the *Push* maximum velocity and *Glid* end velocity showed similar results in different swimming styles, as the two initial phases are the same for them (only for backstroke, the swimmer has a supine posture). The relative RMSE is the highest for *Glid* end velocity estimation (11%) because this goal metric has the lowest value in the whole lap. In the *StPr* phase, the average velocity shows a high amount of variability among the swimmers, and determination coefficient (i.e. the proportion of the variance of the true goal metric value explained by the regression model) is relatively lower for it (less than 0.8 in all techniques) compared to other goal metrics in all techniques, because a linear model is not efficient enough in reflecting the variation of this goal metric, and a non-linear model might estimate it better.

Average velocity per cycle is estimated in all techniques with a determination coefficient more than 0.84 and an RMSE less than 0.076 m/s and relative error less than 6%. However, estimating the average velocity of the whole *Swim* phase achieved poorer results (R^2 of 0.71-0.90 in different techniques). As estimating each cycle average velocity is more accurate in all techniques, the average value of all cycles in *Swim* phase can also be used for estimating *Swim* phase average velocity. The regression models for estimating T_{5m} show less accuracy (R^2 less than 0.80 in different techniques), making it difficult to trust the estimation results. Depending on swimming technique and swimmers' pace, they might start *StPr* phase earlier than five meters from the wall. So T_{5m} is partly affected by *StPr* phase and using only *Push* and *Glid* phases might not be enough for estimation. On the contrary, the first three phases (*Push*, *Glid* and *StPr*) finish before 15 meters from the wall and using them for estimating the T_{15m} results in more accurate regression models (R^2 more than 0.75 in different techniques). Finally, the lap average velocity is estimated using a selection of the kinematic parameters from all phases with a relatively small error (RMSE less than 0.063 m/s for all techniques). The results have been only slightly improved when using cameras for phase detection (section 4.6.1 of appendix).

4.4.2 Micro parameters selection

As shown in Table 4.4 and Figure 4.4 during the *Push* phase, the kinematic parameters related to φ and Acc_Y are ranked as more important, which shows the significance of keeping the right posture and generating high propulsion in *Push* phase. The *Mean* (Gyr_Z) and *Eff* (Acc_Y) are selected at last. The weight contribution of *Push* kinematic parameters can be categorized more in propulsion and posture groups, which is the same for other techniques (Figure 4.4), as the *Push* movement is the same. During *Glid* phase, phase duration is chosen the first, since the longer the *Glid* phase is, the more velocity will be lost. *Momentum* (Acc_Y) and *Int* (Acc_Y) are also considered important since they represent the effect of water drag on swimmer's body. High *Range* (φ) and *Mean* (φ) during *Glid* are a sign of bad posture, which causes more drag. In terms of categories, none of the micro parameters can be categorized in propulsion because *Glid* phase does not include any propulsive motion. As a result, the categories of posture and duration/rate are the dominant groups in this phase, regardless of the technique.

StPr phase has the highest amount of velocity variation on speedometer data and the average velocity during this phase is related to a combination of forward acceleration, accelerating efficiency, number of kicks and phase duration. Two types of efficiency-related parameters are selected for this phase. *Eff* (Acc_Y) represents the ratio of positive to all forward acceleration and *Eff_dir* (Acc_Y) is the ratio of forward acceleration to the acceleration norm. Since this phase includes strong kicking, generating the highest amount of acceleration in forward direction (Acc_Y) with respect to other axes is selected as an important parameter. *StPr* phase is the same for front crawl, butterfly and backstroke as it includes butterfly kicks in all of them. Figure 4.4 also shows similar categories of propulsion, efficiency and duration/rate for the parameters selected in this phase. For breaststroke technique, *StPr* phase includes one upper limbs cycle followed by a lower limb action and the posture related parameters are also important compared to other categories (Figure 4.4 - B).

For *Swim* phase goal metrics, the average velocity per stroke is mainly associated with the duration of each cycle and the DPS. The *Mean* (φ) is also selected which relates to the swimmer's posture. This selection is the same in all swimming styles (Figure 4.4 - B, C, D) as the average velocity per stroke can be estimated by dividing the DPS by the cycle duration. The second goal metric of *Swim* phase is the average velocity of the whole phase. The parameters related to the rate and number of strokes are more dominant as the swimmers increase the stroke rate for fast swimming. The *SD* (Acc_Y), *Mean* (φ) and *Range* (θ) are other kinematic parameters selected for estimating this goal metric, highlighting the significance of consistent propulsion and body posture in *Swim* phase. As a result, the three categories of duration/rate, posture and propulsion are more pronounced for estimating *Swim* phase average velocity in all techniques.

T_{5m}, T_{15m} and lap average velocity are dependent on more than one phase, and the parameter selection algorithm picks several parameters from each phase. Most of the selected parameters for these goal metrics were already selected for relevant phases such as selecting *Momentum* (Acc_Y) of *Glid* for T_{5m}, *Glid* duration for T_{15m} or stroke rate for lap average velocity, proving the significance of such parameters even in a larger scale. Moreover, this shows the dependence of overall swimmer's performance on their local performance in each phase. Among the techniques, T_{5m} and T_{15m} are estimated with a mixture of propulsion, posture and duration/rate categories in front crawl, breaststroke and butterfly, whereas during backstroke, the propulsion is dominant for both goal metrics. This emphasises on the tendency of the swimmers to longer underwater phases in backstroke (De Jesus et al., 2011), that asks for highly propulsive butterfly kicks.

With an overall observation on Figure 4.4, it is noted that the dominant categories in swimming phases are in line with the swimming phase biomechanics. *Push* phase asks for high propulsion, and *Glid* phase is more about keeping the right posture to avoid the drag. *StPr* phase is a combination of propulsion, posture and efficiency. Since the parameter selection algorithm chooses the best parameters for goal metric estimation, the parameters which have the strongest relationship with the goal metrics are selected. As a result, we cannot assert that the rest of the parameters are of no importance in swimming. For example, the *DPS* and cycle duration were dominant in estimating the average velocity per cycle in *Swim* phase, while no one can ignore the importance of orientation-related parameters (e.g. θ angle) (Psycharakis and Sanders, 2010) or propulsion (Toussaint, 2002) in this phase. However, having a longer *DPS* in a shorter cycle duration is the result of correct orientation and high propulsion so the selected parameters include other parameter categories implicitly.

This study shows that a single sacrum IMU can provide kinematic parameters relevant to the performance of the swimmer, in different techniques and phases for performance evaluation without using complex instrumentation such as speedometers or cameras. This offers new tools for training, where for example output of the IMU can be transferred to a mobile application for coaches and swimmers to easily follow the progress of the swimmers. Although using wearables induces more drag on swimmer body (Magalhaes et al., 2015), it needs extremely less effort than cameras for preparation and use, and it overcomes many of the limits of video-based systems (Callaway et al., 2010). The kinematic parameters that were found dominant in our study were already analyzed using IMU of video-based methods but their relationship with the goal metrics were not studied. Swimmer's posture during *Push* and *Glid* (Pereira et al., 2015), *Glid* duration (Guimaraes and Hay, 1985), *StPr* kicking rate (Shimojo et al., 2014), *Swim* stroke rate (Beanland et al., 2014) or DPS (Bächlin et al., 2008) are examples of the micro parameters that were found relevant to performance, and we also found them significant in this study.

Both male and female swimmers were included for generating the results of this study to have a larger, more variant dataset. Comparing the swimmers due to their individual differences is out of the scope of our study. The estimations are done over all swimming velocities so the results are valid for 70 to 100 percent of swimmers' paces. The synchronization error between the three systems of IMU, cameras and speedometer is a source of error in this study. Since tethered speedometer was used as reference in this study, the measurements were done over one-way trials without turn and turn motion is not evaluated. In this study, we used linear regression to have interpretable models highlighting the main parameters correlated to the goal metrics. More complex non-linear models could be used if the goal is more accurate prediction of goal metrics.

4.5 Conclusion

Using the IMU data, we extracted numerous kinematic parameters related to propulsion, posture, efficiency and duration/rate of motion in four main swimming phases, associated with the goal metrics defined over velocity and time of swimming in each swimming phase. These kinematic parameters were biomechanically interpretable and were able to predict the goal metrics using LASSO linear regression. The generated models fit the data with an R^2 value more than 0.75 for most goal metrics. The RMSE of the regression were less than 0.15 $m/_s$ and 11% for goal metrics defined over velocity and 0.52 s and 7.6% for goal metrics defined over time. Our study shows that a single sacrum-worn IMU has the potential to evaluate the swimmer performance in different swimming phases in line with standard goal metrics. Practically, our proposed method can be useful for coaches to identify the weakness and strength of their swimmers and track their progress during training sessions with a single IMU. This study can be continued with implementation of the regression models on new dataset for validation, using more complex models (e.g. non-linear regression) for better goal metric estimation, completing the analysis for diving start and turn and using other sensor positions for estimation accuracy comparison.

4.6 Appendix

4.6.1 Performance evaluation (phase detection via IMU vs. camera)

We evaluate the impact of phase detection using IMU on goal metrics estimation using LASSO regression as the estimator. This can be achieved by incorporating IMU-based swimming phases and camera-based swimming phase (CAM) separately and incorporating them as input to the regression model. The cross-validated values (R^2, RMSE and the relative RMSE in percent) of regression are reported for each swimming style using both methods for comparison in Table 4.5.

In the worst case (*Push* maximum velocity of butterfly technique), R^2 has decreased 0.08, while it is affected less than 0.05 for most of other goal metrics. Moreover, the relative RMSE has increased no more than 3.5% for any goal metric. This shows that the error of IMU phase detection is small enough, not to affect the goal metrics estimation accuracy.

Table 4.5 – The results of evaluating LASSO regression for goal metrics estimation using IMU-based or camera-based (CAM) phase detection. The determination coefficient (R^2) and root mean square of error (RMSE) and the relative RMSE (in %) of regression are reported for each swimming style.

Goal metric	**Front crawl**				**Breaststroke**			
	CAM		**IMU**		**CAM**		**IMU**	
	R^2	**RMSE (%)**	**R^2**	**RMSE (%)**	**R^2**	**RMSE (%)**	**R^2**	**RMSE (%)**
Push maximum velocity (m/s)	0.80	0.133 (5.4)	0.74	0.140 (5.7)	0.81	0.114 (4.6)	0.75	0.131 (5.3)
Glid end velocity (m/s)	0.83	0.105 (8.7)	0.76	0.123 (10.1)	0.70	0.135 (11.0)	0.64	0.139 (11.1)
StPr average velocity (m/s)	0.72	0.075 (4.4)	0.72	0.075 (4.4)	0.64	0.054 (5.8)	0.58	0.058 (5.9)
Swim – average velocity per cycle (m/s)	0.96	0.029 (4.8)	0.89	0.050 (8.3)	0.86	0.062 (5.9)	0.84	0.044 (5.7)
Average velocity of *Swim* phase (m/s)	0.90	0.044 (2.7)	0.90	0.044 (2.7)	0.76	0.059 (5.1)	0.71	0.061 (5.3)
$\boldsymbol{T_{5m}}$ (s)	0.67	0.155 (7.5)	0.64	0.158 (7.6)	0.77	0.206 (6.8)	0.74	0.209 (6.9)
$\boldsymbol{T_{15m}}$ (s)	0.80	0.345 (4.0)	0.75	0.369 (4.3)	0.82	0.430 (6.7)	0.81	0.430 (6.7)
Lap average velocity (m/s)	0.95	0.031 (2.3)	0.95	0.032 (2.4)	0.90	0.042 (3.8)	0.85	0.038 (3.4)
	Butterfly				**Backstroke**			
Push maximum velocity (m/s)	0.79	0.110 (3.8)	0.71	0.149 (5.9)	0.75	0.105 (4.8)	0.72	0.107 (4.9)
Glid end velocity (m/s)	0.81	0.104 (8.5)	0.80	0.111 (9.1)	0.86	0.104 (6.5)	0.84	0.104 (6.4)
StPr average velocity (m/s)	0.75	0.153 (6.7)	0.75	0.152 (6.7)	0.77	0.070 (5.2)	0.75	0.079 (5.3)
Swim – average velocity per cycle (m/s)	0.88	0.067 (4.9)	0.88	0.067 (4.9)	0.89	0.076 (5.7)	0.89	0.076 (5.7)
Average velocity of *Swim* phase (m/s)	0.79	0.048 (3.3)	0.79	0.049 (3.3)	0.73	0.056 (4.3)	0.73	0.056 (4.3)
$\boldsymbol{T_{5m}}$ (s)	0.66	0.204 (6.8)	0.63	0.209 (7.0)	0.72	0.197 (6.2)	0.71	0.202 (6.4)
$\boldsymbol{T_{15m}}$ (s)	0.86	0.342 (3.5)	0.79	0.344 (4.6)	0.82	0.499 (4.8)	0.77	0.521 (5.0)
Lap average velocity (m/s)	0.86	0.048 (3.3)	0.86	0.049 (3.3)	0.84	0.052 (3.8)	0.80	0.063 (4.6)

4.6.2 Parameter selection

Table 4.6 to Table 4.8 represent the parameters that were selected using LASSO method for each swimming phase in breaststroke, butterfly, and backstroke techniques. Refer to section 2.1 in the main text for definition of anatomical axes.

Table 4.6 – Table of the selected parameters for each goal metric in breaststroke technique. The parameters are ordered according to their weights in the regression model.

Goal metric	Selected parameters
Push maximum velocity	*Int* (Acc_Y), *Max* (Gyr_Z), *Max* (Acc_Y), *Range* (Acc_Y), *SD* (φ), *Momentum* (Acc_Y), *Eff* (Acc_Y) , *SD* (Acc_Y), *Mean* (Acc_Y)
Glid end velocity	*Glid* duration, *Int* (Acc_Y), *Momentum* (Acc_Y), *Max* (Acc_Y), *Range* (φ), *Mean* (φ), *Range* (Acc_Y), *SD* (φ)
StPr average velocity	*Range* (Acc_Y), *StPr* duration, *Range* (φ), *Mean* (φ), *Eff* (Acc_Y), *SD* (Gyr_Y), *Mean* (Gyr_Y),
Swim – average velocity per cycle	Cycle duration, DPS, *SD* (Acc_Y), *Range* (Gyr_Z), *Range* (Acc_Y), *Range* (Gyr_Y)
Average velocity of *Swim* phase	*SD* (Acc_Y), Stroke rate, number of strokes, *Range* (φ), *SD* (φ)
$\boldsymbol{T_{5m}}$	*Max* (Gyr_Z) in *Push*, *Momentum* (Acc_Y) in *Glid*, *Max* (Gyr_Z) in *Glid, SD* (φ) in *Glid*, *Range* (φ) in *Push*
$\boldsymbol{T_{15m}}$	*SD* (Acc_Y) in *StPr, Range* (Acc_Y) in *Glid*, *Mean* (Gyr_Z) in *Glid*, *Range* (φ) in *Push, SD* (φ) in *Push, Range* (Acc_Y) in *StPr, Max* (Gyr_Z) in *Push*, *Max* (Acc_Y) in *Glid*
Lap average velocity	Stroke rate, *Max* (Acc_Y) in *StPr*, *SD* (Acc_Y) in *Swim*, number of strokes, *Max* (Acc_Y) in *Push*, *SD* (θ) in *Swim, Momentum* (Acc_Y) in *Push*, *Eff* (Acc_Y), *Max* (Acc_Y) in *Glid*

Table 4.7 – Table of the selected parameters for each goal metric in butterfly technique. The parameters are ordered according to their weights in the regression model.

Goal metric	Selected parameters
Push maximum velocity	*SD* (φ), *Int* (Acc_Y), *SD* (Acc_Y), *Momentum* (Acc_Y), *Max* (Gyr_Z), *Mean* (Acc_Y), *Max* (Acc_Y), *Eff* (Acc_Y)
Glid end velocity	*Glid* duration, *Int* (Acc_Y), *Range* (φ), *Range* (Gyr_Z), *Mean* (φ), *Max* (Acc_Y),
StPr average velocity	*Range* (Acc_Y), *Eff_dir*(Acc_Y), *Mean* (Gyr_Y), *Eff* (Acc_Y), *Range* (Gyr_Y)
Swim – average velocity per cycle	Cycle duration, DPS, *SD* (Acc_Y), *Range* (φ), *SD* (Gyr_Z)
Average velocity of *Swim* phase	*SD* (Acc_Y), Stroke rate, number of strokes, *Range* (φ), *SD* (φ)
$\boldsymbol{T_{5m}}$	*Range* (Gyr_Z) in *Glid, Range* (Acc_Y) in *Glid, Range* (φ) in *Push, Max* (Gyr_Z) in *Push, Momentum* (Acc_Y) in *Push, Push* duration, *SD* (Acc_Y) in *Push, Mean* (φ) in *Glid*
$\boldsymbol{T_{15m}}$	*Glid* duration, *Range* (Acc_Y) in *StPr*, *SD* (Acc_Y) in *StPr*, *SD* (Acc_Y) in *Push, Mean* (φ) in *Push, Momentum* (Acc_Y) in *Glid, SD* (Gyr_Z) in *StPr*, *Mean* (Acc_Y) in *StPr*
Lap average velocity	Stroke rate, *SD* (Acc_Y) in *Swim*, number of strokes, *Max* (Acc_Y) in *Push*, *SD* (Gyr_Z) in *StPr*, *Range* (φ) in *Swim, SD* (φ) in *Swim*

Table 4.8 – Table of the selected parameters for each goal metric in backstroke technique. The parameters are ordered according to their weights in the regression model.

Goal metric	Selected parameters
Push maximum velocity	*Max* (Acc_Y), *Mean* (φ), *SD* (φ), *Momentum* (Acc_Y), *SD* (Acc_Y), *Max* (Gyr_Z), *Mean* (Acc_Y), *Int* (Acc_Y)
Glid end velocity	*Int* (Acc_Y), *Momentum* (Acc_Y), *Mean* (Gyr_Z), *Glid* duration, *SD* (φ), *SD* (Acc_Y), *Range* (φ)
StPr average velocity	*Range* (Acc_Y), *Eff*(Acc_Y), *SD* (Gyr_Z), *StPr* duration, *Range* (Gyr_Y)
Swim – average velocity per cycle	Cycle duration, DPS, *SD* (Acc_Y)
Average velocity of *Swim* phase	Stroke rate, *SD* (Acc_Y), number of strokes, *Range* (φ)
$\boldsymbol{T_{5m}}$	*Momentum* (Acc_Y) in *Push*, *SD* (Acc_Y) in *Push*, *Push* duration, *Mean* (φ) in *Glid*, *Mean* (φ) in *Push*
$\boldsymbol{T_{15m}}$	*Max* (Acc_Y) in *Push*, *Momentum* (Acc_Y) in *Push*, *SD* (Acc_Y) in *StPr*, *Eff*(Acc_Y) in *StPr*, *Glid* duration, *Int* (Acc_Y) in *Glid*, *SD* (Acc_Y) in *Glid*, *Range* (Gyr_Z) in *StPr*,
Lap average velocity	Stroke rate, *Momentum* (Acc_Y) in *Push*, *Max* (Acc_Y) in *Push*, *Range* (Gyr_Z) in *StPr*

4.6.3 Performance evaluation based on head IMU

Since the head is an interesting sensor position for swimmers (easy integration of the sensor under the swim cap), a sensor was also used on head for this study. A similar analysis was performed with the head sensor acceleration and angular velocity data for comparison. The results of goal metrics estimation are shown in Table 4.9 for each swimming style. It is obvious that the error values have increased and that this method does not work as well with a head sensor data as it does with a sacrum's. Moreover, if phase detection is performed using data from IMU, the error increases in a similar manner to the sacrum, making this position unsuitable for performance evaluation.

Table 4.9 – The results of evaluating LASSO regression for goal metrics estimation based on the data from head sensor and using camera-based phase detection (best case). The determination coefficient (R^2) and root mean square of error (RMSE) and the relative RMSE (in %) of regression are reported for each swimming style.

Goal metric	Front crawl		Breaststroke	
	R^2	RMSE (%)	R^2	RMSE (%)
Push maximum velocity (m/s)	0.57	0.183 (7.5)	0.50	0.184 (5.1)
Glid end velocity (m/s)	0.78	0.118 (9.1)	0.46	0.146 (14.2)
StPr average velocity (m/s)	0.50	0.091 (5.4)	0.51	0.060 (6.2)
Swim – average velocity per cycle (m/s)	0.55	0.17 (23.4)	0.91	0.035 (3.2)
Average velocity of *Swim* phase (m/s)	0.75	0.051 (3.1)	0.64	0.041 (3.7)
$\boldsymbol{T_{5m}}$ (s)	0.35	0.21 (13.5)	0.74	0.171(6.5)
$\boldsymbol{T_{15m}}$ (s)	0.74	0.25 (3.4)	0.72	0.582 (7.7)
Lap average velocity (m/s)	0.81	0.06 (4.3)	0.70	0.056 (4.4)
	Butterfly		**Backstroke**	
Push maximum velocity (m/s)	0.45	0.210 (6.9)	0.45	0.149 (6.3)

Glid end velocity (m/s)	0.69	0.134 (9.2)	0.63	0.139 (7.9)
StPr average velocity (m/s)	0.57	0.183 (7.2)	0.58	0.085 (6.0)
Swim – average velocity per cycle (m/s)	0.93	0.032 (3.7)	0.83	0.079 (5.9)
Average velocity of *Swim* phase (m/s)	0.64	0.053 (3.8)	0.79	0.051 (4.1)
$\boldsymbol{T_{5m}}$ (s)	0.61	0.166 (6.1)	0.57	0.204 (6.8)
$\boldsymbol{T_{15m}}$ (s)	0.65	0.395 (4.1)	0.76	0.295 (5.9)
Lap average velocity (m/s)	0.71	0.066 (3.9)	0.84	0.052 (3.8)

4.6.4 Glossary of terms

Here is the table of glossary of all the terms used for swimming performance evaluation using one sacrum IMU.

Table 4.10 – Table of glossary for Chapter 4

Term	Definition
IMU	Inertial measurement unit
CAM	Camera
Acc	Acceleration data (m/s^2)
Gyr	Angular velocity data (°/s)
$\mathbf{Acc_X}, \mathbf{Acc_Y}, \mathbf{Acc_Z}$	Acceleration on X, Y or Z axis of global frame
$\mathbf{Gyr_X}, \mathbf{Gyr_Y}, \mathbf{Gyr_Z}$	Angular velocity on X, Y or Z axis of global frame
φ	Pitch angle
θ	Roll angle
ψ	Yaw angle
q	Quaternion
LASSO	least absolute shrinkage and selection operator
RMSE	Root mean square error
Swimming bout	The swimming parts (in any swimming style) during a training session that includes one or more laps.
Swimming lap	The wall-to-wall period of swimming (in any swimming style) that starts with wall push-off and ends when the swimmer touches the wall.
Swimming style	The technique of swimming which is one among this list: Front crawl, Breaststroke, Butterfly, Backstroke
Swimming phase	Each lap is divided in four swimming phases (wall push-off, glide, stroke preparation and swimming)
Push	Wall push-off phase
Glid	Glide phase
StPr	Stroke preparation phase
Swim	Swimming phase
$\mathbf{T_{5m}}$	Time to reach 5 meters from the wall
$\mathbf{T_{15m}}$	Time to reach 15 meters from the wall
SD	The standard deviation of a parameter
Max	Maximum value of a parameter
Int	The integral of a parameter
DPS	Distance per stroke
Eff	Efficiency defined as the ratio of positive to negative forward acceleration
Eff_dir	Directional efficiency defined as the ratio of forward acceleration to total acceleration

PART III – PHASE-BASED FEEDBACK FOR COACHING WITH IMU

Chapter 5 Sensitivity analysis of phase-based goal metrics for training

Publication Note: this chapter is adapted from the following journal paper:

Rad, Mahdi Hamidi, et al. "Monitoring weekly progress of front crawl swimmers using IMU-based performance evaluation goal metrics." Frontiers in bioengineering and biotechnology 10 (2022).

Supplementary materials:
https://www.frontiersin.org/articles/10.3389/fbioe.2022.910798/full#supplementary-material

This chapter takes another step to using the phase-based performance evaluation developed in part II to be used as feedback to the swimmers. The purpose of this study was to validate the use of a new phase-based performance assessment with a single IMU worn on the sacrum during training sessions. Sixteen competitive swimmers performed five one-way front crawl trials at their maximum speed wearing an IMU on the sacrum. The coach recorded the lap time for each trial, as it represents the swimmer's performance in competition. The measurement was carried out once a week for 10 consecutive weeks to monitor the improvement in the swimmers' performance. Meaningful progress was defined as a time decrease of at least 0.5s over a 25m lap. Using validated algorithms, we estimated five goal metrics from the IMU signals representing the swimmer's performance in the swimming phases (wall push-off, glide, stroke preparation, free-swimming) and in the entire lap. The results showed that the goal metrics for free-swimming phase and the entire lap predicted the swimmer's progress well (e.g., accuracy, precision, sensitivity, and specificity of 0.91, 0.89, 0.94, and 0.95 for the lap goal metric, respectively). As the goal metrics for initial phases (wall push-off, glide, stroke preparation) achieved high precision and specificity (≥ 0.79) in progress detection, the coach can use them for swimmers with satisfactory free-swimming phase performance and make further improvements in initial phases. Changes in the values of the goal metrics have been shown to be correlated with changes in lap time when there is meaningful progress. The results of this study show that goal metrics provided by the phase-based performance evaluation with a single IMU can help monitoring swimming progress. Average velocity of the lap can replace traditional lap time measurement, while phase-based goal metrics provide more information about the swimmer's performance in each phase. This evaluation can help the coach quantitatively monitor the swimmer's performance and train them more efficiently.

Keywords: *Sports biomechanics, swimming, IMU sensor, swimming phase, phase-based evaluation, swimmer progress.*

5.1 Introduction

Swimming coaches aim to improve the performance of swimmers in intensive training sessions and prepare them for competition. Depending on the event, the swimmer completes multiple sets, each of which includes several swimming phases: a dive or wall push-off, a glide underwater, a stroke preparation, free-swimming to the end, and a turn to continue the next round with the same sequence of phases. Coaches should focus on each phase because a flawless performance by the swimmer in every phase is necessary to win (Mooney et al., 2016b).They mostly rely on observation and personal experience to monitor and evaluate a swimmer's performance. A coach expects swimmers to improve their performance by 1% to 10% during a training season, depending on swimmer's level (Zacca et al., 2020; Ferreira et al., 2021), and usually tracks this progress by measuring lap time over different swimming distances (most commonly 400 m, as it is used to evaluate the swimmer's aerobic performance). However, lap time can only reflect the swimmer's overall progress and not their phase-based performance. The use of biomechanical parameters such as stroke rate, stroke length, and stroke index (product of average velocity and stroke length) (Morais et al., 2013) or body composition (Thng et al., 2022) are other methods proposed by researchers to track swimmer's progress.

The complexity of extracting performance-related parameters has led coaches to use technological tools to obtain an objective and quantitative analysis (Payton and Adrian Burden, 2017). Swimming coaches use a variety of analysis systems such as 2D and 3D cameras (Mooney et al., 2015), inertial measurement unit (IMUs) (Guignard et al., 2017b), or physiological parameters such as heart rate (Crowcroft et al., 2017), or lactate monitors (Smith et al., 2002) to investigate the technical aspects of swimming. Although video-based systems are still the gold standard for swimming analysis, they generally suffer from several limitations in aquatic environments, such as cumbersome installation and calibration, water splashes and reflections, or limited recording volume (Callaway et al., 2010). As a result, there is still a need in the coaching community for supportive analysis systems (Mooney et al., 2016a). Improvements in the accuracy, scalability, and cost of Micro-electromechanical systems (MEMS) have led to IMUs becoming a credible option for swimmer motion tracking, as they can provide quick and easy-to-use feedback on detailed performance-related metrics (Félix et al., 2019).

Several studies have investigated the analysis of swimming with IMUs by extracting kinematic parameters in different phases and techniques such as stroke rate and stroke count (Davey and James, 2008), instantaneous velocity (Dadashi et al., 2012), tumble turn spatio-temporal parameters (Slawson et al., 2012) or wall push-off maximum velocity (Stamm, 2013). Although these studies have demonstrated the application of IMUs for swimming analysis, they have not related the obtained kinematic parameters to the swimmer's performance-related metrics. In our previous study, we used IMUs to automatically segment each swimming lap into wall push-off (*Push*), glide (*Glid*), stroke preparation (*StPr*), free-swimming (*Swim*), and turn phases (Hamidi Rad et al., 2021b). The algorithms developed in this study take a macro-micro approach by swimming bouts detection, lap separation, and swimming style identification at the macro level, and then divide each lap into phases by detecting spatio-temporal events on IMU acceleration and angular velocity data at the micro level. Subsequently, a variety of kinematic parameters were extracted from each phase and used to estimate phase-based goal metrics (*Push* maximum velocity, *Glid* end velocity, *StPr* average velocity, *Swim* average velocity and lap average velocity) for the swimmer's performance evaluation (Hamidi Rad et al., 2021a), indicating how well the swimmer performed the corresponding phase. However, to fully utilize the IMU sensor for training, assessing the sensitivity of IMU-based goal metrics to performance progress is of utmost importance.

Therefore, the main objective of this study was to validate the use of IMU-based goal metrics to monitor swimming performance during training sessions. Using the macro-micro approach to swimming analysis to separate the swimming phases (*Push*, *Glid*, *StPr*, and *Swim*) and the phase-based performance assessment on sacrum IMU, we estimated the goal metrics of each phase. We then analyzed the sensitivity of goal metrics in relation to the swimmer's progress across multiple training sessions. We assumed that **(i)** lap time is the most important representative of performance level and can be used to define meaningful progress, and **(ii)** the goal metrics change in association with lap time when the swimmer makes meaningful progress.

5.2 Materials and Methods

5.2.1 Measurement setup and protocol

Sixteen competitive swimmers from a swimming team participated in this study, and their characteristics are shown in Table 5.1. A waterproof band (Tegaderm, 3M Co., USA) was used to attach an IMU (Physilog® IV, GaitUp, CH.) to the swimmer's lower back on sacrum bone. The sensor recorded 3D angular velocity (±2000 °/s) and 3D accelerometer (±16 g) at a sampling rate of 500 Hz. After installation of the sensor, functional calibration was performed with simple out-of-water movements (upright standing and squatting) to make the data independent of the sensor exact position on swimmer's sacrum (Dadashi et al., 2013c).

After a brief warm-up, swimmers were asked to swim five times one swimming pool length (one lap) in the same direction at maximum velocity, beginning with a five-second upright stance before wall push-off in the water (Figure 5.1-A). During a full lap, the swimmer went through all swimming phases so that we could analyze the goal metrics of each phase (Figure 5.1-B). The coach recorded the lap time of all swimmers with a stopwatch during each attempt (Figure 5.1-C). Each swimmer had five minutes rest between trials to avoid fatigue. To track the swimmers' progress, the same measurement was repeated once a week for ten sessions. Prior to participation, the measurement procedure was explained to each swimmer, and they provided written informed consent. The measurement protocol of this study was approved by the EPFL Human Research Ethics Committee (HREC, No. 050/2018).

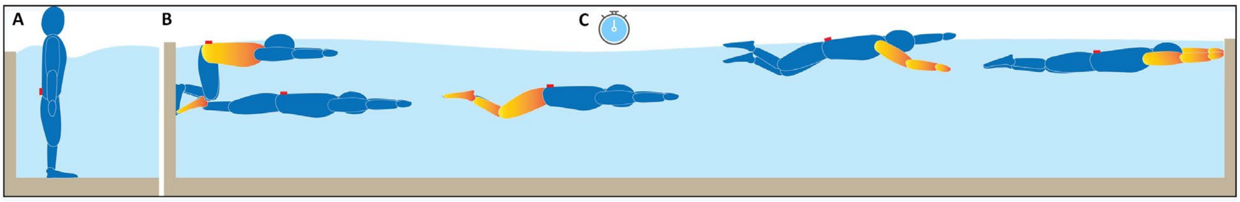

Figure 5.1 – Measurement protocol with IMU (red box) attached to the sacrum. After functional calibration, the swimmer starts in the water with an upright posture (A) and performs all swimming phases at maximum speed while swimming to the other side in front crawl (B). The coach records the lap time with a stopwatch during each lap (C).

Table 5.1 – Statistics of the swimmers. The values are presented as mean ± standard deviation.

Male	Female	Age (yrs)	Height (cm)	Weight (kg)	50m Front crawl record (s)
9	7	14.6 ± 0.8	171.6 ± 6.9	55.9 ± 10.1	28.60 ± 2.04

5.2.2 Lap segmentation and phase-based performance evaluation

First, swimming bouts and laps were determined during each training session according to the validated algorithms of our macro-micro approach and then divided into four swimming phases of *Push*, *Glid*, *StPr* and *Swim* (Hamidi Rad et al., 2021b). *Push* phase begins with the forward movement of the swimmer's trunk and ends when the feet leave the wall. *Glid* phase lasts until the beginning of the dolphin kicks in front crawl style. *StPr* phase is the next phase that ends with the first arm stroke, which is the beginning of the *Swim* phase, and *Swim* phase ends when the swimmer's hand touches the wall. The method uses motion biomechanics to identify the events corresponding to the beginning and end of each phase for lap segmentation. Subsequently, based on our phase-based performance evaluation method (Hamidi Rad et al., 2021a), a set of spatio-temporal parameters reflecting various aspects of swimmer’s performance were extracted from each phase. These parameters are categorized as propulsion, posture, efficiency, and duration/rate to represent the most important aspects of performance. They were fed into *LASSO* (Least Absolute Shrinkage and Selection Operator) regression models to estimate five phase-based goal metrics that quantify the performance within each phase: *Push* maximum velocity, *Glid* end velocity, *StPr* average velocity, *Swim* average velocity, and lap average velocity respectively for phases of push, glide, stroke preparation, swim and the entire lap. These goal metrics were tracked during the measurements to assess their sensitivity to swimmer progress during weeks of training.

5.2.3 Sensitivity analysis

Sensitivity analysis was performed to assess how phase-based goal metrics react to swimmer’s progress in two steps. In the first step, we considered all sessions of each swimmer with a significant change in lap time, as lap time is considered representative of swimming performance (Robertson et al., 2009). Using the data from the weekly measurements, we compared the swimmer's performance in each session to other sessions to find significant progress. According to the measurement protocol, five values (for each goal metric and for lap time) are obtained from each participant per session. Because the sample size for comparison between two sessions is small, we used Cliff's Delta (d) effect size analysis as a nonparametric method (Macbeth et al., 2011). This method allowed us to determine whether the achieved lap times and goal metrics differed significantly from one session to another. Each comparison set is assigned an effect size value to quantify the change (Equation 5.1).

$$d = \frac{\#(x_i > x_j) - \#(x_i < x_j)}{n_1 n_2} \tag{5.1}$$

Where the cardinality symbol # indicates counting, x_i and x_j are the lap time or goal metric values of sessions *i* and *j*, respectively. n_1 and n_2 are the sizes of the two data sets, both equal to five in our study (i.e., the number of laps). The value of d estimates the probability that a value selected from the *ith* session is greater than a value selected from the *jth* session, minus the inverse probability. This can be referred to as a measure of dominance, indicating the degree of overlap between values from two test sessions. The d value is generally within the closed interval of [-1, +1] indicating the degree of overlap between the values from two sessions (effect size of +1.0 or -1.0 for no overlap and 0 for complete overlap). The effect size is considered significant if the confidence interval (*CI*) does not include zero. The upper and lower bounds of the asymmetric *CI* (range of δ_{lower} to δ_{higher}) for Cliff's d are constructed based on Equations 5.2 to 5.4 as a more robust and conservative method (Feng and Cliff, 2004). $t_{\alpha/2}$ is the critical value of the t-distribution for the corresponding confidence level.

$$d_i = \frac{\#(x_i > x_j) - \#(x_i < x_j)}{n_1}, d_j = \frac{\#(x_j > x_i) - \#(x_j < x_i)}{n_2} \tag{5.2}$$

$$s_d{}^2 = \frac{n_1{}^2 \sum_{i=1}^{n_1}(d_i - d)^2 + n_2{}^2 \sum_{j=1}^{n_2}(d_j - d)^2 + n_2{}^2 \sum_{i=1}^{n_1}\sum_{j=1}^{n_2}(d_{ij} - d)^2}{n_1 n_2 (n_1 - 1)(n_2 - 1)} \tag{5.3}$$

$$\delta_{lower}, \delta_{higher} = \frac{d - d^3 \pm t_{\alpha/2} s_d (1 - 2d^2 + d^4 + t_{\alpha/2}{}^2 s_d{}^2)^{1/2}}{1 - d^2 + t_{\alpha/2}{}^2 s_d{}^2} \tag{5.4}$$

Thus, the effect size values along with the *CI* ranges were calculated for comparing the five values of goal metrics or lap time between every two sessions using Equations 1 to 4 and the significant pairs were separated. However, all significant changes in lap time should not be considered as meaningful progress. This is because the lap time value itself is subject to recording errors (using the stopwatch). Based on the training plan, the coach expected to see real progress in the swimmers after at least three weeks of training. Therefore, a meaningful lap time change (*MLTC*) was defined as the minimum threshold for meaningful progress. It is indeed similar to the concept of smallest worthwhile enhancement which is defined for competitions to estimate the minimum amount of improvement that is beneficial for athletes to win a race (Hopkins et al., 1999). However, we tend to compare swimmers only with themselves and not with others in training sessions. So we calculated the median lap time of comparisons that were three weeks apart (session 1 and session 4, session 2 and session 5, etc.). *MLTC* is then calculated by taking the average of the differences of all these comparison pairs over all swimmers.

In the second step of the sensitivity analysis, among all significant differences identified in step one between test sessions, only those with a median change more than *MLTC* were retained as meaningful progress. The entire process of the two steps for detecting significant pairs and then selecting the pairs with meaningful progress is explained by the following pseudocode, where *m* and *n* are two different session numbers that vary across all sessions with two loops and $LT_{i,j}$ is *ith* lap time of *jth* session.

```
START
  For m = 1 : (number of sessions – 1)
    For n = m + 1 : number of sessions
      Calculate d, δlower and δhigher for LT1:5,m and LT1:5,n with Equations 1-4
        If 0 ∈ [δlower,δhigher] THEN SignificantChange
          If Median(LT1:5,m) - Median(LT1:5,n) > MLTC  THEN MeaningfulProgress
          Else SignificantChange but not MeaningfulProgress
        Else InsignificantChange
END
```

After obtaining all the pairs with meaningful progress, the relationship between changes of goal metrics and changes in lap time was examined for these pairs to analyze the sensitivity of goal metrics to progress by answering three questions:

I. "Do the goal metrics predict meaningful progress, as does lap time?"

II. "How well do the goal metrics represent the swimmer's performance compared to the lap time?"

III. "What is the contribution share of each goal metric to swimming progress?"

To answer the first question, we analyzed the correspondence between progress detection by each goal metric and lap time. For each pair of sessions, we calculated whether the change (i.e., improvement) in the values of goal metrics was significant (i.e., true) or not significant (i.e., false) and then compared it to the meaningfulness of the change in lap time. The performance of goal metrics in predicting meaningful progress (i.e., a significant lap time more than *MLTC*) was assessed using the following association rules:

- True positive (*TP*): goal metric shows a significant change when there is a meaningful progress.
- True negative (*TN*): no significant change is observed with goal metric when there is no meaningful progress.
- False positive (*FP*): no meaningful progress, while the goal metric changes significantly.

- False negative (*FN*): meaningful progress, while the goal metric does not show significant change.

The values for accuracy, precision, specificity, and sensitivity to predict meaningful progress are calculated for each goal metric using Equations 5.5 to 5.8.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.5}$$

$$Precision = \frac{TP}{TP + FP} \tag{5.6}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{5.7}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5.8}$$

To answer the second question, how well the goal metrics represent swimming performance, effect size values were estimated for each significant change in the goal metric and compared to the effect size of lap time if there was a meaningful progress. The third question is about the relationship between the magnitude of change in each goal metric (i.e., change of *Push* maximum velocity (Δ*Push*), *Glid* end velocity (Δ*Glid*), *StPr* average velocity (Δ*StPr*), *Swim* average velocity (Δ*Swim*), and lap average velocity (Δ*Lap*)) and the change in lap time (Δ*LapTime*) when there is a meaningful progress. This analysis is performed by calculating the Pearson correlation (Benesty et al., 2009) between the changes in goal metrics and lap time values.

5.3 Results

A post-hoc sample size analysis was performed (Jones et al., 2003) considering the lowest acceptable sensitivity and specificity of 0.90 and 0.80, respectively, with a confidence interval of 90%, resulting in a sample size of 107 for this study. This means that at least this number of meaningful comparisons are needed to make a valid comparison between the change in goal metrics and the change in lap time. During the ten measurement sessions, there were seven absences due to swimmers being unavailable, and a total of 750 swimming laps were recorded. Each swimmer is compared to themselves during all measurement sessions, and 642 comparisons were made for all swimmers. 272 of the comparisons showed statistically significant progress (based on Cliff's delta analysis at a 95% confidence level). The accuracy, precision, sensitivity, and specificity of each of the goal metrics used to detect this significant change in lap time (i.e., the first step of the sensitivity analysis) can be found in the appendix (Figure 5.4). Next, comparison of sessions three weeks apart for the second step of the analysis yielded an *MLTC* value of $0.5 \pm 0.2s$, resulting in 122 pairs of sessions with meaningful progress which is higher that the sample size. Each swimmer showed at least four comparison pairs with meaningful progress. The slower the swimmer was during the first test session (higher median of lap time), the higher the number of comparison pairs with meaningful progress (significant correlation coefficient of

0.70), because the swimmers who swim relatively slower have more room for performance improvement. The accuracy, precision, sensitivity, and specificity of each goal metric for detecting meaningful progress are shown in Figure 5.2.

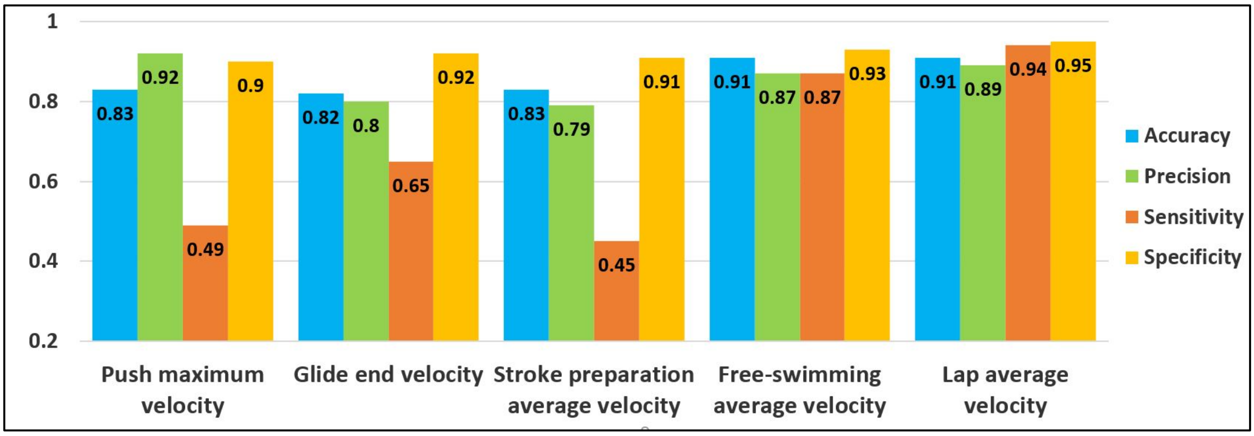

Figure 5.2 – Accuracy, precision, sensitivity and specificity of goal metrics for detecting a meaningful progress (lap time change)

Among the five metrics, lap and *Swim* average velocity achieved the highest values for accuracy, sensitivity, precision, and specificity (≥ 0.87). For the three metrics related to the initial phases of *Push*, *Glid* and *StPr*, precision and specificity were relatively high (≥ 0.79), whereas sensitivity was low (0.45-0.65). For the comparisons in which both meaningful progress in lap time was detected and the goal metric was significant, the effect size values and confidence interval were calculated (Table 5.2). Comparison of the effect size values for each goal metric and lap time shows lap average velocity and *Swim* average velocity are the best ones for progress detection (difference of 0.04 between effect size values). However, the other three goal metrics achieved lower effect size values than lap time.

Table 5.2 – Effect size and confidence interval of all goal metrics and lap time for the comparisons with both meaningful progress and significant goal metric change.

Goal metric		***Push* maximum velocity**	***Glid* end velocity**	***StPr* average velocity**	***Swim* average velocity**	***Lap* average velocity**
Effect size [CI]	**By goal metric**	0.67 [0.26,0.85]	0.78 [0.30,0.90]	0.75 [0.26,0.89]	0.92 [0.25,0.96]	0.93 [0.27,0.97]
	By lap time			0.96 [0.25,0.98]		

The final set of results addresses the correlation analysis between the magnitude of changes in the goal metrics (Δ*Push*, Δ*Glid*, Δ*StPr*, Δ*Swim*, and Δ*Lap*) and in lap time (Δ*LapTime*) across all comparisons with meaningful progress. Histograms of the changes in the goal metrics are displayed in Figure 5.3. The root mean squared error (*RMSE*) for the estimation of each goal metric is extracted from our previous study (Hamidi Rad et al., 2021a) and shown specifically for each goal metric in vertical red lines in Figure 5.3.

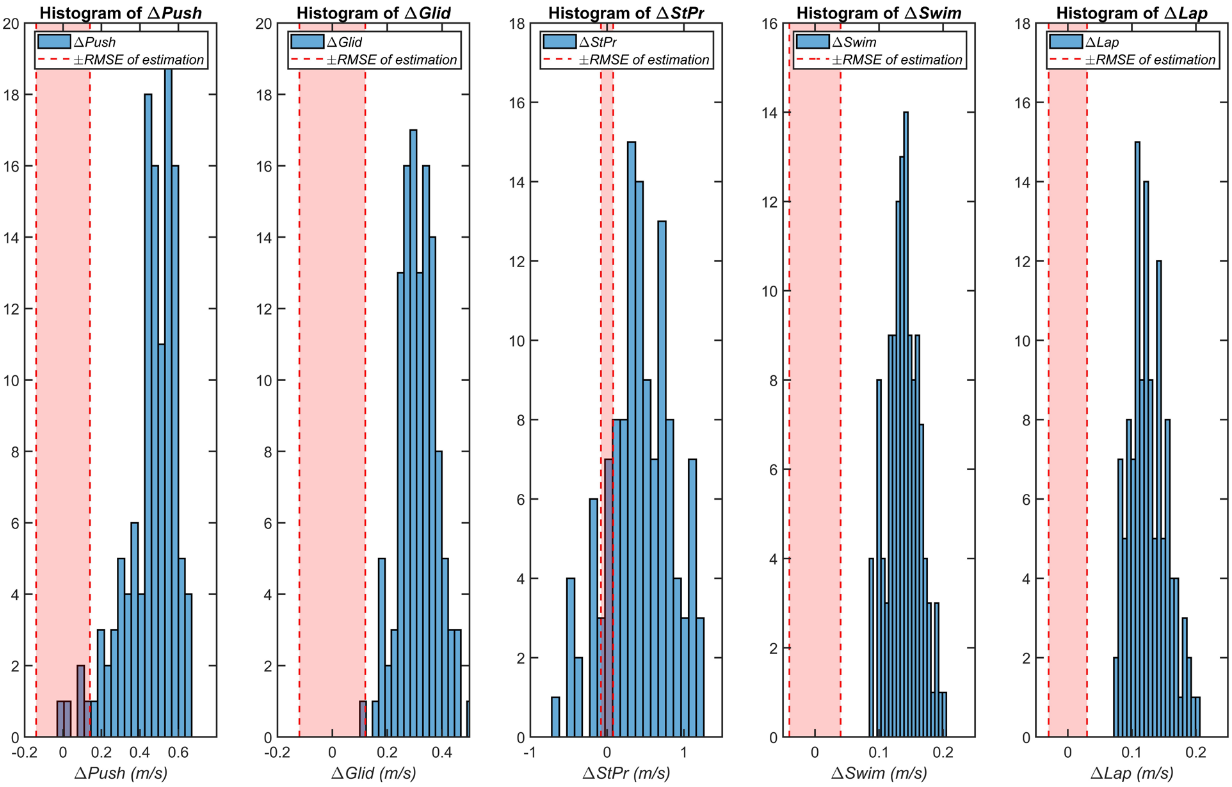

Figure 5.3 – Histograms of changes in the five IMU goal metrics (Δ*Push*, Δ*Glid*, Δ*StPr*, Δ*Swim*, and Δ*Lap*) for the comparisons with meaningful progress. The estimation *RMSE* range of each goal metric is displayed with red dashed lines.

The delta values lying inside the range of *RMSE* (±*RMSE* range) are too small to be valid as they might happen due the model errors and should be removed. After removing the invalid delta values for each goal metric, we analyzed the contribution of each metric to the progress of swimming performance. Table 5.3 shows the average, standard deviation, and range for the changes in the goal metrics, as well as their correlation coefficient (*r*) with Δ*LapTime*. Of the five goal metrics, Δ*StPr* shows the highest standard deviation (0.40 *m*/*s*). Apart from Δ*Push*, the change values of all goal metrics were significantly correlated with Δ*LapTime*, however with weak correlation coefficients (Table 5.3).

Table 5.3 – Average, standard deviation, and range of each goal metric change and its correlation coefficient (*r*) with Δ*LapTime* for all meaningful progress comparisons. The change values that are below *RMSE* of each goal metric are removed.

Goal metric change	Δ*Push*	Δ*Glid*	Δ*StPr*	Δ*Swim*	Δ*Lap*
Average (*m/s*)	0.49	0.33	0.50	0.14	0.13
Standard deviation (*m/s*)	0.09	0.06	0.40	0.02	0.03
Range (*m/s*)	0.52	0.44	1.89	0.16	0.17
Correlation coefficient (*r*) with Δ*LapTime*	-0.04	-0.21**	-0.17**	-0.29***	-0.31***

***p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001**

5.4 Discussion

In this study, a single IMU, worn on sacrum, was used to identify the four major phases of a swimming lap and calculate a performance-based goal metric for each of these phases and the entire lap. These goal metrics were then used to follow the swimmers' progress over ten training sessions. The results obtained confirmed our hypothesis of association between the phase-based goal metrics and swimmers' progress, but with varying sensitivity and degree of association in each phase.

As shown in Figure 5.2, lap average velocity and *Swim* average velocity achieved the highest accuracy, precision, sensitivity, and specificity (≥0.87) among all goal metrics to predict meaningful progress. Because lap time is used as a representative of performance, lap average velocity was expected to be highly associated with it. This goal metric could replace traditional lap time because it is not affected by human recording error. Furthermore, since the *Swim* phase is the longest phase of a lap, it should contribute more to lap time compared to other phases. Although the sensitivity of *Push* maximum velocity, *Glid* end velocity, and *StPr* average velocity are low, their specificity and precision are either at or above 0.80. Considering Equations 6 and 8, the high specificity and precision is mainly due to a low number of false positives. It can be concluded that the three initial goal metrics are less good at detecting meaningful progress than the other two metrics. However, when they do detect progress, it is correct, indicating that they are relevant to progress assessment despite their low sensitivity. The results represent that the coach focused on the free-swimming phase as it contributes the more to the overall performance and then improved the initial phases for making more progress, making this method a valuable assistant for training sessions.

Compared with similar results using goal metrics to detect significant (and not meaningful defined by *MLTC*) progress shown in Figure 5.4 of the appendix, using meaningful progress improved the results. The accuracy, precision, sensitivity, and specificity of all five goal metrics for detecting significant progress were lower because the procedure was affected by the lap time recording error. However, the sensitivity of the goal metrics for the initial phase remained low for the same reason. Overall, it appears that all phases are important for improving overall performance and progress is the result of mastering all phases of swimming. The coach can use the three metrics of the initial phases to provide an additional quantitative assessment. However, this argument does not apply in reverse, and a change in lap time is not essentially the result of better performance in the initial phases. It increases the number of false negatives and lowers the sensitivity of the initial phases goal metrics to overall progress.

In terms of effect sizes and confidence interval ranges, Table 5.2 shows that the effect size values of the goal metrics for lap average velocity and *Swim* average velocity are closest to the effect size of lap time, such that these two metrics are as strong as lap time in indicating progress. However, the effect size values of the goal metrics *Push* maximum velocity, *Glid* end velocity, and *StPr* average velocity are lower than lap time because they cannot represent the overall performance of the swimmers as well as lap time. It can be argued that if the swimmer is not making more progress in the *Swim* phase, there is still room for improvement in the initial phases and the coach should focus on these goal metrics to make further progress.

Figure 5.3 shows that among the five changes in the goal metric, only $\Delta StPr$ has worsened in some cases, while there is a meaningful progress on lap performance (negative values of the histogram). Due to the coaching strategy at this period of the season, the coach did not emphasize working on this phase for the swimmers with weak performances, and asked them to focus on other phases to compensate. Most of the change values of all goal metrics are outside the range of the *RMSE* of the goal metric estimation. The correlation coefficients of the changes of all goal metrics with $\Delta LapTime$ are weak (<0.4) (Table 5.3). Since the change values of the goal metrics are reliable after removing the samples lying inside the $\pm RMSE$ range (Figure 5.3), the main reason for the weak correlation is the error in recording the lap time, since it is recorded by the coach with a handheld stopwatch, while this analysis requires a more precise method. However, since the correlations are significant, we can conclude that improving goal metrics contributes to swimmer's progress and the coach should use all these metrics in the training sessions.

To obtain a larger, more varied data set, both male and female swimmers were used to generate our results, and comparison based on individual differences is beyond the scope of this study. For technical reasons, only front crawl technique is examined here. However, based on our previous research (Hamidi Rad et al., 2021a), similar goal metrics can be extracted from other main swimming styles (backstroke, butterfly, and breaststroke) to perform the same study. The lap time was recorded using stopwatch which is prone to human error and using more precise measurement methods such as cameras can increase the quality of this analysis. Since we had only one-way laps in the measurements, the turn phase was not evaluated in this study. The number of lap repetitions per swimmer was limited to five to avoid a fatigue effect that could affect the assessment of progress. However, collection of a larger data set would be required to perform a more powerful statistical analysis.

This study shows that the goal metrics calculated from a single sacrum IMU can provide valuable information about performance in different swimming phases. Coaches can forgo measuring lap time with a stopwatch and use the goal metric for lap average velocity, which can be automatically estimated based on IMU as a substitute for traditional lap timing. They can then focus on the goal metric for each phase to get a more detailed analysis of the swimmer's performance. Compared to other studies monitoring swimmers' performance that focused mainly on either overall performance or free-swimming phase parameters (Morais et al., 2013, 2015), our proposed goal metrics allow the coach to track swimming performance in each phase separately. Furthermore, tracking progress using conventional methods such as video-based systems or heart rate and lactate monitors is very time-consuming and only possible at selected times during a season (Ferreira et al., 2021), whereas IMUs have the least impact on swimmers' training and can be used on a daily basis.

The dominance of coaching philosophy and qualitative analysis in training sessions invariably leads to subjective, inaccurate assessments (Mooney et al., 2016a). Therefore, providing phase-based goal metrics serves as an assistant to the coach, allowing him or her to quantitatively monitor each swimming phase and track a swimmer's progress during training sessions. Using this information, the coach can customize training strategies for each swimmer, which usually takes a lot of time and effort. Although wearables induce more drag on the swimmer's body (Magalhaes et al., 2015), they require an extremely small amount of preparation and analysis from the coach to provide personalized feedback. The coach can access performance evaluation reports for the entire team after each training session and plan further training for each swimmer based on their phase-specific progress.

5.5 Conclusion

By using IMU based goal metrics to monitor the performance of a team of swimmers, we have demonstrated the possibility of objective evaluation of swimmers' progress during training sessions. Of the goal metrics considered in this study, lap average velocity and Swim average velocity had the highest accuracy, precision, sensitivity, and specificity (≥ 0.87) to predict swimmers' progress. The goal metrics related to *Push*, *Glid* and *StPr* achieved high specificity and precision (≥ 0.79) for progress, confirming the role of initial phases in overall swimming performance. Lap average velocity and *Swim* average velocity are as sensitive as lap time to swimming progress and can be used as precise performance-related indicators. Other goal metrics provide additional quantitative information about the swimmer's phase-related performance that is not available in traditional coaching approaches. It is illustrated that the value of changes in goal metrics also correlates with swimmer progress. In summary, the coach can use the phase-based report to obtain a comprehensive view of the swimmer's performance. This study opens new training horizons in swimming by providing objective feedback based on goal metrics and analyzing the effects of feedback on the swimmer's performance.

5.6 Appendix

5.6.1 Sensitivity analysis with significant progress

To find meaningful progress, we defined meaningful lap time change (*MLTC*) based on the hypothesis that significant lap time change does not necessarily represent meaningful performance change and could be transient. To compare the results before and after using *MLTC*, Figure 5.4 presents the accuracy, precision, sensitivity, and specificity of each goal metric for detecting a significant change in lap time (based on Cliff's delta confidence interval only).

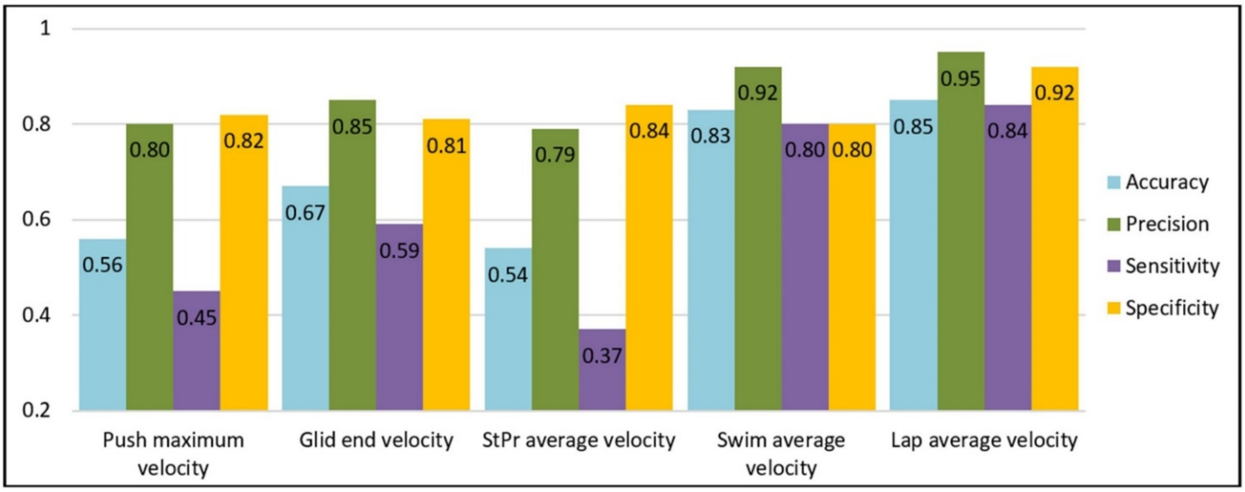

Figure 5.4 – Accuracy, precision, sensitivity and specificity of goal metrics for detecting a significant progress (lap time change).

5.6.2 Phase-based Goal metrics sensitivity to functional calibration

As explained in the measurement protocol, a functional calibration is required before each measurement because the estimation of the phase-based goal metric is based on the alignment between the axes of the sensor and the anatomical frames. This calibration compensates for the effects of varying positioning of the sensor on the swimmer's body. Removing the functional calibration procedure may facilitate the use of the system but it introduces an error in the estimated goal metric. Assuming that the position of the sensor is verified by visual observation rather than functional calibration, the impact of possible misalignment due to visual observation on the error of the goal metric estimation can be evaluated. Therefore, an analysis is performed where the correct sensor position (determined by functional calibration) is manually rotated to evaluate the change in each goal metric compared to the values determined with the functionally calibrated data.

For this purpose, data from swimmers during one session (16 swimmers, 80 laps) were used and both acceleration and angular velocity data were rotated by three rotation angles of 10°, 20°, and 30° about each axis (x, y, and z) in both directions (Figure 5.5). The difference between the estimated goal metrics based on the calibrated data and the distorted data is plotted in Figure 5.6 for each goal metric. The RMSE for the estimation of each goal metric (from Chapter 1) and their duplicate values are also plotted in Figure 5.6 for comparison, since the changes in the goal metrics below the RMSE are negligible.

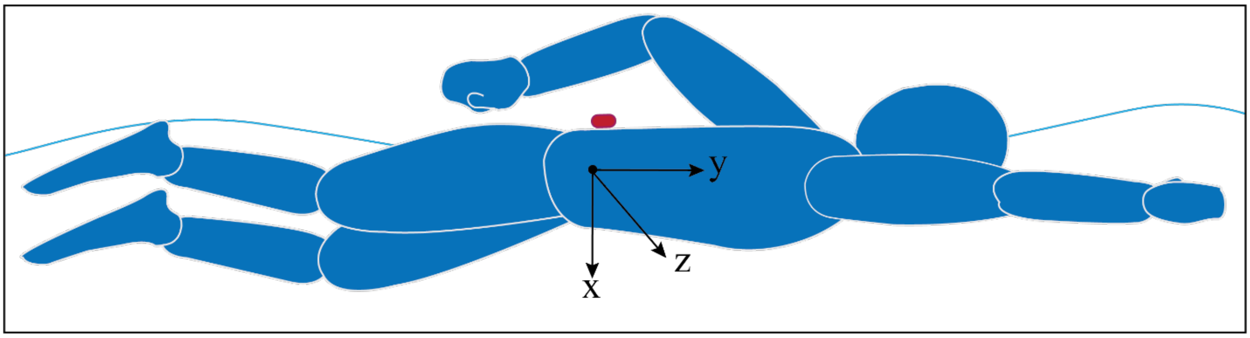

Figure 5.5 – The anatomical coordination system for swimmer's sacrum.

As the results show, the larger the angle of rotation about one of the three axes, the higher the error values. Up to a rotation angle of 10° about one of the three axes in both directions, the changes in the goal metrics are almost within the range of the RMSE. With the increase of the rotation angle to 20°, the goal metrics for the stroke preparation phase and swim phase (for the entire phase) become unreliable, while the remaining goal metrics do not change more than the RMSE range. A rotation of 30° about each axis causes a large change in all goal metrics (more than the RMSE) and makes them unreliable. Of the three axes, rotation about the Z axis causes the greatest change in estimated value for the goal metric, which should be considered by the user when installing the sensor on swimmer's body.

In case the sensor is integrated into the swimmer's suit, its position and orientation is nearly fixed except for small movement with respect to the skin during the training session. Considering the robustness of the phase-based performance assessment and the estimation of the goal metrics up to a rotation of 10° around each of the three axes, the functional calibration can be removed from the protocol if the sensor attachment is reliable enough.

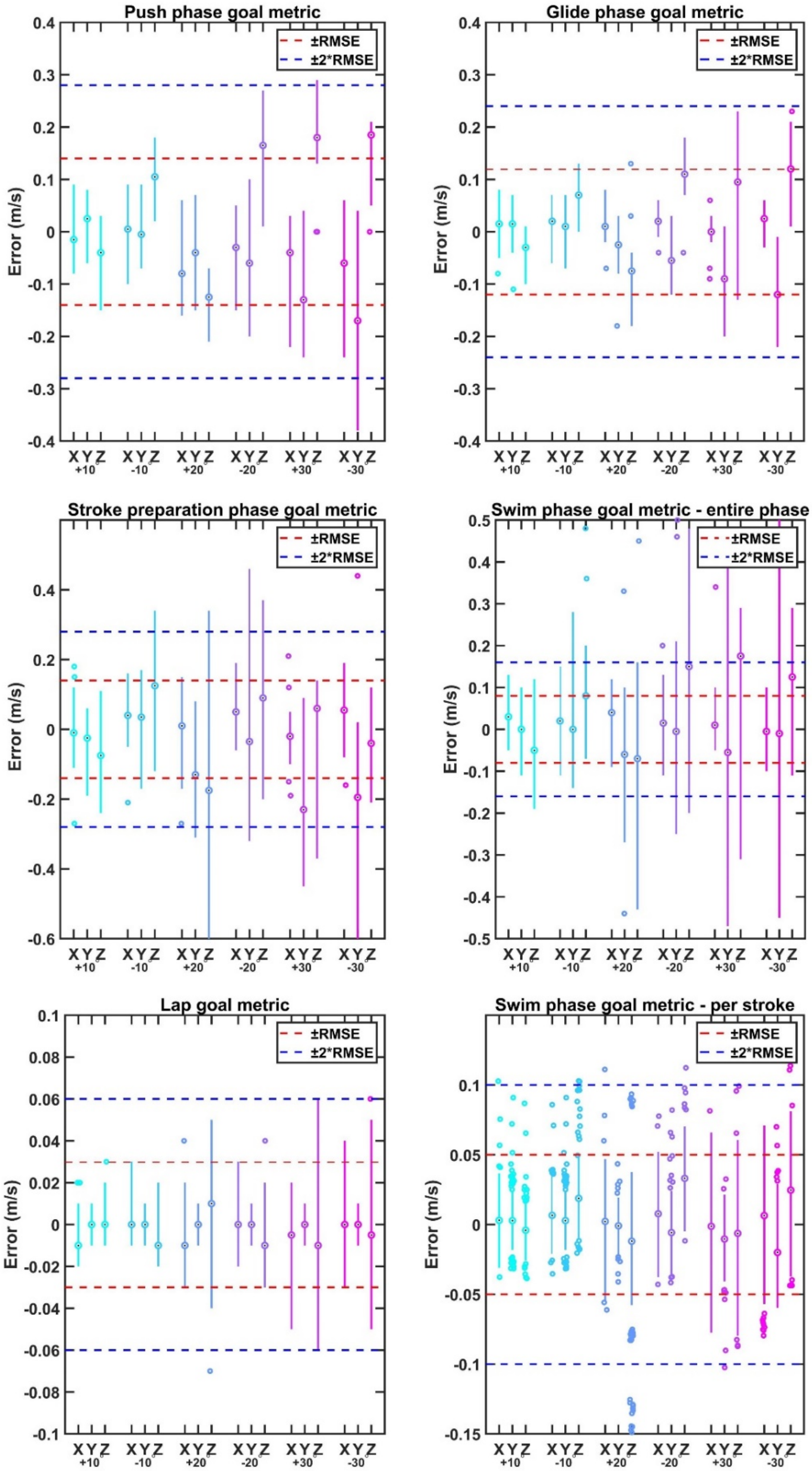

Figure 5.6 – Estimated goal metrics change with and without functional calibration along with the corresponding estimation RMSE. The rotation angle varies between 10° to 30° about each axis in both positive and negative directions.

5.6.3 Glossary of terms

Here if the table of glossary of all the terms used in this research.

Table 5.4 – Table of glossary for Chapter 5

Term	Definition
IMU	Inertial measurement unit
LASSO	least absolute shrinkage and selection operator
RMSE	Root mean square error
Push	Wall push-off phase
Glid	Glide phase
StPr	Stroke preparation phase
Swim	Swimming phase
d	Cliff's Delta effect size
CI	Confidence interval
MLTC	Meaningful lap time change
TP	True positive
TN	True negative
FP	False positive
FN	False negative
ΔPush	Change in push maximum velocity
ΔGlid	Change in glide end velocity
ΔStPr	Change in stroke preparation average velocity
ΔSwim	Change in swim average velocity
ΔLap	Change in lap average velocity
ΔLapTime	Change in lap time

Chapter 6 SmartSwim, phase-based feedback for training and exercise

Publication Note: this chapter is adapted from the following journal paper:

Hamidi Rad, Mahdi, et al. "SmartSwim, a Novel IMU-Based Coaching Assistance." Sensors 22.9 (2022): 3356.

Having demonstrated the sensitivity of the phase-based performance evaluation method in the previous chapter, this chapter presents the impacts of its use as feedback on swimmers' performance. Swimming coaches provide regular timed and technical feedback to swimmers and guide them efficiently in training sessions. Due to the complexity of swimmers' performance, which is not visible in qualitative observation, quantitative and objective performance evaluation can better assist the coach in this regard. In this study, we propose a new performance evaluation feedback (SmartSwim) using IMU and investigate its effects on the swimmer's weekly progress. Measurements were conducted each week with 15 competitive swimmers for 10 weeks using a Sacrum IMU. The SmartSwim report included a comprehensive representation of performance based on goal metrics of each phase extracted from the IMU signals. The swimmers were divided into two groups, the experimental and control groups. The SmartSwim report for each swimmer in the experimental group was given to the coach, who used it to adjust the training accordingly. The results showed that the experimental group outperformed the control group when comparing each swimmer, each session, and the whole sessions. At the level of each individual, more members of the experimental group showed significant downward trend of average lap time (Mann-Kendall trend test, 95% confidence level). While comparing the sessions, the experimental group showed significantly lower lap time than the control group from the sixth session onwards (p-value < 0.05 from T-test). Considering all sessions, the experimental group showed significantly higher progress, lower average lap time, and more consistent records (Mann-Whitney U-test at 95% confidence level) than the control group. This study demonstrated that SmartSwim can assist coaching by quantitatively assessing swimmers' performance, leading to more efficient training.

Keywords: *Sports biomechanics, swimming, IMU sensor, performance evaluation, feedback*

6.1 Introduction

Swimming can be classified as a complex task because it cannot be mastered in a single session and has multiple degrees of freedom (Wulf and Shea, 2002). Learning such a complex physical activity and mastering the optimal technique for its execution depend on the continuous assessment of its performance. When it comes to complex tasks in sport, augmented extrinsic feedback has been shown to be necessary and effective for the athlete progress and development (Sigrist et al., 2013), regardless of the feedback modality. Therefore, the goal for successful coaching in swimming is clear: provide high-quality feedback concurrently or shortly after the activity on a frequent basis (Jefferies et al., 2012).

As in any other sport, swimming coaches rely mainly on their observations and coaching experience to monitor and evaluate swimmers' performance. However, such subjective and qualitative analysis is not accurate enough to provide precise information about a swimmer's strengths and weaknesses (Mooney et al., 2016a). The complex nature of swimming has also led the research community to study it with new tools and systems from different perspectives, such as physiology (Berger et al., 1997; Pendergast et al., 2003), motor control (Seifert et al., 2011a), and biomechanics (Payton and Bartlett, 1995; Nikodelis et al., 2005). As a result, more attention has been paid to the use of sophisticated analytical systems by both researchers and coaches to obtain an objective and quantitative assessment of swimming performance (Payton and Adrian Burden, 2017). Despite all the novel analysis methods that have been proposed for swimming analysis, there is a lack of an appropriate analysis system that can help both coaches and swimmers in better performance analysis (Mooney et al., 2016a). Video-based systems, most commonly used as the gold standard in swimming, suffer primarily from shortcomings such as the time-consuming process of calibrating and digitizing landmarks, image distortion due to water reflections and air bubbles, and small capture volume in aquatic environments (Callaway et al., 2010). In contrast, ease of use, accessibility, easy-to-understand results, and feedback are the top four priorities of coaches in an analysis system (Mooney et al., 2016a).

In one of the oldest studies of feedback in swimming, Chollet et al. converted hydrodynamic pressure applied to the swimmer's palm into auditory information. The swimmer was able to maintain stroke velocity, and improve motion stability and control through real-time sonification (Chollet et al., 1992). Visual feedback using a robot swimming under the swimmer for qualitative performance correction (Ukai and Rekimoto, 2013) or a complicated integrated system consisting of LED markers, a force plate, a high-speed video camera, an underwater camera, and a pressure pad for start, swimming and turn analysis (Le Sage et al., 2012) are examples of other studies using bulky systems to provide real-time feedback to swimmers. The use of such complicated sensor networks makes it difficult to use these systems in daily training. However, recent rapid improvements in the accuracy, size, and cost of inertial measurement units (IMUs) have made IMUs a credible option for swimmer motion tracking, as they can provide fast and easy-to-use feedback on detailed performance-related metrics (Félix et al., 2019).

Many studies have extracted kinematic parameters from IMUs and shown them to be a powerful tool for swimming analysis (Slawson et al., 2012; Dadashi et al., 2013c; Stamm et al., 2013a), but some of them transmitted the results as feedback to the swimmer or coach. SwimMaster is a system based on three accelerometers at the wrist, lower back, and upper back that provides visual, tactile, and auditory feedback on average swim velocity, stroke time, and body orientation (Bächlin et al., 2009). Rocha et al. used a network of five IMUs, a heart rate sensor, and a temperature sensor in a swimsuit to communicate information about the swimmer's heart rate, stroke rate, and body temperature to the coach (Rocha and Correia, 2006). Silva et al. placed an IMU on the upper back of the swimmers to transmit information about the type of technique, laps, and strokes detection to the coach (Silva et al., 2011). ISwimCoach is another analysis system that transmits to the coach the correct hand movement during strokes using a wrist IMU (Ehab et al., 2020). The system achieved 91% accuracy in detecting the correct strokes. Mangin et al. developed the idea of an instrumented glove that monitors hand movement during strokes and differentiates between recreational and elite swimmers using a wrist IMU (Mangin et al., 2015). According to the literature, the use of IMUs for feedback is still in its early stages. Although performed with a variety of parameters, techniques, and modalities, researchers have focused mainly on the strokes of swim phase. These studies also led to numerous interferences in the normal swimming style through a complex multi-sensor network. Moreover, the previous studies have rarely reached the field test to show the effect of feedback on swimmers' performance.

Using the signals of a single sacrum-worn IMU, we developed a new approach in a previous study to segment a swimming lap into push, glide, stroke preparation, and swim phases (Hamidi Rad et al., 2021b). Then, a phase-based performance evaluation was conducted to estimate goal metrics representing a swimmer's performance in each swimming phase (Hamidi Rad et al., 2021a). The objective of this study was to evaluate the in-field use of a comprehensive phase-based performance evaluation obtained from a single IMU as feedback to the coach. The goal metrics were shared with the coach to provide objective advice to swimmers in an experimental group and to adjust each individual's training. We hypothesize that the objective feedback based on SmartSwim will improve the performance of experimental group to a higher degree compared to a control group that received routine feedback.

6.2 Materials and methods

6.2.1 Measurement setup

Fifteen swimmers (9 males, 7 females, age: 14.6±0.8 years, height: 171.6±6.9cm, body mass: 55.9±10.1 kg) of a competitive team participated in this study. They had similar performance levels (50m front crawl record: 28.60±2.04s) and were placed on the same team by the swimming club. The swimmers had similar training experiences and regularly trained together six days per week under the supervision and guidance of the same coach. A single IMU (Physilog® IV, GaitUp, CH.) was attached to the swimmer's sacrum with a waterproof tape (Tegaderm, 3M Co., USA) and recorded 3D angular velocity (±2000 °/s) and 3D accelerometer (±16 g) at a sampling rate of 500 Hz. To make the sensor data independent of sensor placement on the swimmer's sacrum, a functional calibration with simple movements (standing upright and squats) was performed before starting the test out of the water (Dadashi et al., 2013c).

After a brief warm-up set by the coach, each swimmer completed five laps of one-way front crawl at maximum speed. Each participant had five minutes rest between two consecutive trials to avoid fatigue. Swimmers were asked to complete all swimming phases (push, glide, stroke preparation, swim) so that we could analyze their performance within each phase (Figure 6.1). Lap time was measured and recorded by the coach using a stopwatch for each lap during all test sessions. The average of the five lap times was used as their performance level. The same measurement was repeated once at the end of each week for ten weeks. The order in which the swimmers participated was the same in all sessions. The testing procedure was presented to each swimmer, and they were asked to provide written informed consent prior to participation. The measurement protocol of this study was approved by the EPFL Human Research Ethics Committee (HREC, No. 050/2018).

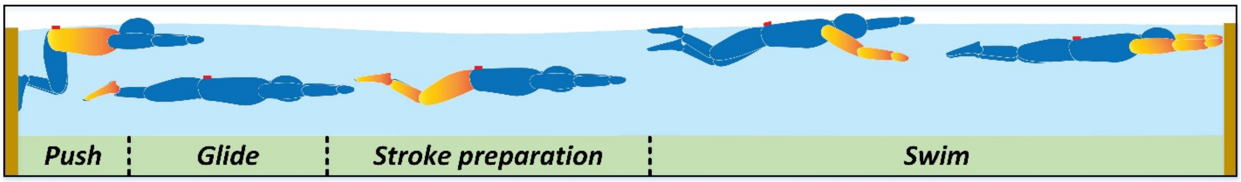

Figure 6.1 – Measurement protocol. The swimmer starts in the water with a wall push-off and performs all swimming phases of push, glide, stroke preparation and swim. The coach records the lap time with a stop watch, while the phase-based goal metrics were extracted from the IMU (red box) worn on the sacrum.

6.2.1.1 Experimental and control groups

The swimmers were divided into two groups, an experimental and a control group. Since performance is assumed to be related to lap time as a key metric, the lap times of the first test session were considered as the baseline and used to select the swimmers of the two groups. The two groups were selected to have similar performance levels (as measured by lap time), similar age range, similar physical characteristics (body mass and height), and similar gender. The characteristics of the two groups are shown in Table 6.1. The coach received the feedback from IMU report only for the experimental group.

Table 6.1 – Characteristics of the swimmers in the experimental and control groups. The swimmers were selected to have similar characteristics

Group	Male	Female	Age (yrs)	Height (cm)	Body mass (kg)	First session record in seconds (baseline)
Experimental	4	4	14.5 ± 0.5	170.1 ± 6.5	55.5 ± 8.3	14.74 ± 0.87
Control	4	3	14.6 ± 0.4	171.2 ± 7.1	54.9 ± 7.2	14.75 ± 0.79

6.2.2 SmartSwim solution for swimming analysis and feedback

The SmartSwim solution proposed in this study consists of two parts. In the first part, we performed a phase segmentation of each lap using our previously validated algorithms (Hamidi Rad et al., 2021b), and then estimated the goal metrics for performance evaluation in the different phases (Hamidi Rad et al., 2021a). In the second part, we introduce a new feedback report based on these goal metrics to give the coach a comprehensive view of the performance and progress of each swimmer and the group.

6.2.2.1 Phase-based performance evaluation

Following our previous study evaluating swimming performance with a sacrum-worn IMU, each lap was segmented into the push, glide, stroke preparation, and swim phases (Hamidi Rad et al., 2021b). The following goal metrics corresponding to each phase were estimated using a selection of kinematic parameters by the data obtained from IMU (Hamidi Rad et al., 2021a):

1. Push phase: push maximum velocity
2. Glide phase: glide end velocity
3. Stroke preparation phase: stroke preparation average velocity
4. Total Swim phase: swim phase average velocity
5. Swim phase strokes: average velocity per stroke of the swim phase
6. Whole lap: lap average velocity

The errors attributed to lap segmentation and goal metrics estimation are explained in the corresponding papers. Although this analysis was performed for both the experimental and control groups, only the reports of the experimental group members were given to the coach.

6.2.2.2 Feedback reports and illustrations

For the experimental group, three types of feedback were given to the coach: **(i)** individual performance per session, **(ii)** individual multi-session performance, and **(iii)** comparison of swimmers per session. The reporting format was visually tailored to the coach's needs to facilitate understanding and make it more efficient.

An example of the individual feedback provided after each session is shown in Figure 6.2. For each of the five laps (L1 to L5), a goal metric value was provided on each axis of a radar chart. In addition, the average and best performance in each phase for all five laps were added (Figure 6.2, right). In this type of representation, the pentagon of best performance is an imaginary lap that the swimmer can complete if he/she does their best in all swimming phases. In addition to the radar chart, a stroke velocity diagram was added to show the average velocity per stroke during the five laps (Figure 6.2, left). Furthermore, in this diagram, the stroke regularity can be observed by the variability of the inter-stroke velocity variability represented by the standard deviation values of each lap.

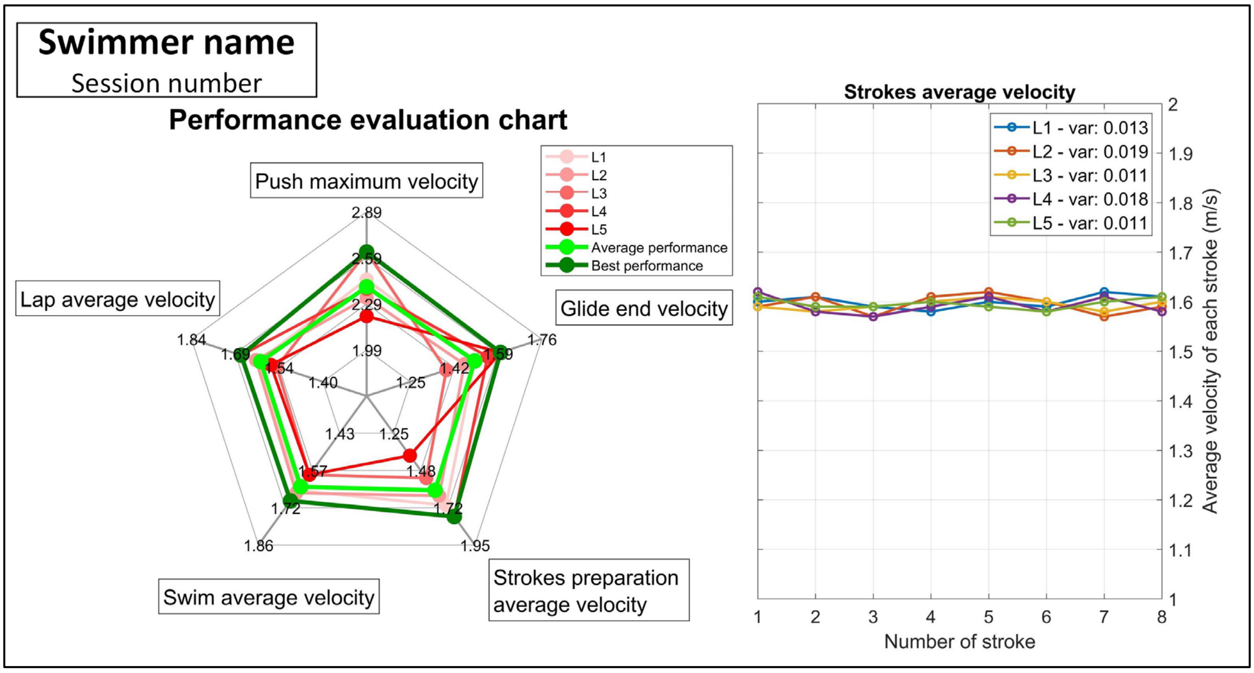

Figure 6.2 – Individual feedback for the swimmer after the test session. The performance evaluation chart (**left**) shows the goal metrics for five laps, the average performance (light green) and the best performance (dark green). The stroke average velocity chart (**right**) shows the average velocity per stroke during five laps and its variation ("var", corresponding to standard deviation) in the legend.

The individual multi-session result is the second type of feedback, including the swimmer's average performance graphs during all previous sessions (Figure 6.3, left). The graph shows the swimmer's progress in each goal metric during multiple sessions and indicates the percentage of change from the previous session at the bottom. The average lap time recorded by the coach for all previous sessions is also included in the report (Figure 6.3, right), allowing the coach to simultaneously observe the effect of the change in the goal metric on the lap time.

The third type of feedback per session is to compare the swimmers by plotting the average performance of each swimmer on the same radar chart (Figure 6.4). The coach can easily compare the swimmers at each phase and decide how to adjust the training for each individual, or design a specific training modification if all swimmers show the same weaknesses.

We shared the report of the experimental group's performance with the coach. He considered the reports for each swimmer and adjusted the training sessions accordingly. We asked the coach to explain his observations and findings from the feedback and then write down the training changes planned for the next week for each swimmer. The charts for single session and multi-session feedback were also explained and shared with the swimmers so they could self-monitor during the training sessions.

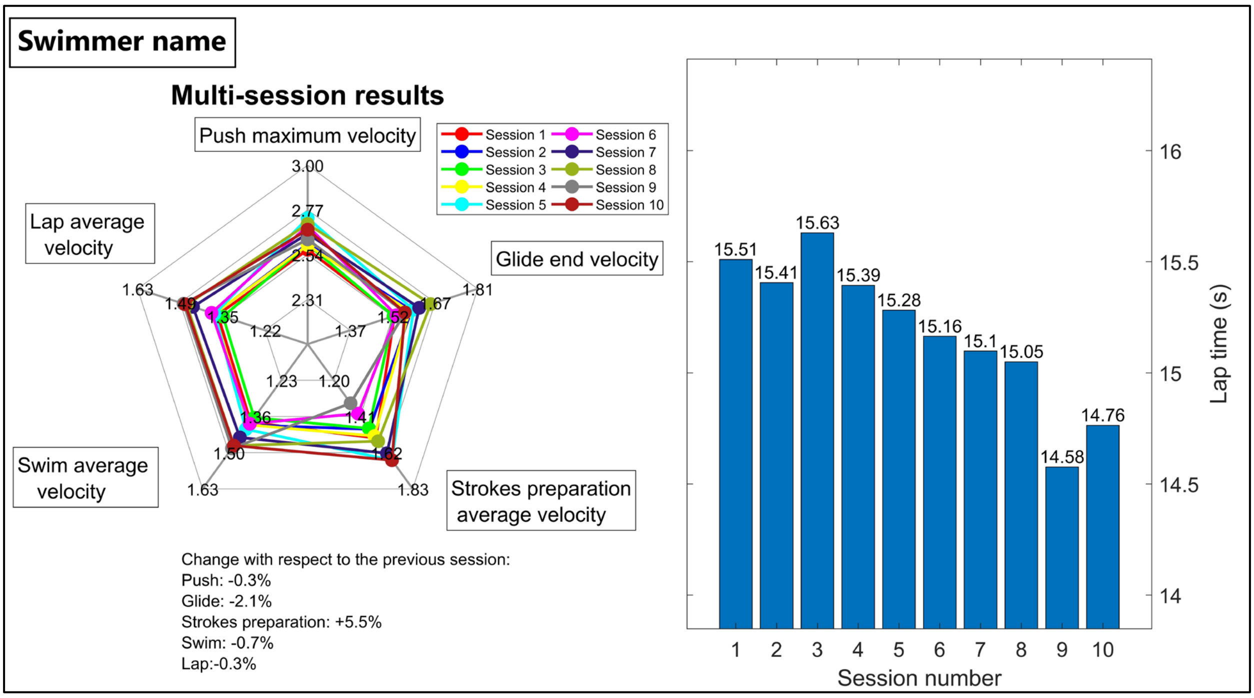

Figure 6.3 – Feedback on Multi-session performance evaluation feedback. The radar chart shows with a different color the average performance of all sessions (left) with changes compared to the previous session. The bar graph shows the average lap time of all sessions recorded by the coach (right).

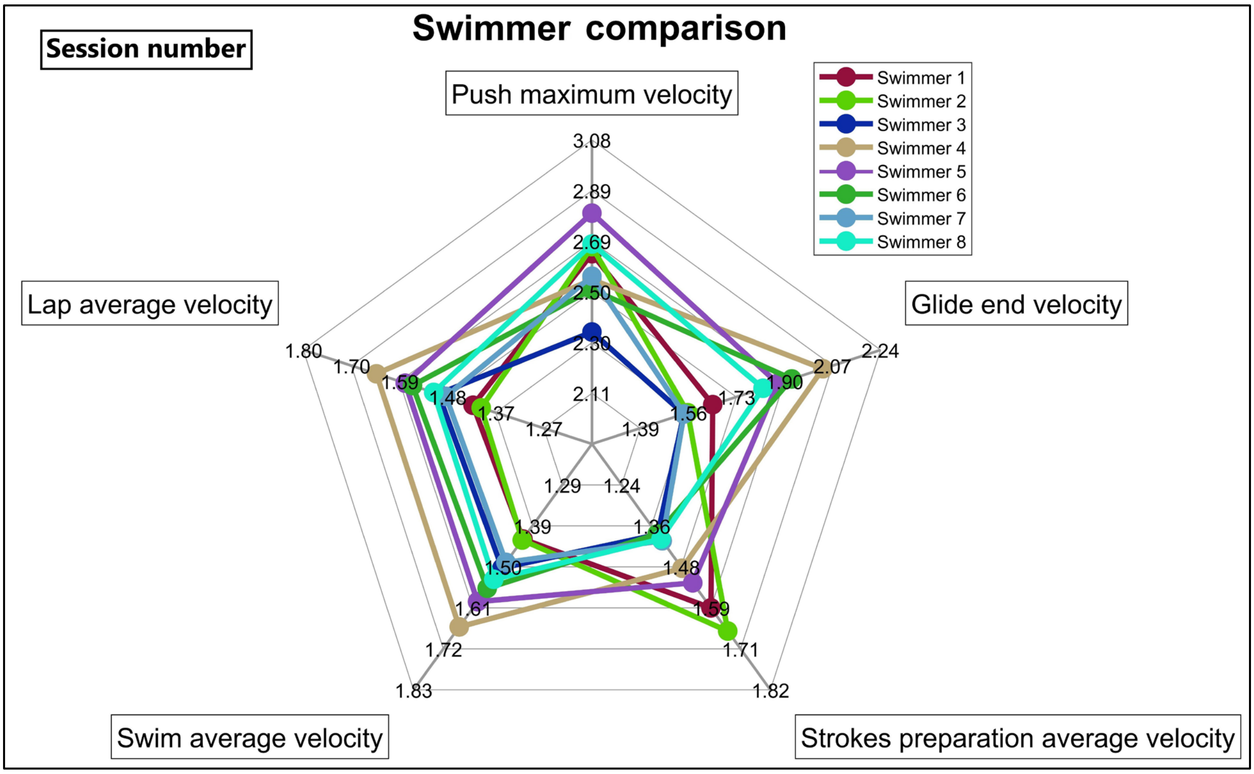

Figure 6.4 – Feedback to compare the swimmer's average performance in different swimming phases. The coach can see the strengths and weaknesses of each swimmer through this comparison.

6.2.3 Feedback effect statistical analysis

Because lap time is considered as the relevant measure of swimming performance, we evaluated the lap times of both groups for performance comparison. The two groups were compared at three levels: **(i)** per person, **(ii)** per session, and **(iii)** all sessions.

At the person-level, the trend of average lap times during the ten sessions for each swimmer was analyzed using the nonparametric Mann-Kendall trend test (Gilbert, 1987; Kendall, 1995). The purpose of this analysis was to determine how many swimmers in each group showed a significant trend of decreasing lap time due to performance progress. The test calculates the S value, which is the number of positive minus the number of negative differences when comparing all observations (equation 6.1).

$$S = \sum_{j-1}^{n-1} \sum_{i-j+1}^{n} sgn(x_i - x_j) \tag{6.1}$$

Where x_i and x_j denote the average lap time obtained in the *ith* and *jth* sessions, respectively, and n is the total number of sessions. For the populations with $n \leq 40$, it is sufficient to determine the corresponding probability of the Mann-Kendall trend test for the calculated value of S to find out whether the trend is significant or not. The trend significance for the swimmers with absences was analyzed for the existing number of records. A significance level of 95% is used for this analysis.

In the level of per session, we compared the lap times of the two groups in each session to determine if the experimental group significantly outperformed the control group. For this comparison, all lap time values for both groups in each session (40 values for eight swimmers in the experimental group and 35 values for seven swimmers in the control group) were compared. Since there is enough data for parametric test, first, the normality of the data distribution was checked using the Kolmogorov-Smirnov normality test (Lilliefors, 1967) and then an independent t-test assuming unequal variances (Kim, 2015) was performed to compare the average values of the two groups, accepting a confidence level of p-value < 0.05 as significant. The second analysis at this level is the comparison of the standard deviation of lap times in each session. For this analysis, the standard deviation of the five lap times for each swimmer was calculated, averaged across the group, and then compared to the other group. Because the sample size for this analysis is small (eight versus seven), the Mann-Whitney U-test, a non-parametric method (Mann and Whitney, 1947; Nachar, 2008) with a 95% confidence level, was used for this comparison.

Finally, to compare the groups across all test sessions, the mean and standard deviation of the five lap times were estimated for each swimmer and then averaged across all swimmers in each group. The Mann-Whitney U-test with a 95% confidence level was used to compare between groups across the ten sessions. Comparison of the means allows us to understand whether the experimental group was faster than the control group, and comparison of the means of the standard deviations evaluates the regularity of the swimmers between laps as a factor of efficient swimming. To test whether the overall progress of the swimmers with feedback was higher, we compared the average progress (average change in lap time compared to the first session) of the swimmers across all sessions using the Mann-Whitney U-test.

6.3 Results

Four swimmers in the control group missed seven sessions due to swimmer unavailability, while swimmers in the experimental group participated in all test sessions. The average lap time of all swimmers during the ten sessions is shown in Figure 6.5. The swimmers of both groups show progress during the ten training sessions.

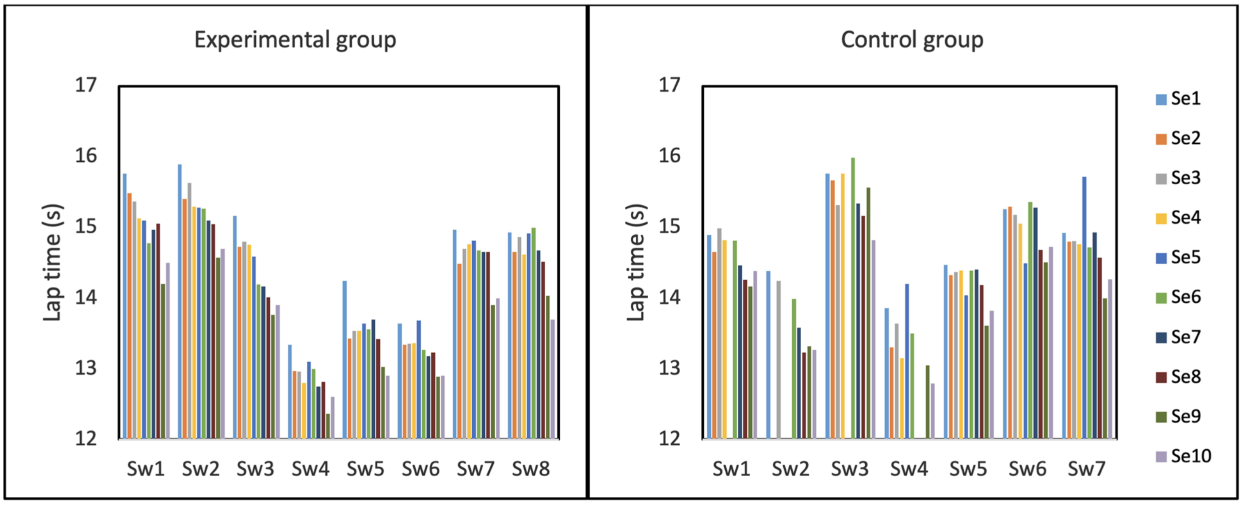

Figure 6.5 – Average lap time of the swimmers in 10 sessions (Se1-Se10), for eight swimmers of the experimental group (Sw1-Sw8, left) and seven swimmers of the control group (Sw1-Sw7, right).

Comparing the first and the last session of all swimmers, the lap times of the last session are significantly lower than those of the first session, based on t-test results (p-value < 0.001 for both groups). For a qualitative comparison, the graphs for goal metrics and lap times of the first and tenth sessions are shown in Figure 6.8 and Figure 6.9 of section 6.6.1 of the appendix for the experimental group and the control group, respectively. On average, each swimmer of the experimental group improved 7.4% with respect to the first session while the control group swimmers improved 5.3%. However, the progress trend and the amount of lap time change seems to be visually different for each swimmer. Moreover, the swimmers who had worse performance (higher average lap time) at the beginning of the measurements made more progress until the end of the measurements compared to others.

6.3.1 Coach interpretation

Based on the reports the coach wrote during the measurements, he used feedback as an additional factor to his observation and Figure 6.6 can be conceptualized for his decision-making process with SmartSwim. In general, he relied on his experience and knowledge to make decisions. He considered the swimmer's profile and existing constraints, such as time until the next competition or injury, to make a decision for each swimmer. SmartSwim provided the coach with new knowledge that enabled him to make safer and more reliable decisions to adapt each individual's training.

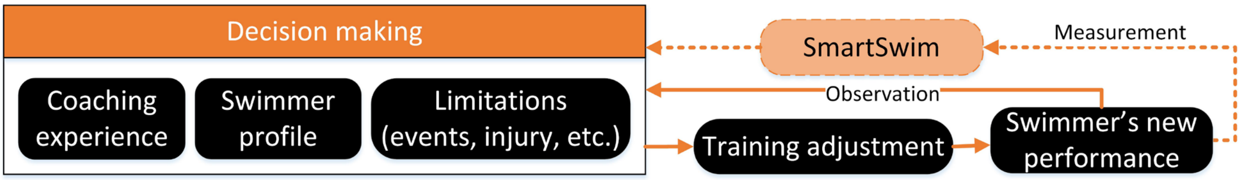

Figure 6.6 – Feedback effect on the training procedure illustrated by the coach

A summary of the main comments and training adjustments mentioned in the coach's reports can be found in Table 6.4 of section 6.6.2 of the appendix. By directly observing the individual performance evaluation chart (Figure 6.2, left), the coach identified the swimmer's weaknesses in each session and evaluated the room for progress in each phase of swimming (by comparing the swimmer's average and best performance). Multi-phase observation was helpful to the coach which is mentioned in coach comments. For example, when the swimmer started with a strong push (observed by push maximum velocity) but slacked off in the goal metrics of subsequent phases, the coach attempted to balance the performance between phases. Stroke average velocity chart (Figure 6.2, right) provided further information about the swim phase. The coach considered the results with little variation during strokes to be for the swimmers who can swim more regularly. He also qualitatively observed the effect of the change in swimming rhythm during breathing in the average velocity of the strokes. The coach also observed a decreasing velocity trend during strokes.

Multi-session feedback is used to monitor the effects of training on swimming performance over several weeks (Figure 6.3, left). Based on the coach's comments, he assumed that any training adjustments would show an effect after three weeks. If he observed satisfactory progress, he continued training in the same manner; otherwise, he chose a different strategy for the swimmer. In addition, by looking at the lap time values in the same graph (Figure 6.3, right), the coach was able to observe the effect of the training adjustment on the swimmer's average lap time and make a more reliable decision. As the final feedback type, the swimmer comparison chart (Figure 6.4) allowed the coach to see the weaknesses and strengths of each swimmer compared to the others. The coach also used this chart to find the swimmers with higher potential to focus on, as the swimmers' progress compared to others was clearly visible when looking at this chart over several sessions.

6.3.2 Statistical analysis

The results of the applied Mann-Kendall trend test for the person-level comparison (Table 6.2) show a decreasing trend in lap time for swimmers in both groups. In the experimental group, this trend was significant for all but one swimmer, while in the control group only two swimmers showed a significant trend. In addition, stronger significance (higher *S* values) was observed for swimmers in the experimental group.

Table 6.2 – Person-level comparison between the experimental group and the control group. *S* value for Mann-Kendall trend test of average lap time values during 10 training sessions. A negative sign indicates a decreasing trend.

Experimental group lap time trends – *S* value							
Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8
-37*	-41*	-39*	-31*	-19	-29*	-25*	-23*

Control group lap time trends – *S* value						
Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7
-24*	-17*	-16	-14	-18	-15	-23*

*** Significant with 95% confidence level**

At the session level comparison, after confirming the normality of the data by Kolmogorov-Smirnov test, an independent t-test was performed for comparing the groups. The two groups showed a significant difference from the sixth session onward (Figure 6.7). The standard deviation results of the groups also showed a significant difference from the sixth session (except for the eighth session) (Table 6.3).

Table 6.3 – Session-level comparison between the experimental and control groups. t score and U score results for comparison of mean and standard deviation lap times, respectively.

# **Test session**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Lap time comp. : t score	0.27	1.62	1.36	1.81	1.12	2.39*	2.79**	2.09*	2.40*	1.99*
Standard deviation comp. : U score	25	18	17	16	10	9*	7*	13	5*	9*

*** p-value < 0.05, ** p-value < 0.01**

Finally, the average lap times of the groups in all 10 test sessions are compared. Although both groups showed a significant decreasing trend in lap time (significant trend from Mann-Kendall test in Figure 6.7), the experimental group scored significantly lower lap times compared to the control group based on the Mann-Whitney U-test with a confidence level of 95% (U_{stat} = 18, $n_1 = n_2$ = 10, p-value < 0.05, two-tailed). The standard deviation of the experimental group is also significantly lower than that of the control group (U_{stat} = 21, $n_1 = n_2$ = 10, p-value < 0.05, two-tailed). By taking the first sessions as the baseline, we quantified the progress of each swimmer as the difference between the lap time of each session and the baseline. According to the result of the Mann-Whitney test, the average progress of the members of the experimental group was significantly higher than that of the control group (U_{stat} = 21, n_1 = 8, n_2 = 7, p-value < 0.05, two-tailed). Considering all swimmers in each group, the swimmers in the experimental group and the control group achieved an average progress of 0.65s (4.4%) and 0.35s (2.3%), respectively.

Since lap average velocity is the division of pool length by lap time, it is expected to correlate with progress. Therefore, we performed the same analysis in session level for lap average velocity to see if it showed the similar difference between the two groups. The results are explained in the appendix (Table 6.5 and Figure 6.10). Similar to lap time, the average and standard deviation of lap average velocity becomes significantly different between the two groups after sixth test session.

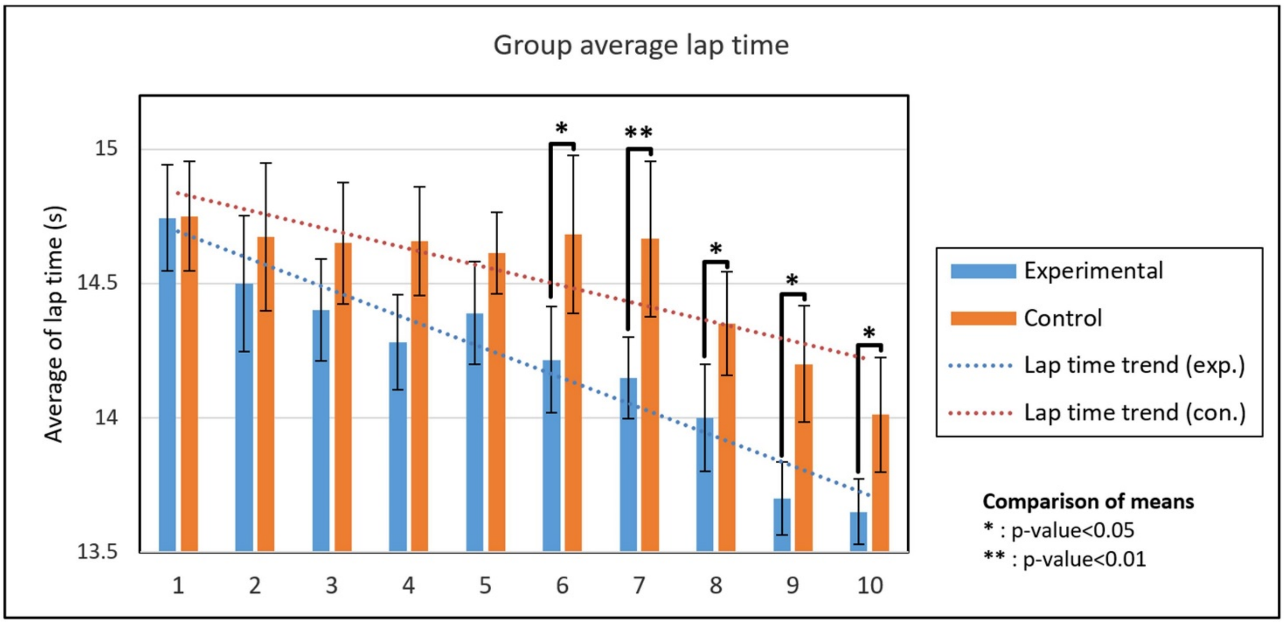

Figure 6.7 – Average and standard deviation of lap times for the experimental and control groups during ten test sessions

6.4 Discussion

In this study, we proposed a new approach for performance evaluation and feedback. We investigated the effects of training with SmartSwim on the performance of a group of swimmers during a 10-week training period. The results obtained confirmed the ability of SmartSwim to provide objective feedback during the training sessions with a lightweight and portable IMU. After each test session, this feedback was communicated to the coach through a comprehensive report that illustrated the main goal metrics of the test to help the coach design the training more efficiently until the next measurement. Comparison with a control group that received only the usual feedback confirmed our hypothesis that the experimental group achieved better progress in terms of target performance (i.e., lap time) when they received advice based on performance-related goal metrics.

6.4.1 Using feedback for training

Based on the evaluations of the coaches' reports, he quickly understood how to use SmartSwim feedback. Unlike traditional methods, he could easily identify and focus on the phase with a higher chance of progress, while it takes more time to determine a swimmer's potential through subjective observation. He also observed the interaction between swimming phases and examined how well the swimmer managed to improve all phases together. Finding the optimal training for each swimmer requires trial and error (Irwin et al., 2004), which is reduced when the coach has a quantitative assessment of performance. The coach mentioned that he had more confidence in leading the swimmers in the experimental group than in the control group. He found that the feedback was consistent with his personal judgement, and followed the swimmers with numbers rather than pure observation. Using the graph of strokes average velocity, the coach recognized the skilled swimmers with low velocity variation (Dadashi et al., 2016), detected the breathing effect on swimming rhythm (Lerda et al., 2001) and identified the swimmers' endurance level (Wakayoshi et al., 1992). The swimmers in the experimental group also received the feedback and review of their weekly progress with great enthusiasm, as none of them missed a single testing session.

In this study, the SwimSmart feedback report functioned as an assistant to the coach. The involvement of the coach is essential because the final decision to optimize training depends on the coach's judgment and the swimmer's profile. The coach usually relies on his or her personal experience, based on which he or she can usually make a qualitative assessment of the training sessions (Mooney et al., 2016a). Our results show that objective and quantitative goal metrics complement the coach's qualitative observations and allow him to better personalize his advice and test different strategies using the same goal metrics. Compared to similar studies (Mangin et al., 2015; Ehab et al., 2020), we were able to provide feedback on all phases of swimming, not just the swim phase, allowing the coach to obtain a more comprehensive assessment. Moreover, the feedback was tested in-field for the evaluation of its effect on real training sessions of the team.

6.4.2 Experimental and control group comparison

Starting with the person-level comparison, the results of Mann-Kendall trend test with 95% confidence level showed that the decreasing trend in lap time during the ten training sessions is significant for seven out of eight swimmers in the experimental group, while only two swimmers in the control group showed such a significant trend. According to the logic of the Mann-Kendall trend test, a significant trend exists when the lap time decreases continuously from week to week. This confirms that although the swimmers in both groups achieved a lap time at the end of the ten weeks that was significantly lower than the baseline time, the swimmers in the experimental group made continuous progress during the measurements, which is a crucial factor in efficient training (Toner and Moran, 2015). In addition, the S-values calculated for the swimmers in the experimental group (a range of [-41, -23]) are consistently lower than those in the control group (a range of [-24, -17]), reflecting the stronger improvement trends when using SmartSwim for coaching.

For the session-level assessment, the two groups had a similar lap time average and standard deviation in the first session (p-value > 0.05). During the training sessions, the coach trained the experimental group based on feedback, while for the control group he relied only on his own coaching experience. Consequently, the experimental group's progress in the remaining sessions is influenced by feedback-based training. The results show that the average lap time and standard deviation of the experimental group are significantly lower than those of the control group from the sixth session (p-value < 0.05). This shows that the swimmers in the experimental group performed not only faster, but also more consistent and systematic (Stewart and Hopkins, 2000) than the control group.

Focusing on the swimmers' weaknesses and comparing personal observation with feedback helps the coach sharpen his critical thinking skills (Nash et al., 2017). The coach provided more relevant and personalized feedback to each swimmer, which was reflected in higher progress of these swimmers during the same period compared to the control group. In addition, based on the results of using lap average velocity to perform the session-level assessment shown in Table 6.5 and Figure 6.10 of section 6.6.3 in the appendix, similar results were obtained and the two groups differed significantly from the sixth session. The coach can use the lap average velocity as a substitute for lap time and focus on other goal metrics during the training sessions.

Finally, swimmers in the experimental group show lower lap time and standard deviation and higher progress when all test sessions are considered together (Mann-Whitney U-test, p-value < 0.05). This suggests that the effect of feedback can be observed not only for each swimmer and session, but also in the overall picture of long-term training. Considering the importance of seasonal evaluations of swimmers (Koutedakis, 1995), this level of comparison helps the coach to monitor the performance in entire season and better prepare for competitions. In summary, the superiority of the experimental group over the control group is evident when comparing the swimmers' performance at three levels: per person, per session, and all sessions. Bielec et al. examined the effect of a specific aerobic exercise on the performance of young swimmers and found a significant improvement in males over two months of training (Bielec et al., 2008).

We tried to keep all effective factors the same for the experimental and control groups, but we cannot claim that the superiority of the experimental group over the control group is solely due to feedback. The effects of factors such as psychology (Sheard and Golby, 2006), nutrition (Shaw et al., 2014), or physiology on swimmers' performance were not considered in this study. Moreover, the potential room of progress for each swimmer is different and depends on both technical and personal interests which was not considered in this study. Our study is limited in terms of the number of swimmers, so we had to use non-parametric analyses. A larger data set is needed to more conclusively evaluate the effect of feedback. We mixed male and female swimmers, regardless of their growth and maturation status, in the two groups and their individual comparison is beyond the scope of this study. Among the four main swimming styles, front crawl was analyzed, while the same feedback can be given for the other swimming styles. Lap times are recorded by coaches using a stopwatch, which is a source of error in our measurements. Due to technical limitations, we need to extract the data and analyze it before giving feedback to the coach which takes a few hours. However, the coach can compare his observations with the feedback report if it is provided during or shortly after each lap. SmartSwim also demands the swimmer to perform all swimming phases in sequence, not starting from the middle of a phase.

The main disadvantage of wearables is the increased water drag on the swimmer's body (Magalhaes et al., 2015). The use of a single sensor in SmartSwim minimizes this problem and inconvenience to the swimmer. In addition, it does not interfere with the swimmer's normal performance and can be used during daily training. The use and attachment of the sensor requires extremely little preparation and analysis on the part of the coach, who can therefore easily use the system for all swimmers at the same time. The sensor could be integrated and industrialized into the swimsuit at a later stage. Regarding the complexities of finding the best coaching approach for young swimmers, multiple studies examined the effect of training load (Toubekis et al., 2013), mental training (Bar-Eli et al., 2002) or training intensity (Gussakov et al., 2021) on the performance of young swimmers, rarely reporting significant performance changes. Since technique analysis is of high importance for efficient coaching, training program can be improved by SmartSwim feedback. Sharing the phase-based feedback of a larger group of swimmers with the coach and developing the appropriate real-time algorithms to provide feedback simultaneously can be offered as next steps in this research.

6.5 Conclusion

In this study, we examined the effects of coaching with SmartSwim, a new phase-based performance evaluation feedback, on swimmers' performance during 10 weeks of training. The coach used a comprehensive report of phase-based goal metrics from IMU as an assistant for eight swimmers in the experimental group and adjusted their training accordingly, while he guided seven swimmers in the control group based only on his observations and coaching experience. The results showed that the experimental group outperformed the control group when considering the performance of each swimmer, the performance of the group in sessions, and the group performance in all training sessions. Most of the swimmers in the experimental group showed a significant downward trend in their average lap times in 10 test sessions. The experimental group significantly outperformed the control group in terms of lap times from the sixth session onward. In addition, the swimmers in the experimental group showed more consistent results than those in the control group. Finally, considering all 10 sessions, the swimmers in the experimental group showed significantly higher progress, lower average lap times, and more consistent records than the control group. The coach found the feedback reports very helpful in "diagnosing" the swimmers' weaknesses and monitoring their progress more efficiently during the training sessions. This study has helped meet the needs of the coaching community and promote objective coaching in swimming.

6.6 Appendix

6.6.1 First and tenth weeks comparison

The average values for five goal metrics and lap times during the first and last test sessions are shown in Figure 6.8 and Figure 6.9 for the swimmers in the experimental and control groups, respectively.

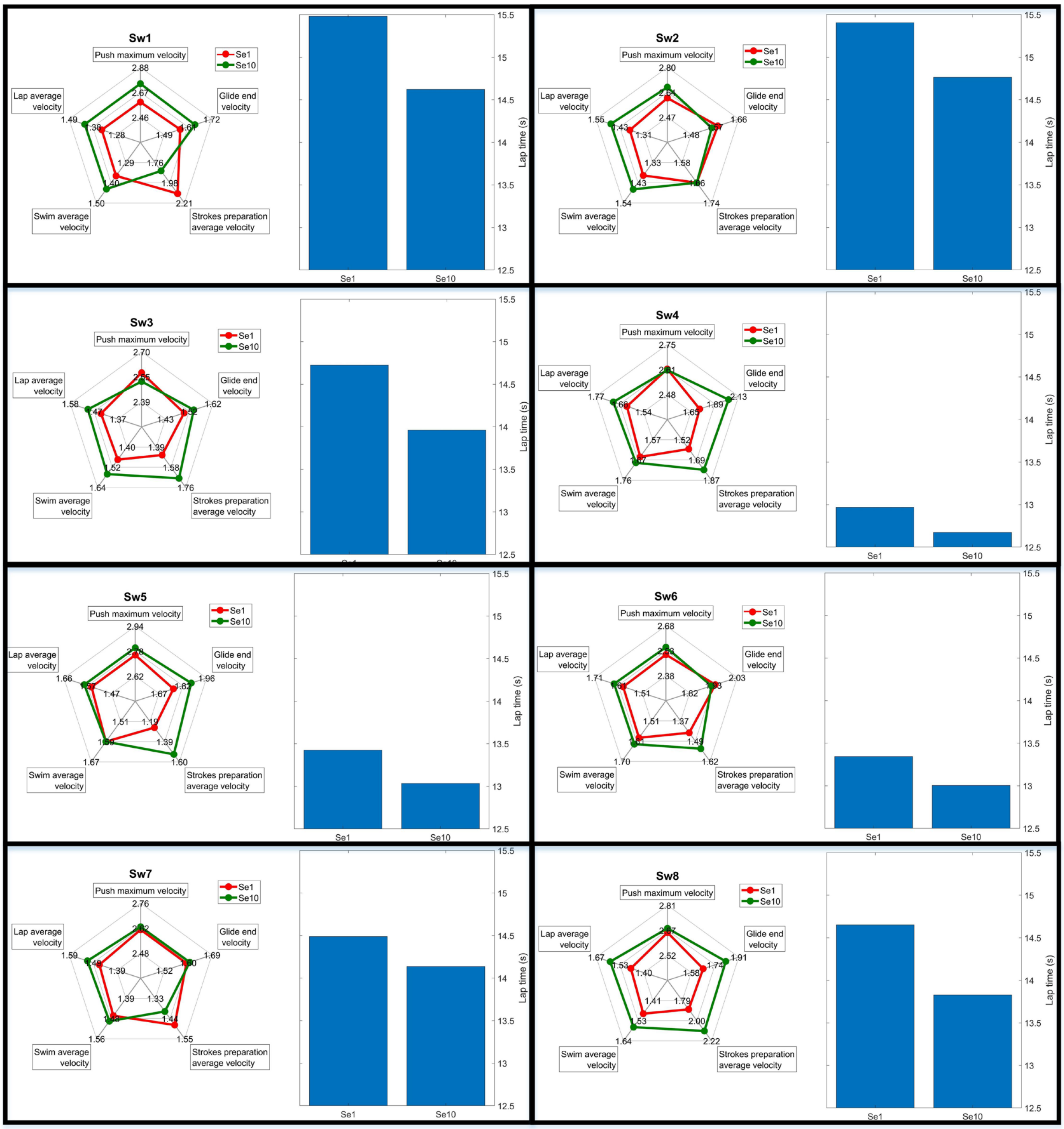

Figure 6.8 – Average values of goal metrics and lap times in first (Se1) and last (Se10) session, for the swimmers of the experimental group

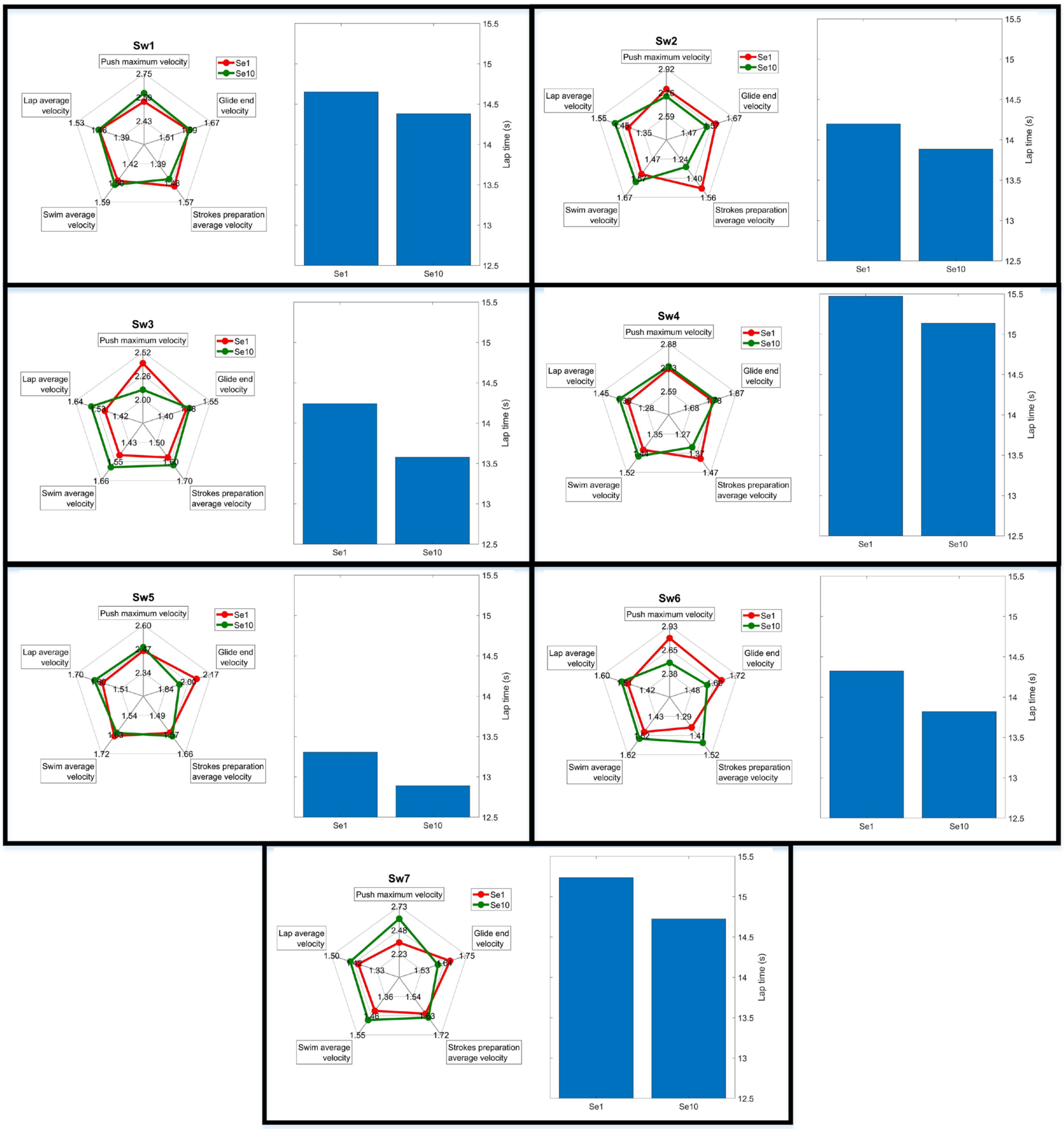

Figure 6.9 – Average values of goal metrics and lap times in first (Se1) and last (Se10) session, for the swimmers of the control group

6.6.2 Coach's observations and interpretations

The key observations and training adaptations that the coach made based on SmartSwim feedback were collected in reports after each session. Table 6.4 shows a list of his observations, comments and proposed trainings or tests for the swimmers in four main swimming phases.

Table 6.4 – Summary of coach observations and training adaptations using SmartSwim

<table>
<tr><th>Phase</th><th>Sample observations</th><th>Comments, new training and tests</th></tr>
<tr><td>Push</td><td rowspan="3">• Percentage of progress in the report shows the room for enhancement in each phase.
• The swimmer is not good at phase A but good at phase B.
• The swimmer is strong in phase A but he loses it in the following phases.
• The training strategy is working as the swimmer have improved compared to the two previous sessions.
• Swimmer A is weaker than others in phase B and he has not improved enough.</td><td rowspan="3">• More repetitions with and without fins
• Decreasing the time to reach 10m
• Increasing the distance travelled after a strong push on the wall with 6 kicks and then 2 strokes without breathing
• More lower body workout in dry-land training.
• Travelling as much distance as possible using only the initial push on the wall
• Several stroke preparation trainings with fins to observe the hip motion range.
• Noticing the balance between the depth and length of stroke preparation after start</td></tr>
<tr><td>Glide</td></tr>
<tr><td>Stroke prep.</td></tr>
<tr><td>Swim</td><td>• There a lowering trend in stroke average velocity chart
• High variability and irregularity is clear in strokes velocity
• The respiration causes higher velocity variation in the lap.
• Swim phase average velocity is lower than previous sessions.</td><td>• Arm positioning and stroke rhythm correction
• More long distance, low intensity trainings for increasing the endurance
• Limiting the number of breaths in repetitions
• Smoother strokes and more use of the force</td></tr>
</table>

6.6.3 Session-level comparison using lap average velocity goal metric

Lap average velocity is the goal metric that was highly associated with lap time in our previous study. Therefore, a similar comparison is made between the experimental group and the control group at the session level. After confirming the normality of the data with Kolmogorov-Smirnov test for the data of both groups, an independent t-test was performed to compare the differences between the two groups. They showed a significant difference from the sixth session (Figure 6.10). The standard deviation results of the groups also showed a significant difference between them from the sixth session (except for 8th session) (Table 6.5).

Table 6.5 – Session-level comparison between the experimental and control groups. t score and U score results for the comparison of the means and standard deviations, respectively, of lap average velocities.

# **Test session**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Lap time comp. : t score	0.29	0.44	0.78	1.02	0.86	2.33*	3.59**	2.63*	2.01*	1.99*
Standard deviation comp. : U score	26	24	14	23	12	4*	7*	15	8*	9*

*** p-value < 0.05, ** p-value < 0.01**

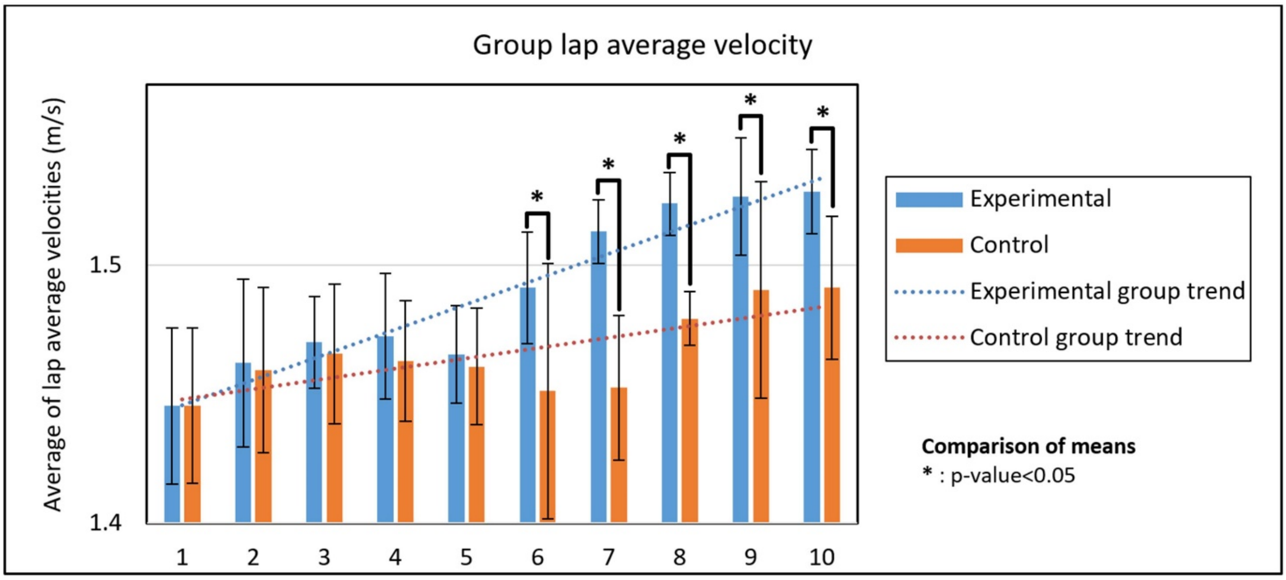

Figure 6.10 – Average and standard deviation of lap average velocity goal metric for the experimental and control groups during ten test sessions.

6.6.4 Feasibility study of phase-based performance evaluation system as a minimally viable product

After observing the effects of phase-based feedback on coach performance and subsequently on swimmers, we conducted a survey among a group of swimming coaches in Swiss swimming clubs to evaluate the feasibility of our solution. In this survey, we asked them about **(i)** the analysis systems they use for swimming analysis, **(ii)** the parameters they would like to track throughout the training session and specifically during each swimming phase, **(iii)** their opinion on the use of wearable motion sensors for monitoring swimmers, and **(iv)** what they would think of the solution offered by SmartSwim. 25 swimming coaches participated in this survey (39.8±8.6 years old with 14±6 years of professional coaching experience) whose focus is on training professional swimmers for regional or national competitions. The survey was conducted with an online questionnaire[1] and the coaches were informed about the results of the survey.

6.6.4.1 Swimming analysis systems

95% of the coaches are familiar with cameras and use them daily, weekly, or quarterly underwater or above water for swimmer motion analysis. However, other types of measurement systems for kinetic analysis (e.g., force platforms, hand pressure sensors) or physiological analysis (e.g., heart rate monitors, blood lactate monitors) are used less (Figure 6.11). Among the coaches who used cameras, 65% used the cameras only qualitatively, while the rest used them in a mixed qualitative and quantitative manner, with none using them exclusively quantitatively.

[1] The questionnaire is accessible with this link: https://doi.org/10.5281/zenodo.7067156

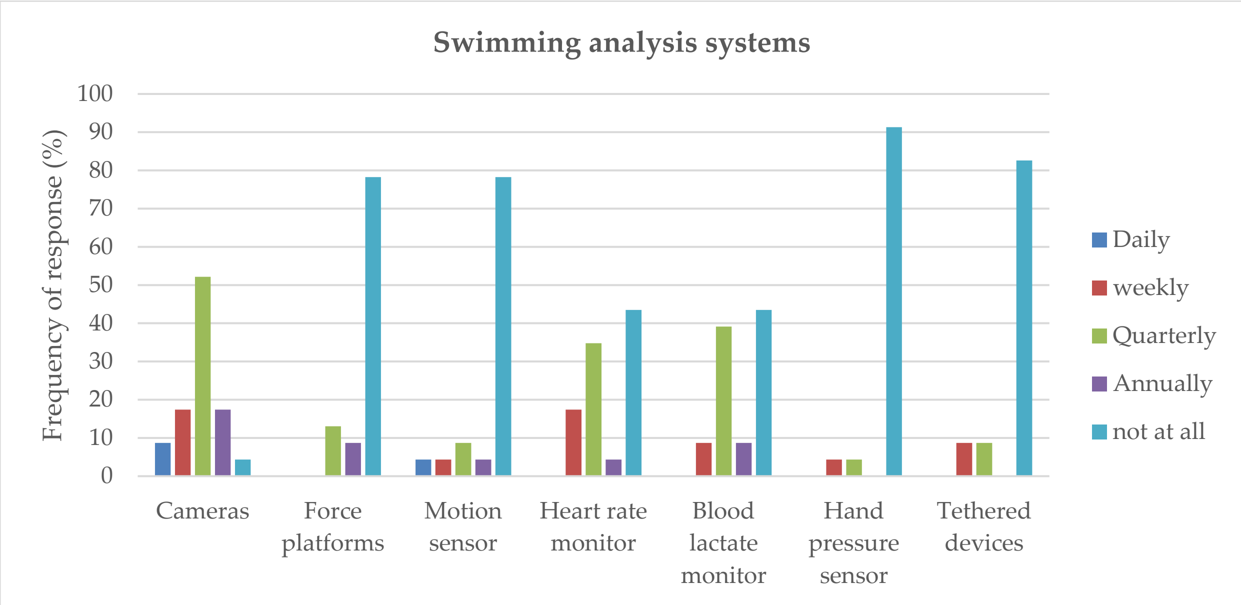

Figure 6.11 – The swimming analysis systems used by coaches along with the usage frequency.

When asked about the advantages and disadvantages of the measurement systems used, most of the coaches mentioned "quick feedback" and "easy to understand results" as the most important feature of an ideal analysis system. However, they believed that existing systems on the market are very "time-consuming" and require them to put in "a lot of effort" to provide the results, which is a well-known drawback of the cameras (Figure 6.12). The survey results indicate that while cameras are used by most coaches as a common measurement system, they are dissatisfied with the amount of time and effort they have to spend using them, which is consistent with the findings of our literature review.

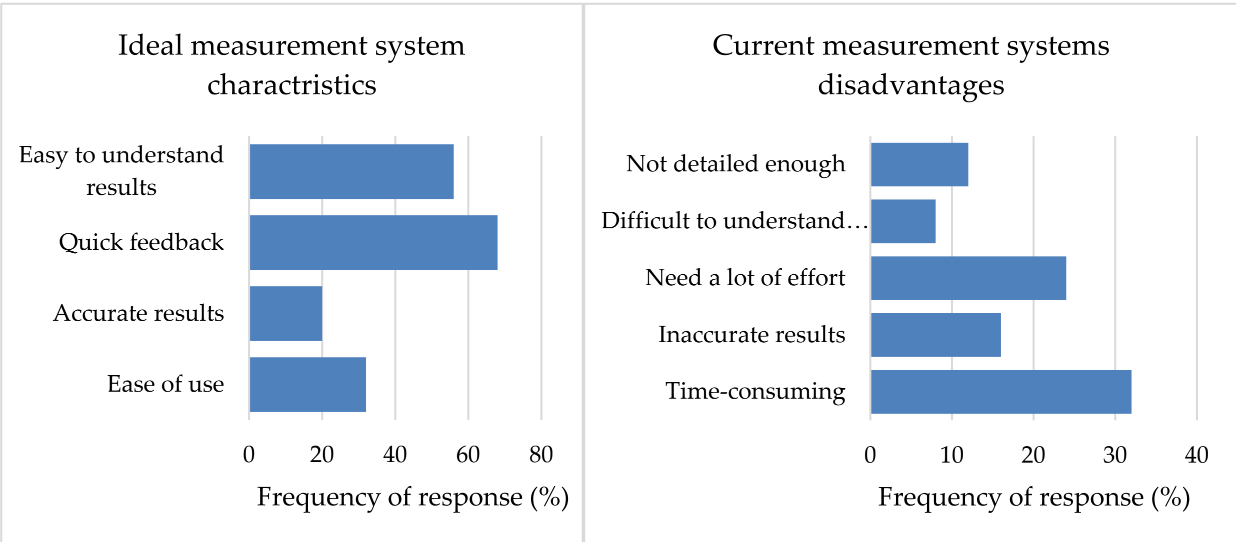

Figure 6.12 – The features of an ideal swimming measurement system (on the left) and the disadvantages of the current measurement systems used by swimming coaches (on the right).

6.6.4.2 Important parameters to monitor

Among the general parameters that can reflect the swimmer's overall performance during a training session, coaches record the number and duration of swimming laps with stopwatches. Regarding the spatio-temporal parameters during the swimming phases of start, free-swimming and turn, the response frequency of the coaches to different parameters is shown in Figure 6.13. During the start phase, body posture and kinematics (velocity and acceleration during dive or push) are the most interesting for the coaches, while kinetic parameters or duration of sub-phases are less noticed. During the free-swimming phase, stroke count, and rate and distance per stroke receive a great deal of attention, which is consistent with the literature as these are easily measured parameters commonly believed to relate to performance. Similar to the start phase, the kinetic parameters are ranked lower than the kinematic parameters in relation to the stroke. During the turn phase, performance evaluation is qualitative and coaches mainly pay attention to the time of the turn or from 5 m before the turn to 10 m after, which is a common rule of thumb for turn evaluation.

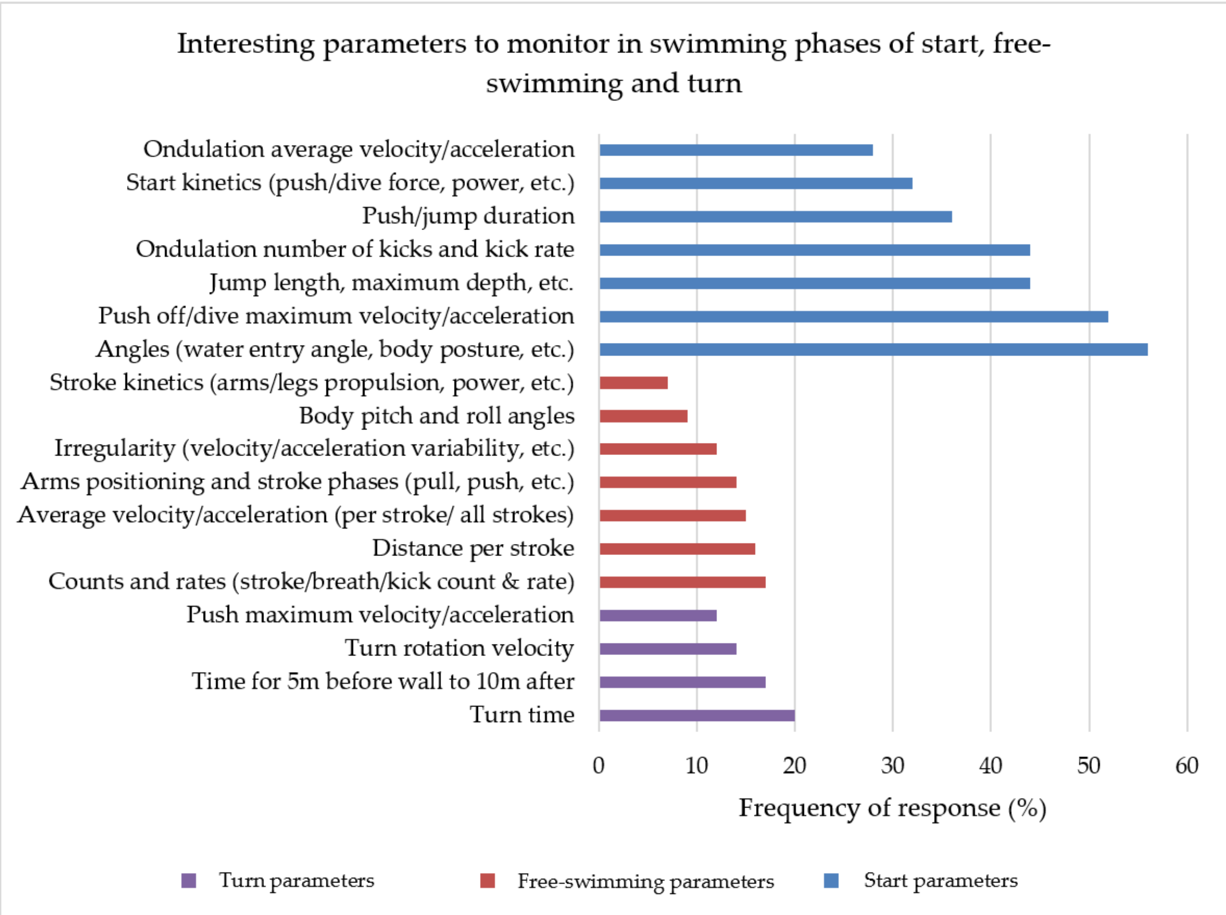

Figure 6.13 – The start, free-swimming and turn parameters ranked by coaches in order of importance

6.6.4.3 IMUs and SmartSwim solution

When asked about the use of wearable motion sensors, most coaches (80%) said they do not use them mainly because of high price (52%), unfamiliarity with the technology (28%), or low accuracy (24%). Because of the coaches' deep trust in their subjective training philosophy and coaching experience, using a simple waterproof camera is much easier and cheaper for everyone than using an IMU sensor for every swimmer. However, both the accuracy and the amount of information provided by IMUs are not comparable to that obtained through the qualitative use of cameras. After explaining the SmartSwim system, which consists of an IMU sensor integrated into the swimsuit that provides phase-based feedback, they rated the comfortability (3.8 out of 5) and practicality (3.9 out of 5) of such an analysis system in training. The responses showed that most of them are willing to use SmartSwim at every training session (40%) or once a week (36%).

6.6.4.4 Survey results discussion

The survey results show that Swiss swimming clubs still use traditional analysis systems such as cameras and are not yet sufficiently aware of the possibilities of IMU technology in this sport. However, they are well aware that using cameras requires a lot of time and effort, which makes them less practical for daily use. Therefore, they need to observe how the detailed parameters obtained from a single IMU can help them improve their training strategy, guide swimmers more efficiently in training, and subsequently achieve better results in competitions.

Among the parameters of each swimming phase, a tendency can be observed towards the postural and kinematic parameters. They rely on the parameters that are usually measured and observed (either qualitatively or with the stopwatch, e.g. stroke count and stroke rate), and the IMU-based parameters about the swimmer's velocity and acceleration are of interest to them. The fact that IMU technology can give swimming coaches a new insight and is not known to many Swiss coaches makes this market more suitable for the introduction of this technology. However, this technology would need to become better known in order to show its true potential in practice and also to lower the price to compete with other measurement systems. Considering the drawbacks shown in Figure 6.12, SmartSwim provides detailed and easy to understand results about swimming phases. Compared to cameras, SmartSwim has the advantage of being less time consuming and requiring less effort from the coach to use in daily training. SmartSwim goes a step further to meet the needs of coaches by providing a new, comprehensive insight into swimmer performance that is simple enough to use on a daily basis. The overall promising evaluation of SmartSwim by swimming coaches makes it all more encouraging to move it closer to a minimally viable product by more conveniently integrating the sensor into the swimming suit and transmitting the data during the training after each trial to show the results to the coach after each practice. The system also needs further development to analyse the swim start from the dive (instead of wall push-off) and the swimming turn

PART IV – CONCLUSIONS

Chapter 7 Contributions, limitations, and future work

The current chapter summarizes the main contributions of this thesis, limitations, and possible future work to continue the proposed system. The main objective of this thesis was to develop an IMU-based analysis system for competitive swimming that provides coaches with an overview of the entire training session that is both comprehensive and detailed. The proposed system, named SmartSwim, is based on a single sensor on sacrum and uses validated algorithms to start from a general overview of the training session and then go deep into the swimmer's performance in all phases of the wall-to-wall swimming. Such insight can help the coach focus on the swimmer's weaknesses and strengths and make the training session more efficient.

7.1 Main contributions

This thesis has been divided into four parts, each on including different chapters. Part I of this thesis contains an introduction to the topic (Chapter 1) and a review of the state-of-the-art in application of IMUs in sports with a focus on swimming (Chapter 2). As introduced in Chapter 1, swimmers require continuous supervision and feedback from a coach to improve their performance and perform at their best during competitions. Due to the complicated nature of swimming, the coach must perform multiple tasks during each session to optimize the training process for the swimmer. The need for measurement systems is unavoidable due to the amount and accuracy of data required, as coaches must accurately and objectively monitor performance-related metrics during each swimming phase, which is impossible with traditional training approaches. This assumption is more confirmed with our survey among Swiss swimming coaches explained in section 6.6.4. The advantages of using IMU in analysis of swimming performance-related parameters, swimming style, and providing feedback have been demonstrated.

In Chapter 2 of this thesis, we took a broader perspective and explored the importance of motion analysis for evaluating athletes' technique and providing feedback as two main tasks of a coach that contribute to improving performance. Among motion analysis methods for swimming, IMUs have shown promising results in providing swimming coaches with detailed and accurate estimates of performance-related metrics. This technology has overcome the limitations of vision-based systems specifically in aquatic environments, allowing for easier application and quick feedback to coaches and swimmers. However, despite a large body of research on the use of inertial sensors, coaches still lack a suitable measurement system. In most studies, the main focus has been on free-swimming phase, while other phases such as start and turn have been largely ignored.

The literature review in Chapter 2 also showed that the parameters extracted by IMUs in swimming have been studied in isolation and the relationship between them and performance is still an open discussion. The importance of feedback for learning a skill is undeniable, especially in complex activities such as swimming. Typically, coaches provide this feedback during or after each trial either verbally, visually on videos or by feedback from wearables. Although the detailed parameters measured by IMUs can be used as valuable feedback for the coach and swimmers, studies have rarely achieved the in-field application of IMUs to provide feedback. As a result, the contribution of this technology to training session has not been adequately explored, and its effects on swimmers' progress have yet to be investigated. Therefore, we discussed the need of a new approach to IMU-based analysis of swimming to deep-dive into the details of swimmer's performance at each phase. This approach provides a phase-based performance assessment that is then used as feedback for competitive swimmers to evaluate its application in practice. In part II, we introduced the analysis approach and described its underlying logic and its potential to provide the coach with more detailed insight into training at both macro and micro levels. In part III, we first assessed the sensitivity of the proposed method to swimmers' progress, then used it as feedback during training as an assistant to the coach, and examined its impact on swimmers' performance.

7.1.1 Part II – phase-based technique analysis

In part II of this thesis, we have proposed a new approach to IMU-based swimming analysis to provide a solution to the above-mentioned gaps. In Chapter 3, we proposed a macro-micro approach for swimming analysis based on IMU data, inspired from gait analysis, and validated it against 2D cameras. In macro level, the analysis starts by detecting the swimming bouts in the whole test session. Then the swimming bouts were separated into laps and the swimmer’s style (i.e. frontcrawl, breaststroke, butterfly, and backstroke) was identified for each lap. The micro level algorithms go deeper into each lap and segment them into swimming phases of *Push*, *Glid*, *StPr*, *Swim* and *Turn*, by processing the acceleration and angular velocity signals based on motion and its effect on the IMU data. The algorithms detect the beginning of each phase for lap segmentation and the detected sample is compared with the frame on the videos for validation. The algorithms were developed for four sensor positions of sacrum, head, wrists and shanks for comparison.

In macro level, an overall accuracy of 0.83-0.98, 0.80-1.00, and 0.83-0.99 was achieved for swimming bouts detection, lap detection and swimming style identification on selected sensor positions, respectively, with the highest accuracy at the sacrum. In micro analysis, the lowest mean and standard deviation were obtained at the sacrum for the onset of wall push-off, glide and turn (-20 ± 89 ms, 4 ± 100 ms, and 23 ± 97 ms, respectively), on shank for the beginning of stroke preparation (0 ± 88 ms), and at the wrist for the onset of swimming (-42 ± 72 ms). This study showed that the macro-micro approach with the developed algorithms can cover not only the major events, but also the detailed motions of each limb during all swimming phases. Unlike other studies that concentrate on a specific parameter during one of the swimming phases, this approach expands the possibility of IMU application in swimming and contributes to a comprehensive understanding of a swimming session which is more useful for the coach.

As an additional outcome, sacrum was found to provide equally good or more promising results than other sensor positions in both macro and micro levels. From a practical point of view, using the least number of wearable sensors is an important factor in swimming because of its effect on swimmer's body profile and drag. With the idea of a single sensor analysis system for swimming, it is essential to find a relatively optimum position. However, there are few studies comparing different sensor positions and researchers usually chose the easiest sensor position based on the goal measurands. Thus, the next contribution of this chapter would be finding an optimal IMU position to monitor swimming at any level, regardless of the swimming style and phase. The successful use of macro-micro approach in swimming proves it as a promising approach in sports which can be used in other disciplines where athletes' various activities during each training session are important both from general and detailed perspectives.

Built upon the validated macro-micro approach, in Chapter 4 we continued the micro analysis by extracting more detailed spatio-temporal parameters (micro parameters) in each swimming phase. A few of these parameters were previously extracted in the literature as they were interesting to the coach such as number of strokes or stroke rate. Based on the literature, several goal metrics were first extracted from the instantaneous velocity (e.g. average velocity per stroke cycle) and displacement (e.g. time to reach 15m from the wall) data from a tethered speedometer as the reference system for the swimming phases, each representing how well the swimmer performed the corresponding phase(s). Assuming that the micro parameters are related to the performance of the swimmer, they should vary between swimmers with different performance levels. To show how IMU-based micro parameters can associate with swimming performance, we studied the relationship between them and each goal metric. Previously, one goal metric for the free-swimming phase (average velocity per stroke) was investigated using a single IMU (Dadashi et al., 2013d, 2015) , and we extended it to all swimming phases with a new approach.

First the micro parameters that are highly associated with the corresponding performance goal metrics were identified by parameter selection. It was the first time that the extracted parameters from IMUs were shown to be related to the three principle aspects of swimming biomechanics which are higher propulsion, correct posture, and higher efficiency. The micro parameters that did not fit into any of these categories and reflected the duration or rate of an action were classified in a fourth group. So, the selected micro parameters were categorized into four groups of propulsion, posture, efficiency and duration/rate. We could show that the phase-based selected micro parameters can represent the performance elements that are more needed for the corresponding phase. For example, no matter the swimming style, the selected parameters during *Push* phase are more related to the propulsion and then to posture and efficiency categories consistent with the phase biomechanics. This analysis showed that the micro parameters extracted by IMUs can be interpreted from a biomechanical point of view and reflect various aspects of swimming in each swimming phase and extended the potential of IMUs to performance evaluation.

The selected micro parameters in each phase were then used to estimate the corresponding goal metrics by LASSO linear regression models. The generated models fit the data with an R2 value more than 0.75 for most goal metrics. The RMSE of the regression were less than 0.15 $m/_s$ and 11% for velocity-based goal metrics and 0.52 s and 7.6% for time-based goal metrics. The results of this study showed that a single sacrum-worn IMU has the potential to evaluate the swimmer performance in different swimming phases in line with standard goal metrics. Practically, our proposed method can be useful for coaches to identify the weakness and strength of their swimmers and track their progress during training sessions.

Following the gaps identified in Part I, the results obtained in Part II have shown that IMU can be used to provide a more comprehensive overview of the training session and should not be limited to the free-swimming phase or front crawl style. The application of this technology is expandable to all swimming phases and swimming styles, which is a key feature for the use of a swimming analysis system in daily training. The coach can get an overview of all activities during the training session, regardless of the style, and compare them during a training session (between the swimming trials at the beginning and end of the session) or even more generally over the entire season or year.

7.1.2 Part III – phase-based feedback

Part III of the thesis aims to use the phase-based goal metrics for tracking swimmers' progress and providing feedback to them and the coach. Few studies have used the parameters obtained from IMU in practice for providing feedback and evaluated their effects in real training. So the next step after technical validation of the phase-based goal metrics (Chapter 4) for providing them as feedback to the coach is assessing the sensitivity of the goal metrics to swimmers' progress. In Chapter 5 we validated the use of phase-based performance evaluation method with a single IMU worn on the sacrum for tracking the progress of the swimmers. During 10 consecutive weeks of measurement, the changes in goal metrics were monitored along with swimmers' lap time change as the principal representative of their performance level. A lap time decrease of at least 0.5s over a 25m lap was considered as a meaningful progress. Using the algorithms validated in chapters 3 and 4, we estimated five goal metrics from the IMU signals representing the swimmer's performance in the swimming phases of *Push*, *Glid*, *StPr* and *Swim* and in the entire lap.

The results showed that the goal metrics for *Swim* phase and the entire lap predicted the swimmer's progress well (e.g., accuracy, precision, sensitivity, and specificity of 0.91, 0.89, 0.94, and 0.95 for the lap goal metric, respectively). The goal metrics for initial phases (*Push*, *Glid*, and

StPr) achieved high precision and specificity (≥ 0.79) but lower sensitivity and accuracy (≤ 0.67) in progress detection, we concluded that these goal metrics improved when the swimmer made a meaningful progress, but a meaningful progress is not merely attributed to the initial phases. The lap goal metric can replace traditional lap time measurement, other goal metrics provide additional quantitative information about the swimmer's phase-related performance that is not available in traditional coaching approaches. This evaluation can help the coach quantitatively monitor the swimmer's performance and train them more efficiently and the coach can use the phase-based report to obtain a comprehensive view of the swimmer's performance. This study opens new horizons in swimming by providing objective feedback based on goal metrics and analyzing the effects of feedback on the swimmer's performance.

Finally, Chapter 6 describes the in-field effects of using our validated performance evaluation feedback (SmartSwim) on training procedure and swimmer's weekly progress. The SmartSwim report was provided for an experimental group of swimmers (vs. a control group with no feedback) during 10 consecutive weeks and included a comprehensive representation of performance based on goal metrics of each phase during each session and in comparison to other sessions. The coach used SmartSwim as an assistant for training swimmers in the experimental group and adjusted their training accordingly, while he guided the swimmers of control group only based on his observations and coaching experience. The feedback was also shared with the swimmers of the experimental group so they could observe the outcome of their training not only during each session, but also over the course of multiple weeks.

The results showed that the experimental group outperformed the control group when comparing each swimmer, each session, and all sessions. At the level of each individual, more members of the experimental group showed significant decreasing trend of average lap time (Mann-Kendall trend test, 95% confidence level). While comparing the sessions, the experimental group showed significantly lower lap time than the control group from the sixth session onwards (p-value < 0.05 from T-test). Considering all sessions, the experimental group showed significantly higher progress, shorter average lap time, and more consistent records (Mann-Whitney U-test at 95% confidence level) than the control group. This study demonstrated that SmartSwim can assist coaching by quantitatively assessing swimmers' performance, leading to more efficient training. The coach found the feedback reports very helpful in "diagnosing" the swimmers' weaknesses and monitoring their progress more efficiently during the training sessions. This study has helped meet the needs of the coaching community and promote objective coaching in swimming.

Part III aimed to use the algorithms developed in part II to provide feedback to swimmers and coaches, as another major gap observed in part I was the lack of studies that reach the application of IMUs in the field and investigate the feedback effect on swimmers' performance. Although we only had access to one swim team of 15 swimmers to test the feedback effect, the coach viewed our intervention positively because he gained new insight into the performance of the experimental group, which was not possible through routine training. He agreed that the feedback from each swimmer was consistent with and quantified his subjective assessment, and also provided additional details that he used to adjust training. As a result, our research in part III takes the use of IMUs in the field a step further and proves the potential of this technology to replace the existing measurement systems.

7.1.3 Summary of thesis contributions

In summary, the results of the present work provide the following contributions to the application of IMUs for swimming analysis:

- Extension of the potential application of IMUs in swimming to all swimming phases through a novel macro-micro approach.
- Comparing the feasible IMU sensor positions on swimmer's body for providing a comprehensive performance evaluation
- Demonstrating the association between parameters extracted from IMUs and the three main aspects of swimming - propulsion, posture, and efficiency
- Bridging the gap between kinematic features extracted from IMU in the literature and swimming performance
- Tracking swimmers' progress using phase-based goal metrics estimated by IMU over several weeks of training
- Showing the positive effect of IMU in practice to support swimming coaches by providing personalized, phase-based performance evaluation
- Collection of a database of accelerometer, gyroscope, magnetometer, and barometer data from IMUs (on swimmer's wrists, shanks, sacrum, and head), speedometer synchronized with videos from 2D cameras inside and outside the water.

7.2 Limitations

Our study limitations are stemming from two sources namely measurement constraints and algorithmic limitations, detailed in the next sections.

7.2.1 Measurement constraints

Although a big dataset from IMUs, speedometer and cameras were collected, the measurements conducted for the thesis were limited in number of participants only form the competitive level, which affected the diversity of the datasets collected. To compensate for this limitation, we asked swimmers to perform multiple trials (Chapters 3, 5, and 6) or to change pace (Chapter 4) to make the datasets richer in terms of technique and performance diversity. We included either a moderate pace in our measurements (80% of the best pace in Chapter 3) or a progressive pace (70%-100% in Chapter 4); the algorithms are not generalizable to all race speeds and apply only within the range of paces included in the measurements. According to this limitation, male and female swimmers were mixed for developing the algorithms of our macro-micro analysis approach or training the machine learning models for performance evaluation. It is well known that training strategy is gender dependent (Amaro et al., 2019) because of the existing anatomical differences between male and female swimmers.

Depending on the strengths of each swimmer, the coach may direct them to focus on a specific swimming style that they should be proficient in. However, we asked every participant to perform all four swimming styles, regardless of their training experience and performance in that style. While the results are less generalizable, training the models based on a more consistent dataset in terms of swimmer's individual performance can result in style-specific models, more accurate and useful for the swimmers who focus on a particular style (e.g., breaststroke swimmers). Another limitation with respect to the group studied is that all measurements were taken in 25m indoor pools, based on the hypothesis that the phase-based performance difference between swimmers is apparent over a short distance. However, endurance swimmers participating in middle- or long-distance events are interested in parameters such as the cumulative fatigue effect on technique, which is hardly visible in short-distance swimming (Morais et al., 2018).

The use of cameras as a reference system in our study imposes further limitations, as the observer's error in using these cameras affects the accuracy of the lap segmentation into swimming phases (Bland-Altman plots of Figure 3.9 in Chapter 3). In addition, when using cameras from the side view, it is difficult to detect some events, such as the beginning of the free-swimming phase in breaststroke or butterfly, because they are easier to detect in front view, and using multiple cameras from different angles makes validation for accurate. The tethered speedometer used as a reference system in Chapter 4 was affected by systematic mechanical constraints (e.g., additional overstretching or loosening of the nylon line). In addition, due to the attachment of the nylon line, the measurements in Chapter 4 had to be performed only in one direction without turn and we could not evaluate turns by estimating the goal metrics of this phase. Synchronization between IMU and speedometer is also based on a sudden shock and matching of the acceleration peaks on the two systems, which is also prone to error, since the speedometer line should overcome the system inertia during the shock motion. In Chapter 5, due to practical limitations, lap time was recorded using a stopwatch, which is prone to human error; using more precise measurement methods such as cameras could improve the quality of this analysis.

7.2.2 Algorithmic and analytical limitations

Our algorithm does separate swimming from non-swimming by recognizing swimming bouts, but it is trained only on the four main swimming styles and cannot distinguish between training drills (e.g., sculling) and main swimming styles. The optimal timing for coaches is to get the feedback with the shortest delay after the movement so that they can immediately compare their observation with it. The macro-micro approach needs the entire training session for the analysis and it does not provide real-time feedback to the coach but only after each measurement. However, it is possible to limit the data to each trial and transfer it for analysis so the coach can compare their observations with the feedback report if it is provided shortly after each trial. Another limitation in providing real-time feedback to the coach is the data transfer from the IMU, located on lower back, to display the results to the coach, which is challenging because the sensor is usually underwater during the training session. Possible solutions include using other sensor locations with easier data transfer, such as head, or integrating an embedded system into the IMU, which analyses the data and transmits only the final results to the coach, reducing the feedback delay.

Based on the results of our method sensitivity to functional calibration, coaches who wish to use SmartSwim without functional calibration should consider sensor orientation when attaching to the swimmer's lower back. We demonstrated that our method is robust to misalignment of the sensor attachment up to 10 degrees for all goal metrics. However, when the misalignment angle increases to 20°, the estimation of some goal metrics becomes unreliable and functional calibration is recommended. Among the three axes, rotation about the mediolateral axis causes the greatest change in the estimated value for the goal metric, which should be considered by the user when installing the sensor on the swimmer's body. This limitation can be mitigated by integrating the IMU into the swimmers' swimming suit, resulting in a tighter fixation to the body and less possibility of sensor motion during measurement.

The attitude and heading reference system used in Chapter 4 to transfer the data to the global frame required a known initial body orientation to be used as a reference and the calculation of the subsequent orientation quaternions with respect to it. In addition, since the algorithm is based on a gradient-descent optimization method, it may not converge if the initial condition is not chosen correctly (Madgwick et al., 2011). Since the measurements started from in-water situation, the swimmers were asked to keep the upright posture facing forward at the beginning of each trial. In addition, the algorithms did not cover the dive at the beginning, but this can be integrated in our proposed method. The main influence is to replace the push-off phase from the wall with the dive phase and fine-tune the other algorithms. Also, we asked the swimmer to perform all swimming phases in sequence and not to start in the middle of a phase.

In analyzing the feedback effect on swimmers' performance in Chapter 6, we tried to keep all effective factors the same for the experimental and control groups. Our study is limited in this sense, and it cannot be claimed that the superiority of the experimental group over the control group was due solely to feedback. Furthermore, there is a possibility that the swimmers performed differently during the measurement and modified their technique in response to the awareness of being observed, which is also known as the Hawthorn effect (Wickström and Bendix, 2000). Although it was necessary to include the coach in the feedback loop, his subjective opinion of each swimmer influenced the feedback he gave to the swimmers in the experimental group, which was unavoidable in this study.

7.3 Future developments

There are several ideas for future research to improve SmartSwim's capabilities and bring it closer to being used as a coach's assistant during daily training.

7.3.1 SmartSwim for low-level swimmers

SmartSwim feedback was developed based on the needs of competitive swimmers and provides coaches with insights into the outcome of technique rather than the details of movement. In the models used to estimate the phase-based goal metrics in Chapter 4, several spatio-temporal parameters reflecting the swimmer's propulsion, posture, and efficiency were extracted and used as inputs to the regression models. However, these parameters can provide valuable insight into how the swimmer performed each phase, which is more useful for low-level swimmers who want to learn professional swimming. For these swimmers, the coach should focus primarily on how the technique is executed, not just the outcome. For example, it is necessary to focus on body angles to reduce drag as one of the factors that can contribute to better overall performance. As a result, training the models using data from low-level or beginner swimmers and tailoring the feedback to them is a possible continuation of this research and expands the potential target market for SmartSwim.

7.3.2 Use of additional sensors

During the measurements, we isolated the Physilog devices (integrating IMU with barometer) with a waterproof tape, making them a closed pressure capsule. When viewing the measured pressure from barometer data on wrist Physilog during the free-swimming phase, sudden jumps in pressure were observed as the wrist entered the water. Using a high-pass filter, the sudden changes in the signal were easily located by sharp peaks on the filtered signal, which is shown along with the raw data in Figure 7.1. It is impossible to determine the exact time for hand entry using only the acceleration or angular velocity signals, and using the barometer data can help the accurate detection of this event. Since the pressure is hypothetically related to force, it can also be used to estimate the propulsion during stroke cycles. Thus, additional features can be extracted from barometer signals to provide feedback to the coach along with SmartSwim phase-based goal metrics.

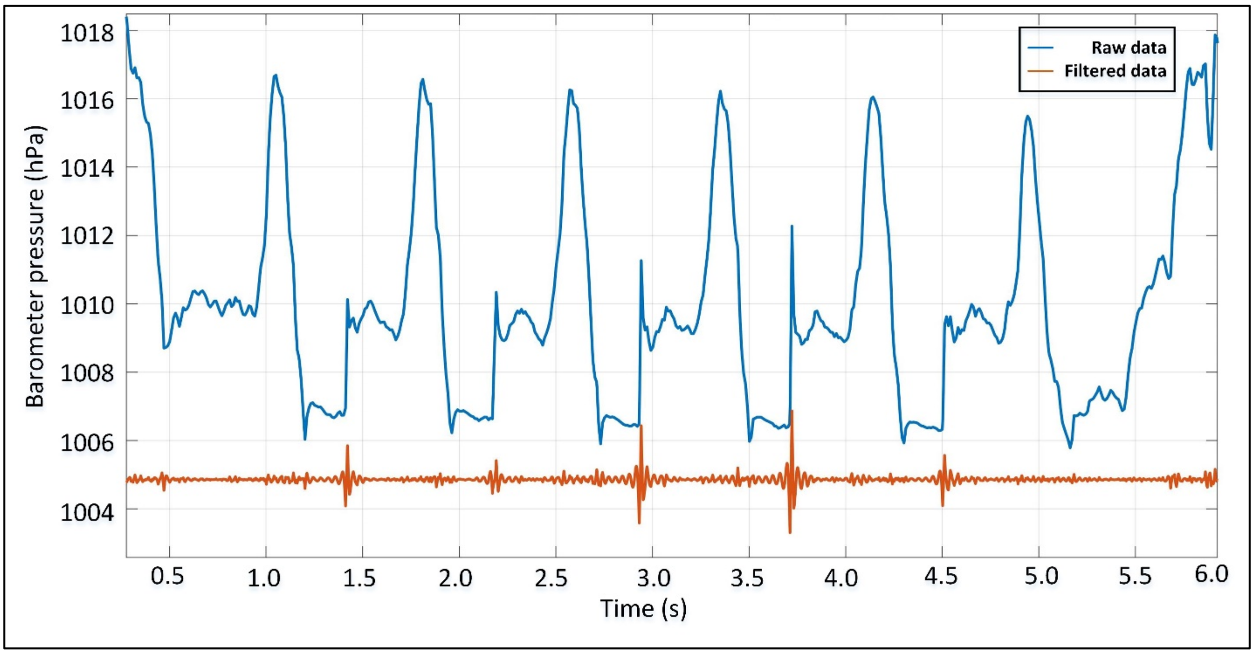

Figure 7.1 – Pressure profile of signal measured by the wrist barometer and its high pass component illustrating the water entering events.

7.3.3 Real-life application

A practical swimming analysis system should be as close to a "plug-and-play" system as possible so that it can be used more conveniently in daily training. Therefore, some improvements are still needed for the use of our proposed system in training sessions. During the measurements, IMUs were waterproofed and attached to swimmer's sacrum with double-sided tapes and then covered by waterproof tape for better fixation, which is impractical for daily use. Using a waterproof IMU integrated into the swimming suit on the swimmer's lower back can be an option for real-life application of our system (Figure 7.2). This design might differ for female swimmers in terms of fixation and sensor attachment due to the different swimsuit designs (one-piece or two-piece). In this case, it should be investigated how much the sensor moves with respect to swimmer’s body during the training session and whether this affects the accuracy of goal metric estimation. In addition, the comfort of the swimmers should be surveyed after using the system to ensure that the proposed design will affect their technique the least possible. Also the additional drag created by the wearable is a known disadvantage that should be evaluated for the proposed design.

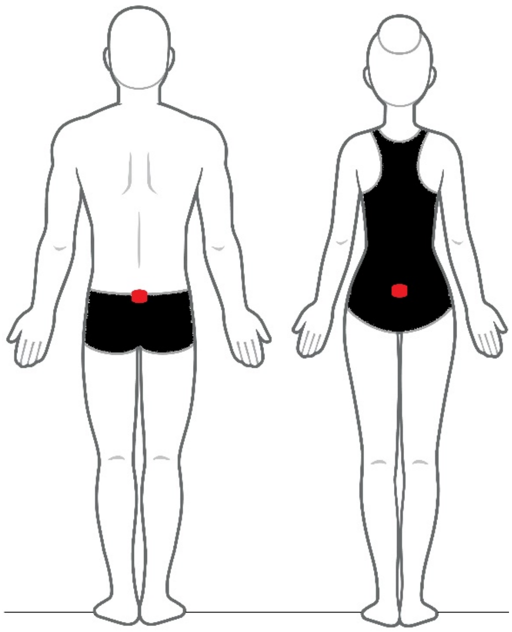

Figure 7.2 – Possible schematic for sensor integration into the swimming suit of swimmers (M/F)

7.3.4 Real-time feedback

The benefits of phase-based performance evaluation feedback were demonstrated in Chapter 6, but we were only able to provide it in an offline mode after the training session. One of the features mentioned by coaches in published surveys (Mooney et al., 2016a) and in our survey discussed in Section 6.6.4 is providing the fastest possible feedback to the coach, which is an important feature for an ideal swimming analysis system. Coaches can compare their observations with the quantitative feedback and take immediate action to improve swimmer's training. It can also help the coach gain a stronger biomechanical perspective on the swimming movement. To reach a near real-time feedback, several adaptations are required for SmartSwim. The developed algorithms for macro-micro analysis (Chapter 3) are based on signal processing techniques that look for biomechanics-related features in acceleration and angular velocity signals, as the developed algorithms should be justified by the swimmer's movements. However, pattern recognition methods followed by deep networks can be used to detect the swimming phases through a moving window on the signal, which is the first step towards near real-time feedback for each swimming phase.

The next step should be to extract the micro parameters described in Chapter 4 from each phase, most of which are based on the data from the entire phase. Depending on the constraints of the embedded system (e.g., available buffer, and computational power) and data transfer (due to limitations in an aquatic environment), this procedure can be performed at the end of each trial, when the data is transferred and analyzed via cloud computing or on a processing unit with sufficient resources. Depending on the computation time required, the goal metrics can be estimated using the linear models developed and then provided to the coach via the individual feedback charts presented in Chapter 6. Another constraint to consider is that the data must be transferred to the global frame for parameter extraction, which requires an initial known orientation. This initial orientation can be manually selected by a trigger before the start of the trial when the swimmer is asked to keep an upright posture and then start to swim.

In addition, the current orientation drift is corrected using the gradient decent optimization algorithm, which ignores the heading angle (yaw angle), causing the orientation to deviate in the long run, e.g., when swimming long distances. In this case, fusion of accelerometer and gyroscope signals with magnetometer data is a possible solution to correct the angle (Madgwick et al., 2011; Bergamini et al., 2014), since the Earth's magnetic field can provide a sufficiently constant vector field for orientation correction. However, magnetometers are highly sensitive to ferromagnetic objects, which complicates their application. Since the swimmer generally moves away from the walls when swimming, the effects of environmental disturbance on magnetometers are likely to be less than for other activities.

BIBLIOGRAPHY

Amaro, N. M., Morouço, P. G., Marques, M. C., Batalha, N., Neiva, H., and Marinho, D. A. (2019). A systematic review on dry-land strength and conditioning training on swimming performance. *Sci. Sport.* 34, e1–e14. doi:10.1016/j.scispo.2018.07.003.

Andreoni, G., Perego, P., Fusca, M. C., Lavezzari, R., and Santambrogio, G. C. (2015). Smart garments for performance and training assessment in sport. *Proc. 2014 4th Int. Conf. Wirel. Mob. Commun. Healthc. - "Transforming Healthc. Through Innov. Mob. Wirel. Technol. MOBIHEALTH 2014*, 267–270. doi:10.1109/MOBIHEALTH.2014.7015962.

Ascenso, G., Yap, M. H., Allen, T. B., Choppin, S. S., and Payton, C. (2020). FISHnet: Learning to Segment the Silhouettes of Swimmers. *IEEE Access* 8, 178311–178321.

Aung, M. S. H., Thies, S. B., Kenney, L. P. J., Howard, D., Selles, R. W., Findlow, A. H., et al. (2013). Automated detection of instantaneous gait events using time frequency analysis and manifold embedding. *IEEE Trans. Neural Syst. Rehabil. Eng.* 21, 908–916. doi:10.1109/TNSRE.2013.2239313.

Bächlin, M., Förster, K., Schumm, J., Breu, D., Germann, J., and Tröster, G. (2008). An automatic parameter extraction method for the 7×50m Stroke Efficiency Test. *2008 3rd Int. Conf. Pervasive Comput. Appl. ICPCA08* 1, 442–447. doi:10.1109/ICPCA.2008.4783628.

Bächlin, M., Förster, K., and Tröster, G. (2009). SwimMaster: A Wearable Assistant for Swimmer. *Proc. 11th Int. Conf. Ubiquitous Comput. - Ubicomp '09*, 215. doi:10.1145/1620545.1620578.

Bächlin, M., and Tröster, G. (2012). Swimming performance and technique evaluation with wearable acceleration sensors. *Pervasive Mob. Comput.* 8, 68–81. doi:10.1016/j.pmcj.2011.05.003.

Bao, Y., Fang, H., and Xu, J. (2021). Effects of Currents on Human Freestyle and Breaststroke Swimming Analyzed by a Rigid-Body Dynamic Model. *Machines* 10, 17.

Bar-Eli, M., Dreshman, R., Blumenstein, B., and Weinstein, Y. (2002). The effect of mental training with biofeedback on the performance of young swimmers. *Appl. Psychol.* 51, 567–581.

Barbosa, T. M., Bragada, J. A., Reis, V. M., Marinho, D. A., Carvalho, C., and Silva, A. J. (2010). Energetics and biomechanics as determining factors of swimming performance: Updating the state of the art. *J. Sci. Med. Sport* 13, 262–269. doi:10.1016/j.jsams.2009.01.003.

Barbosa, T. M., Keskinen, K. L., Fernandes, R., Colaço, P., Lima, A. B., and Vilas-Boas, J. P. (2005). Energy cost and intracyclic variation of the velocity of the centre of mass in butterfly stroke. *Eur. J. Appl. Physiol.* 93, 519–523. doi:10.1007/s00421-004-1251-x.

Barden, J. M., Kell, R. T., and Kobsar, D. (2011). The effect of critical speed and exercise intensity on stroke phase duration and bilateral asymmetry in 200-m front crawl swimming. *J. Sports Sci.* 29, 517–526.

Barré, A., Jolles, B. M., Theumann, N., and Aminian, K. (2015). Soft tissue artifact distribution on lower limbs during treadmill gait: influence of skin markers' location on cluster design. *J. Biomech.* 48, 1965–1971.

Beanland, E., Main, L. C., Aisbett, B., Gastin, P., and Netto, K. (2014). Validation of GPS and accelerometer technology in swimming. *J. Sci. Med. Sport* 17, 234–238. doi:10.1016/j.jsams.2013.04.007.

Benesty, J., Chen, J., Huang, Y., and Cohen, I. (2009). Pearson Correlation Coefficient. *Springer Top. Signal Process.* 2, 1–18. doi:10.1007/978-3-642-00296-0_7.

Bergamini, E., Ligorio, G., Summa, A., Vannozzi, G., Cappozzo, A., and Sabatini, A. M. (2014). Estimating orientation using magnetic and inertial sensors and different sensor fusion approaches: Accuracy assessment in manual and locomotion tasks. *Sensors* 14, 18625–18649.

Berger, M. A., Hollander, A. P., and De Groot, G. (1997). Technique and energy losses in front crawl swimming. *Med. Sci. Sports Exerc.* 29, 1491–8.

Berrar, D. (2018). Cross-validation. *Encycl. Bioinforma. Comput. Biol. ABC Bioinforma.* 1–3, 542–545. doi:10.1016/B978-0-12-809633-8.20349-X.

Bielec, G., Makar, P., and Foliñski, P. (2008). Biomechanical effects of application of the technique exercises in young swimmer training. *Swim. II*, 51.

Blandin, Y., Toussaint, L., and Shea, C. H. (2008). Specificity of practice: interaction between concurrent sensory information and terminal feedback. *J. Exp. Psychol. Learn. Mem. Cogn.* 34, 994.

Brunner, G., Melnyk, D., Sigfússon, B., and Wattenhofer, R. (2019). Swimming style recognition and lap counting using a smartwatch and deep learning. *Proc. - Int. Symp. Wearable Comput. ISWC*, 23–31. doi:10.1145/3341163.3347719.

Butterfield, J., Tallent, J., Patterson, S. D., Jeffries, O., Howe, L., and Waldron, M. (2021). The validity of a head-worn inertial sensor for measurements of swimming performance. *Mov. Sport. Sci. - Sci. Mot.* 2021-Janua, 3–8. doi:10.1051/sm/2019027.

Callaway, A. J. (2015). Measuring kinematic variables in front crawl swimming using accelerometers: A validation study. *Sensors (Switzerland)* 15, 11363–11386. doi:10.3390/s150511363.

Callaway, A. J., Cobb, J. E., and Jones, I. (2009). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *Int. J. Sports Sci. Coach.* 4, 139–153. doi:10.1260/1747-9541.4.1.139.

Callaway, A. J., Cobb, J. E., and Jones, I. (2010). A Comparison of Video and Accelerometer Based Approaches Applied to Performance Monitoring in Swimming. *Int. J. Sports Sci. Coach.* 4, 139–153. doi:10.1260/1747-9541.4.1.139.

Camomilla, V., Bergamini, E., Fantozzi, S., and Vannozzi, G. (2018). Trends supporting the in-field use of wearable inertial sensors for sport performance evaluation: A systematic review. *Sensors (Switzerland)* 18. doi:10.3390/s18030873.

Carr, G., and Carr, G. A. (1997). *Mechanics of sport: a practitioner's guide*. Human Kinetics Publishers.

Cesarini, D., Calvaresi, D., Farnesi, C., Taddei, D., Frediani, S., Ungerechts, B. E., et al. (2016). MEDIATION: An eMbEddeD System for Auditory Feedback of Hand-water InterAcTION while Swimming. *Procedia Eng.* 147, 324–329. doi:10.1016/j.proeng.2016.06.301.

Ceseracciu, E., Sawacha, Z., Fantozzi, S., Cortesi, M., Gatta, G., Corazza, S., et al. (2011). Markerless analysis of front crawl swimming. *J. Biomech.* 44, 2236–2242. doi:10.1016/j.jbiomech.2011.06.003.

Chakravorti, N., Le Sage, T., Slawson, S. E., Conway, P. P., and West, A. A. (2013). Design and implementation of an integrated performance monitoring tool for swimming to extract stroke information at real time. *IEEE Trans. Human-Machine Syst.* 43, 199–213. doi:10.1109/TSMC.2012.2235428.

Chardonnens, J., Favre, J., Cuendet, F., Gremion, G., and Aminian, K. (2013). A system to measure the kinematics during the entire ski jump sequence using inertial sensors. *J. Biomech.* 46, 56–62. doi:10.1016/j.jbiomech.2012.10.005.

Chardonnens, J., Favre, J., Le Callennec, B., Cuendet, F., Gremion, G., and Aminian, K. (2012). Automatic measurement of key ski jumping phases and temporal events with a wearable system. *J. Sports Sci.* 30, 53–61. doi:10.1080/02640414.2011.624538.

Chew, D.-K., Ngoh, K. J.-H., and Gouwanda, D. (2018). Estimating running spatial and temporal parameters using an inertial sensor. *Sport. Eng.* 21, 115–122.

Chollet, D., Chalies, S., and Chatard, J. C. (2000). A new index of coordination for the crawl: description and usefulness. *Int. J. Sports Med.* 21, 54–59. doi:10.1055/s-2000-8855.

Chollet, D., Madani, M., and Micallef, J. P. (1992). Effects of two types of biomechanical bio-feedback on crawl performance. *Biomech. Med. Swim. Swim. Sci. VI* 48, 53.

Chollet, D., Seifert, L., Leblanc, H., Boulesteix, L., and Carter, M. (2004). Evaluation of arm-leg coordination in flat breaststroke. *Int. J. Sports Med.* 25, 486–495.

Clément, J., Charbonneau, M., and Thompson, M. (2021). Instantaneous velocity estimation for the four swimming strokes using a 3-axis accelerometer: Validation on paralympic athletes. *J. Biomech.* 117, 110261. doi:10.1016/j.jbiomech.2021.110261.

Colyer, S. L., Evans, M., Cosker, D. P., and Salo, A. I. T. (2018). A Review of the Evolution of Vision-Based Motion Analysis and the Integration of Advanced Computer Vision Methods Towards Developing a Markerless System. *Sport. Med. - Open* 4. doi:10.1186/s40798-018-0139-y.

Cortesi, M., Giovanardi, A., Gatta, G., Mangia, A. L., Bartolomei, S., and Fantozzi, S. (2019). Inertial sensors in swimming: Detection of stroke phases through 3D wrist trajectory. *J. Sport. Sci. Med.* 18, 438–447.

Cossor, J. M., and Mason, B. R. (2001). Swim Start Performances At the Sydney 2000 Olympic Games. *Biomech. Symp. / Univ. San Fr.*, 70–74.

Cronin, J., and Rumpf, M. (2014). Effect of four different step detection thresholds on nonmotorized treadmill sprint measurement. *J. Strength Cond. Res.* 28, 2996–3000. doi:10.1519/JSC.0000000000000497.

Crowcroft, S., McCleave, E., Slattery, K., and Coutts, A. J. (2017). Assessing the measurement sensitivity and diagnostic characteristics of athlete-monitoring tools in national swimmers. *Int. J. Sports Physiol. Perform.* 12, 95–100. doi:10.1123/ijspp.2016-0406.

Dadashi, F. (2014). Objective Assessment of Swimming Biomechanics Using Wearable Inertial Sensors. 6055. doi:10.5075/epfl-thesis-6055.

Dadashi, F., Aminian, K., Crettenand, F., and Millet, G. P. (2013a). Towards estimation of front-crawl energy expenditure using the wearable aquatic movement analysis system (WAMAS). *2013 IEEE Int.*

Conf. Body Sens. Networks, BSN 2013, 0–5. doi:10.1109/BSN.2013.6575467.

Dadashi, F., Arami, A., Crettenand, F., Millet, G. P., Komar, J., Seifert, L., et al. (2013b). A hidden Markov model of the breaststroke swimming temporal phases using wearable inertial measurement units. *2013 IEEE Int. Conf. Body Sens. Networks, BSN 2013*, 1–6. doi:10.1109/BSN.2013.6575461.

Dadashi, F., Crettenand, F., Millet, G. P., and Aminian, K. (2012). Front-Crawl Instantaneous Velocity Estimation Using a Wearable Inertial Measurement Unit. *Sensors* 12, 12927–12939. doi:10.3390/s121012927.

Dadashi, F., Crettenand, F., Millet, G. P., Seifert, L., Komar, J., and Aminian, K. (2013c). Automatic front-crawl temporal phase detection using adaptive filtering of inertial signals. *J. Sports Sci.* 31, 1251–1260. doi:10.1080/02640414.2013.778420.

Dadashi, F., Millet, G. P., and Aminian, K. (2013d). Gaussian process framework for pervasive estimation of swimming velocity with body-worn IMU. *Electron. Lett.* 49, 44–45. doi:10.1049/el.2012.3684.

Dadashi, F., Millet, G. P., and Aminian, K. (2014). Estimation of front-crawl energy expenditure using wearable inertial measurement units. *IEEE Sens. J.* 14, 1020–1027. doi:10.1109/JSEN.2013.2292585.

Dadashi, F., Millet, G. P., and Aminian, K. (2015). A Bayesian approach for pervasive estimation of breaststroke velocity using a wearable IMU. *Pervasive Mob. Comput.* 19, 37–46. doi:10.1016/j.pmcj.2014.03.001.

Dadashi, F., Millet, G. P., and Aminian, K. (2016). Front-crawl stroke descriptors variability assessment for skill characterization. *J. Sports Sci.* 34, 1405–1412. doi:10.1080/02640414.2015.1114134.

Daukantas, S., Marozas, V., and Lukosevicius, A. (2008). Inertial sensor for objective evaluation of swimmer performance. *BEC 2008 - 2008 Int. Bienn. Balt. Electron. Conf. Proc. 11th Bienn. Balt. Electron. Conf.*, 321–324. doi:10.1109/BEC.2008.4657545.

Davey, N., Anderson, M., and James, D. A. (2008). Validation trial of an accelerometer-based sensor platform for swimming. *Sport. Technol.* 1, 202–207. doi:10.1002/jst.59.

Davey, N. P., and James, D. A. (2008). Swimming stroke analysis using multiple accelerometer devices and tethered systems. *Impact Technol. Sport II*, 577–582. doi:10.1201/9781439828427.ch83.

De Jesus, K., De Jesus, K., Figueiredo, P., Gonçalves, P., Pereira, S., Vilas-Boas, J. P., et al. (2011). Biomechanical analysis of backstroke swimming starts. *Int. J. Sports Med.* 32, 546–551. doi:10.1055/s-0031-1273688.

Deschodt, J. V., Arsac, L. M., and Rouard, A. H. (1999). Relative contribution of arms and legs in humans to propulsion in 25-m sprint front-crawl swimming. *Eur. J. Appl. Physiol. Occup. Physiol.* 80, 192–199. doi:10.1007/s004210050581.

Dick, F. W. (2007). *Sports training principles*. A. & C. Black.

Do, T. N., and Tan, U.-X. (2019). Novel velocity update applied for IMU-based wearable device to estimate the vertical distance. in *2019 1st International Conference on Electrical, Control and Instrumentation Engineering (ICECIE)* (IEEE), 1–4.

Effenberg, A. O. (2007). Movement Sonification : Motion perception , behavioral effects and functional data. *Proc. 2nd Int. Work. Interact. Sonification (ISon 2007)*, 1–4.

Effenberg, A. O., and Schmitz, G. (2018). Acceleration and deceleration at constant speed: Systematic modulation of motion perception by kinematic sonification. *Ann. N. Y. Acad. Sci.* 1425, 52–69. doi:10.1111/nyas.13693.

Ehab, M., Mohamed, H., Ahmed, M., Hammad, M., Elmasry, N., and Atia, A. (2020). ISwimCoach: A smart coach guiding system for assisting swimmers free style strokes. *ICMI 2020 Companion - Companion Publ. 2020 Int. Conf. Multimodal Interact.*, 265–269. doi:10.1145/3395035.3425314.

Engel, A., Schaffert, N., Wobbe, J. F., and Mattes, K. (2020). Comparison of video and IMU data for analyzing the underwater dolphin kick. *J. Sport Hum. Perform.* 8.

Fantozzi, S., Coloretti, V., Piacentini, M. F., Quagliarotti, C., Bartolomei, S., Gatta, G., et al. (2022). Integrated timing of stroking, breathing, and kicking in front-crawl swimming: A novel stroke-by-stroke approach using wearable inertial sensors. *Sensors* 22, 1419.

Fasel, B., Favre, J., Chardonnens, J., Gremion, G., and Aminian, K. (2015). An inertial sensor-based system for spatio-temporal analysis in classic cross-country skiing diagonal technique. *J. Biomech.* 48, 3199–3205.

Fasel, B., Spörri, J., Gilgien, M., Boffi, G., Chardonnens, J., Müller, E., et al. (2016). Three-dimensional body and centre of mass kinematics in alpine ski racing using differential GNSS and inertial sensors. *Remote Sens.* 8, 671.

Félix, Silva, Olstad, Cabri, and Correia (2019). SwimBIT: A Novel Approach to Stroke Analysis During Swim Training Based on Attitude and Heading Reference System (AHRS). *Sports* 7, 238. doi:10.3390/sports7110238.

Feng, D., and Cliff, N. (2004). Monte Carlo evaluation of ordinal d with improved confidence interval. *J. Mod. Appl. Stat. Methods* 3, 322–332. doi:10.22237/jmasm/1099267560.

Fernandes, R. A., Alacid, F., Gomes, A. B., and Gomes, B. B. (2021). Validation of a global positioning system with accelerometer for canoe/kayak sprint kinematic analysis. *Sport. Biomech.*, 1–12.

Ferraris, F., Grimaldi, U., and Parvis, M. (1995). Procedure for effortless in-field calibration of three-axis rate gyros and accelerometers. *Sensors Mater.*, 311.

Ferreira, M. I., Barbosa, T. M., Costa, M. J., Neiva, H. P., and Marinho, D. A. (2016). *Energetics, biomechanics, and performance in masters' swimmers: A systematic review*. doi:10.1519/JSC.0000000000001279.

Ferreira, S., Carvalho, D. D., Cardoso, R., Rios, M., Soares, S., Toubekis, A., et al. (2021). Young swimmers' middle-distance performance variation within a training season. *Int. J. Environ. Res. Public Health* 18, 1010.

Figueiredo, P., Barbosa, T. M., Vilas-Boas, J. P., and Fernandes, R. J. (2012a). Energy cost and body centre of mass' 3D intracycle velocity variation in swimming. *Eur. J. Appl. Physiol.* 112, 3319–3326. doi:10.1007/s00421-011-2284-6.

Figueiredo, P., Pendergast, D. R., Vilas-Boas, J. P., and Fernandes, R. J. (2013). Interplay of biomechanical, energetic, coordinative, and muscular factors in a 200 m front crawl swim. *Biomed Res. Int.* 2013. doi:10.1155/2013/897232.

Figueiredo, P., Seifert, L., Vilas-Boas, J. P., and Fernandes, R. J. (2012b). Individual profiles of spatio-temporal coordination in high intensity swimming. *Hum. Mov. Sci.* 31, 1200–1212. doi:10.1016/j.humov.2012.01.006.

Fonti, V., and Belitser, E. (2017). Feature Selection using LASSO. *VU Amsterdam Res. Pap. Bus. Anal.*, 1–25.

Fudickar, S., Kappes, R., Horstmann, M., Isken, M., and Hein, A. (2020). Cycling-monitoring system: sensing cycling performance via a pedal-integrated inertial measurement unit. *Nanomater. Energy* 9, 21–26.

Fulton, S. K., Pyne, D. B., and Burkett, B. (2009). Validity and reliability of kick count and rate in freestyle using inertial sensor technology. *J. Sports Sci.* 27, 1051–1058. doi:10.1080/02640410902998247.

Fulton, S. K., Pyne, D., and Burkett, B. (2011). Optimizing kick rate and amplitude for Paralympic swimmers via net force measures. *J. Sports Sci.* 29, 381–387. doi:10.1080/02640414.2010.536247.

Galipeau, C. (2018). The On-water Instrumentation of a Sprint Canoe Paddle.

Ganzevles, S., Vullings, R., Beek, P. J., Daanen, H., and Truijens, M. (2017). Using tri-axial accelerometry in daily elite swim training practice. *Sensors (Switzerland)* 17. doi:10.3390/s17050990.

Ge, H., Chen, G., Yu, H., Chen, H., and An, F. (2018). Theoretical analysis of empirical mode decomposition. *Symmetry (Basel).* 10. doi:10.3390/sym10110623.

Ghasemzadeh, H., Loseu, V., and Jafari, R. (2009). Wearable coach for sport training: A quantitative model to evaluate wrist-rotation in golf. *J. Ambient Intell. Smart Environ.* 1, 173–184.

Gilbert, R. O. (1987). *Statistical methods for environmental pollution monitoring*. John Wiley & Sons.

Gomez-Piriz, P. T., Sanchez, E. T., Manrique, D. C., and Gonzalez, E. P. (2013). Reliability and comparability of the accelerometer and the linear position measuring device in resistance training. *J. Strength Cond. Res.* 27, 1664–1670.

Gouttebarge, V., Wolfard, R., Griek, N., de Ruiter, C. J., Boschman, J. S., and van Dieën, J. H. (2015). Reproducibility and validity of the myotest for measuring step frequency and ground contact time in recreational runners. *J. Hum. Kinet.* 45, 19.

Groh, B. H., Flaschka, J., Wirth, M., Kautz, T., Fleckenstein, M., and Eskofier, B. M. (2016). Wearable real-time skateboard trick visualization and its community perception. *IEEE Comput. Graph. Appl.* 36, 12–18.

Guignard, B., Ayad, O., Baillet, H., Mell, F., Simbaña Escobar, D., Boulanger, J., et al. (2021). Validity, reliability and accuracy of inertial measurement units (IMUs) to measure angles: application in swimming. *Sport. Biomech.*, 1–33.

Guignard, B., Rouard, A., Chollet, D., Ayad, O., Bonifazi, M., Dalla Vedova, D., et al. (2017a). Perception and action in swimming: Effects of aquatic environment on upper limb inter-segmental coordination. *Hum. Mov. Sci.* 55, 240–254. doi:10.1016/j.humov.2017.08.003.

Guignard, B., Rouard, A., Chollet, D., and Seifert, L. (2017b). Behavioral Dynamics in Swimming: The Appropriate Use of Inertial Measurement Units. *Front. Psychol.* 8, 383. doi:10.3389/fpsyg.2017.00383.

Guimaraes, A. C. S., and Hay, J. G. (1985). A mechanical analysis of the grab starting technique in swimming. *J. Appl. Biomech.*, 25–35.

Gussakov, I., Nurmukhanbetova, D., Kulbayev, A., Yermakhanova, A., Lesbekova, R., and Potop, V. (2021). The impact of the high level of intensity training process on the performance and recovery of young swimmers at the national level. *J. Phys. Educ. Sport* 21, 440–443.

Hagem, R. M., O'Keefe, S. G., Fickenscher, T., and Thiel, D. V. (2013a). Self contained adaptable optical wireless communications system for stroke rate during swimming. *IEEE Sens. J.* 13, 3144–3151.

doi:10.1109/JSEN.2013.2262933.

Hagem, R. M., Thiel, D. V., O'Keefe, S., and Fickenscher, T. (2013b). Real-time swimmers' feedback based on smart infrared (SSIR) optical wireless sensor. *Electron. Lett.* 49, 340–341. doi:10.1049/el.2012.3222.

Hamidi Rad, M., Aminian, K., Gremeaux, V., Massé, F., and Dadashi, F. (2021a). Swimming Phase-Based Performance Evaluation Using a Single IMU in Main Swimming Techniques. *Front. Bioeng. Biotechnol.* 9, 1–10. doi:10.3389/fbioe.2021.793302.

Hamidi Rad, M., Gremeaux, V., Dadashi, F., and Aminian, K. (2021b). A Novel Macro-Micro Approach for Swimming Analysis in Main Swimming Techniques Using IMU Sensors. *Front. Bioeng. Biotechnol.* 8, 1–16. doi:10.3389/fbioe.2020.597738.

Hamlin, M. J., Wilkes, D., Elliot, C. A., Lizamore, C. A., and Kathiravel, Y. (2019). Monitoring training loads and perceived stress in young elite university athletes. *Front. Physiol.*, 34.

Hellard, P., Avalos-Fernandes, M., Lefort, G., Pla, R., Mujika, I., Toussaint, J. F., et al. (2019). Elite swimmers' training patterns in the 25 weeks prior to their season's best performances: Insights into periodization from a 20-years cohort. *Front. Physiol.* 10, 1–16. doi:10.3389/fphys.2019.00363.

Hermosilla Perona, F., Machado, L., Sousa, F., Vilas-Boas, J. P., and González Ravé, J. M. (2020). Differences in force production and EMG activity on underwater and dry land conditions in swimmers and non-swimmers. *Sport. Biomech.*, 1–14.

Hopkins, W. G., Hawley, J. A., and Burke, L. M. (1999). Design and analysis of research on sport performance enhancement. *Med. Sci. Sports Exerc.* 31, 472–485. doi:10.1097/00005768-199903000-00018.

Irwin, G., Hanton, S., and Kerwin, D. (2004). Reflective practice and the origins of elite coaching knowledge. *Reflective Pract.* 5, 425–442. doi:10.1080/1462394042000270718.

Jakus, G., Stojmenova, K., Tomažič, S., and Sodnik, J. (2017). A system for efficient motor learning using multimodal augmented feedback. *Multimed. Tools Appl.* 76, 20409–20421. doi:10.1007/s11042-016-3774-7.

James, D. a., Davey, N., and Rice, T. (2004). An accelerometer based sensor platform for insitu elite athlete performance analysis. *Proc. IEEE Sensors, 2004.*, 1373–1376. doi:10.1109/ICSENS.2004.1426439.

Jarning, J. M., Mok, K.-M., Hansen, B. H., and Bahr, R. (2015). Application of a tri-axial accelerometer to estimate jump frequency in volleyball. *Sport. Biomech.* 14, 95–105.

Jefferies, S. M., Jefferies, C. M., Donohue, S., and Mechanics, M. (2012). The effect of real time feedback on swimming technique. *J. Int. Soc. Swim. Coach.* 2, 41–47.

Jeng, C.-C. (2021). A Low-cost Mobile Real-time Monitoring System for Analyzing Head Position and Breathing Patterns in Front Crawl Swimming. *J. Comput.* 32, 8–22. doi:10.3966/199115992021043202002.

Jensen, U., Prade, F., and Eskofier, B. M. (2013). Classification of kinematic swimming data with emphasis on resource consumption. *2013 IEEE Int. Conf. Body Sens. Networks, BSN 2013*. doi:10.1109/BSN.2013.6575501.

Jidovtseff, B., and Laffaye, G. (2015). Évaluation et analyse de la performance par accélérométrie lors des mouvements de musculation. *978-2-7462-4670-6*.

Jollife, I. T., and Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philos.*

Trans. R. Soc. A Math. Phys. Eng. Sci. 374. doi:10.1098/rsta.2015.0202.

Jones, S. R., Carley, S., and Harrison, M. (2003). An introduction to power and sample size estimation The importance of power and sample size estimation for study design and analysis. *Emerg Med J* 20, 453–458.

Kadi, T., Wada, T., Narita, K., Tsunokawa, T., Mankyu, H., Tamaki, H., et al. (2022). Novel Method for Estimating Propulsive Force Generated by Swimmers ′ Hands Using Inertial Measurement Units and. *Sensors* 22.

Kendall, M. G. (1995). Rank correlation methods. *Hafner Publ. Co.*

Kim, M., and Park, S. (2020). Golf swing segmentation from a single IMU using machine learning. *Sensors* 20, 4466.

Kim, T. K. (2015). T test as a parametric statistic. *Korean J. Anesthesiol.* 68, 540–546. doi:10.4097/kjae.2015.68.6.540.

Knudson, D. V., and Morrison, C. S. (1997). *Qualitative analysis of human movement*. Champaign, IL: Human Kinetics.

Knudson, D. V (2013). *Qualitative diagnosis of human movement: improving performance in sport and exercise*. Human kinetics.

Komar, J., Leprêtre, P. M., Alberty, M., Vantorre, J., Fernandes, R. J., Hellard, P., et al. (2012). Effect of increasing energy cost on arm coordination in elite sprint swimmers. *Hum. Mov. Sci.* 31, 620–629.

Kon, Y., Omae, Y., Sakai, K., Takahashi, H., Akiduki, T., Miyaji, C., et al. (2015). Toward classification of swimming style by using underwater wireless accelerometer data. in *Adjunct Proceedings of the 2015 ACM International Joint Conference*, 85–88.

Koning, B. H. W., van der Krogt, M. M., Baten, C. T. M., and Koopman, B. F. J. M. (2015). Driving a musculoskeletal model with inertial and magnetic measurement units. *Comput. Methods Biomech. Biomed. Engin.* 18, 1003–1013.

Kos, A., and Umek, A. (2018a). *Biomechanical biofeedback systems and applications*.

Kos, A., and Umek, A. (2018b). Smart sport equipment: SmartSki prototype for biofeedback applications in skiing. *Pers. Ubiquitous Comput.* 22, 535–544.

Koutedakis, Y. (1995). Seasonal variation in fitness parameters in competitive athletes. *Sport. Med.* 19, 373–392.

Lanotte, N., Annino, G., Bifaretti, S., Gatta, G., Romagnoli, C., Salvucci, A., et al. (2018). A New Device for Propulsion Analysis in Swimming. 285. doi:10.3390/proceedings2060285.

Lavoie, J. M., and Montpetit, R. R. (1986). Applied Physiology of Swimming. *Sport. Med. An Int. J. Appl. Med. Sci. Sport Exerc.* 3, 165–189. doi:10.2165/00007256-198603030-00002.

Le Sage, T., Bindel, A., Conway, P., Justham, L., Slawson, S., Webster, J., et al. (2012). A multi-sensor system for monitoring the performance of elite swimmers. *Commun. Comput. Inf. Sci.* 222 CCIS, 350–362. doi:10.1007/978-3-642-25206-8_23.

Le Sage, T., Bindel, A., Conway, P., Justham, L., Slawson, S., and West, A. (2010). Development of a real time system for monitoring of swimming performance. *Procedia Eng.* 2, 2707–2712. doi:10.1016/j.proeng.2010.04.055.

Le Sage, T., Bindel, A., Conway, P. P., Justham, L. M., Slawson, S. E., and West, A. A. (2011). Embedded programming and real-time signal processing of swimming strokes. *Sport. Eng.* 14, 1–14. doi:10.1007/s12283-011-0070-7.

Lecoutere, J., and Puers, R. (2016). Tracking elite swimmers in real time with wearable low-power wireless sensor networks. *Procedia Eng.* 147, 627–631.

Lee, J., Leadbetter, R., Ohgi, Y., Thiel, D., Burkett, B., and James, D. A. (2011). Quantifying and assessing biomechanical differences in swim turn using wearable sensors. *Sport. Technol.* 4, 128–133. doi:10.1080/19346182.2012.725171.

Lee, M., Lee, H., and Park, S. (2018). Accuracy of swimming wearable watches for estimating energy expenditure. *IJASS(International J. Appl. Sport. Sci.* 30, 80–90. doi:10.24985/ijass.2018.30.1.80.

Lees, A. (2002). Technique analysis in sports: A critical review. *J. Sports Sci.* 20, 813–828. doi:10.1080/026404102320675657.

Lerda, R., Cardelli, C., and Chollet, D. (2001). Analysis of the interactions between breathing and arm actions in the front crawl. *J. Hum. Mov. Stud.* 40, 129–144.

Li, R., Cai, Z., Lee, W., and Lai, D. T. H. (2016). A wearable biofeedback control system based body area network for freestyle swimming. *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS* 2016-Octob, 1866–1869. doi:10.1109/EMBC.2016.7591084.

Lilliefors, H. W. (1967). On the Kolmogorov-Smirnov Test for Normality with Mean and Variance Unknown. *J. Am. Stat. Assoc.* 62, 399–402.

Lopez, G., Abe, S., Hashimoto, K., and Yokokubo, A. (2019). On-site personal sport skill improvement support using only a smartwatch. in *2019 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)* (IEEE), 158–164.

Lord, S., Galna, B., and Rochester, L. (2013). Moving forward on gait measurement: Toward a more refined approach. *Mov. Disord.* 28, 1534–1543. doi:10.1002/mds.25545.

Luteberget, L. S., Spencer, M., and Gilgien, M. (2018). Validity of the Catapult ClearSky T6 local positioning system for team sports specific drills, in indoor conditions. *Front. Physiol.* 9, 115.

Lyle, J., and Cushion, C. (2010). *Sports Coaching Conceps*.

Macaro, A., Connick, M. J., Beckman, E., and Tweedy, S. M. (2018). Using machine learning techniques and wearable inertial measurement units to predict front crawl elbow joint angle: a pilot study. in *36th Conference of the International Society of Biomechnanics in Sports*, 366–369.

Macbeth, G. E., Razumiejczyk, E., and Ledesma, R. D. (2011). Cliff's delta calculator: A non-parametric effect size program for two groups of observations. *Univ. Psychol.* 10, 545–555. doi:10.11144/javeriana.upsy10-2.cdcp.

Madgwick, S. O. H., Harrison, A. J. L., and Vaidyanathan, R. (2011). Estimation of IMU and MARG orientation using a gradient descent algorithm. *IEEE Int. Conf. Rehabil. Robot.* doi:10.1109/ICORR.2011.5975346.

Magalhaes, F. A. de, Vannozzi, G., Gatta, G., and Fantozzi, S. (2015). Wearable inertial sensors in swimming motion analysis: a systematic review. *J. Sports Sci.* 33, 732–745. doi:10.1080/02640414.2014.962574.

Magill, R. A. (1994). The influence of augmented feedback on skill learning depends on characteristics of the skill and the learner. *Quest* 46, 314–327. doi:10.1080/00336297.1994.10484129.

Maglischo, E. W. (2003). *Swimming fastest*. Human Kinetics.

Maletsky, L. P., Sun, J., and Morton, N. A. (2007). Accuracy of an optical active-marker system to track the relative motion of rigid bodies. *J. Biomech.* 40, 682–685.

Mangin, M., Valade, A., Costes, A., Bouillod, A., Acco, P., and Soto-Romero, G. (2015). An Instrumented Glove for Swimming Performance Monitoring. *Proc. 3rd Int. Congr. Sport Sci. Res. Technol. Support*, 53–58. doi:10.5220/0005609100530058.

Mann, H. B., and Whitney, D. R. (1947). On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. *Ann. Math. Stat.* 18, 50–60.

Mansfield, E. R., and Helms, B. P. (1982). Detecting Multicollinearity. *Am. Stat.* 36, 158–160. doi:10.1080/00031305.1982.10482818.

Marinho, D. A., Barbosa, T. M., Lopes, V. P., Forte, P., Toubekis, A. G., and Morais, J. E. (2020). The Influence of the Coaches' Demographics on Young Swimmers' Performance and Technical Determinants. *Front. Psychol.* 11, 1–10. doi:10.3389/fpsyg.2020.01968.

Martens, J., Daly, D., Deschamps, K., Staes, F., and Fernandes, R. J. (2016). Inter-individual variability and pattern recognition of surface electromyography in front crawl swimming. *J. Electromyogr. Kinesiol.* 31, 14–21. doi:10.1016/j.jelekin.2016.08.016.

Mason, B., and Cossor, J. (2000). What can we learn from competition analysis at the 1999 Pan Pacific Swimming Championships? *Proc. XVIII Int. Symp. Biomech. Sport.*, 75–82.

Matthews, M. J., Green, D., Matthews, H., and Swanwick, E. (2017). The effects of swimming fatigue on shoulder strength, range of motion, joint control, and performance in swimmers. *Phys. Ther. Sport* 23, 118–122.

McGinnis, P. M. (2013). *Biomechanics of Sport and Exercise*.

McPherson, M. (1990). A systematic approach to skill analysis. *Sci. Period. Res. Technol. Sport* 11, 1–10.

Mestre, D. R., Maïano, C., Dagonneau, V., and Mercier, C.-S. (2011). Does virtual reality enhance exercise performance, enjoyment, and dissociation? An exploratory study on a stationary bike apparatus. *Presence Teleoperators Virtual Environ.* 20, 1–14.

Mezêncio, B., Pinho, J. P., Huebner, R., Vilas-Boas, J. P., Amadio, A. C., and Serrão, J. C. (2020). Overall indexes of coordination in front crawl swimming. *J. Sports Sci.* 38, 910–917.

Monnet, T., Samson, M., Bernard, A., David, L., and Lacouture, P. (2014). Measurement of three-dimensional hand kinematics during swimming with a motion capture system: a feasibility study. *Sport. Eng.* 17, 171–181.

Mononen, K. (2007). *The effects of augmented feedback on motor skill learning in shooting*. doi:10.1080/0264041031000101944.

Mooney, R., Corley, G., Godfrey, A., Osborough, C., Newell, J., Quinlan, L. R., et al. (2016a). Analysis of swimming performance: perceptions and practices of US-based swimming coaches. *J. Sports Sci.* 34, 997–1005. doi:10.1080/02640414.2015.1085074.

Mooney, R., Corley, G., Godfrey, A., Osborough, C., Quinlan, L. R., and ÓLaighin, G. (2015). Application of Video-Based Methods for Competitive Swimming Analysis: A Systematic Review. *Sport. Exerc.*

Med. - Open J. 1, 133–150. doi:10.17140/SEMOJ-1-121.

Mooney, R., Corley, G., Godfrey, A., Quinlan, L., and ÓLaighin, G. (2016b). Inertial Sensor Technology for Elite Swimming Performance Analysis: A Systematic Review. *Sensors* 16, 18. doi:10.3390/s16010018.

Mooney, R., Quinlan, L. R., Corley, G., Godfrey, A., Osborough, C., and ÓLaighin, G. (2017). Evaluation of the Finis Swimsense® and the Garmin Swim™ activity monitors for swimming performance and stroke kinematics analysis. *PLoS One* 12, 1–17. doi:10.1371/journal.pone.0170902.

Morais, J. E., Forte, P., Nevill, A. M., Barbosa, T. M., and Marinho, D. A. (2020). Upper-limb kinematics and kinetics imbalances in the determinants of front-crawl swimming at maximal speed in young international level swimmers. *Sci. Rep.* 10, 1–8. doi:10.1038/s41598-020-68581-3.

Morais, J. E., Jesus, S., Lopes, V., Garrido, N., Silva, A., Marinho, D., et al. (2012). Linking selected kinematic, anthropometric and hydrodynamic variables to young swimmer performance. *Pediatr. Exerc. Sci.* 24, 649–664. doi:10.1123/pes.24.4.649.

Morais, J. E., Marinho, D. A., Arellano, R., and Barbosa, T. M. (2018). Start and turn performances of elite sprinters at the 2016 European Championships in swimming. *Sport. Biomech.* 3141, 1–15. doi:10.1080/14763141.2018.1435713.

Morais, J. E., Saavedra, J. M., Costa, M. J., Silva, A. J., Marinho, D. A., and Barbosa, T. M. (2013). Tracking young talented swimmers: Follow-up of performance and its biomechanical determinant factors. *Acta Bioeng. Biomech.* 15, 129–138. doi:10.5277/abb130316.

Morais, J. E., Silva, A. J., Marinho, D. A., Seifert, L., and Barbosa, T. M. (2015). Cluster stability as a new method to assess changes in performance and its determinant factors over a season in young swimmers. *Int. J. Sports Physiol. Perform.* 10, 261–268. doi:10.1123/ijspp.2013-0533.

Morouço, P. G., Marinho, D. A., Keskinen, K. L., Badillo, J. J., and Marques, M. C. (2014). Tethered swimming can be used to evaluate force contribution for short-distance swimming performance. *J. Strength Cond. Res.* 28, 3093–3099.

Morouço, P., Keskinen, K. L., Vilas-Boas, J. P., and Fernandes, R. J. (2011). Relationship between tethered forces and the four swimming techniques performance. *J. Appl. Biomech.* 27, 161–169.

Morouço, P., Pinto, J., Félix, E., Correia, P. L., Humana, F. D. M., Lisboa, U. De, et al. (2020). Development of a Low- Cost Imu for Swimmers ' Evaluation. 952–955.

Muthukrishnan, R., and Rohini, R. (2017). LASSO: A feature selection technique in predictive modeling for machine learning. *2016 IEEE Int. Conf. Adv. Comput. Appl. ICACA 2016*, 18–20. doi:10.1109/ICACA.2016.7887916.

Muthusamy, S., Subramaniam, A., Balasubramanian, K., Purushothaman, V. K., and Vasanthi, R. K. (2021). Assessment of Vo2 Max Reliability with Garmin Smart Watch among Swimmers. *Int. J. Pharma Bio Sci.* 11. doi:10.22376/ijpbs/lpr.2021.11.4.l42-46.

Nachar, N. (2008). The Mann-Whitney U: A Test for Assessing Whether Two Independent Samples Come from the Same Distribution. *Tutor. Quant. Methods Psychol.* 4, 13–20. doi:10.20982/tqmp.04.1.p013.

Nagahara, R., Kameda, M., Neville, J., and Morin, J.-B. (2020). Inertial measurement unit-based hip flexion test as an indicator of sprint performance. *J. Sports Sci.* 38, 53–61.

Nakano, G., Iino, Y., Imura, A., and Kojima, T. (2014). Transfer of momentum from different arm segments to a light movable target during a straight punch thrown by expert boxers. *J. Sports Sci.* 32, 517–523.

Narasimhappa, M., Mahindrakar, A. D., Guizilini, V. C., Terra, M. H., and Sabat, S. L. (2019). MEMS-based IMU drift minimization: Sage Husa adaptive robust Kalman filtering. *IEEE Sens. J.* 20, 250–260.

Nash, C., Sproule, J., and Horton, P. (2017). Feedback for coaches: Who coaches the coach? *Int. J. Sport. Sci. Coach.* 12, 92–102. doi:10.1177/1747954116684390.

Nathan, A. J., and Scobell, A. (2012). How China sees America. *Foreign Aff.* 91, 381. doi:10.1017/CBO9781107415324.004.

Nedergaard, N. J., Kersting, U., and Lake, M. (2014). Using accelerometry to quantify deceleration during a high-intensity soccer turning manoeuvre. *J. Sports Sci.* 32, 1897–1905.

Nedergaard, N. J., Robinson, M. A., Eusterwiemann, E., Drust, B., Lisboa, P. J., and Vanrenterghem, J. (2017). The relationship between whole-body external loading and body-worn accelerometry during team-sport movements. *Int. J. Sports Physiol. Perform.* 12, 18–26.

Neville, J. G., Rowlands, D. D., Lee, J. B., and James, D. A. (2015). A model for comparing over-ground running speed and accelerometer derived step rate in elite level athletes. *IEEE Sens. J.* 16, 185–191.

Nicol, E., Ball, K., and Tor, E. (2019). The biomechanics of freestyle and butterfly turn technique in elite swimmers. *Sport. Biomech.*

Nicol, E., Tor, E., and Ball, K. (2018). The characteristics of an elite swimming turn. *36th Int. Symp. Biomech. Sport. Proc. Arch. 36.1*, 869.

Nikodelis, T., Kollias, I., and Hatzitaki, V. (2005). Bilateral inter-arm coordination in freestyle swimming: Effect of skill level and swimming speed. *J. Sports Sci.* 23, 737–745. doi:10.1080/02640410400021955.

O. Connor, S., McCaffrey, N., Whyte, E., and Moran, K. (2016). The novel use of a SenseCam and accelerometer to validate training load and training information in a self-recall training diary. *J. Sports Sci.* 34, 303–310.

Ohgi, Y., Ichikawa, H., Homma, M., and Miyaji, C. (2003). Stroke phase discrimination in breaststroke swimming using a tri-axial acceleration sensor device. *Sport. Eng.* 6, 113–123. doi:10.1007/BF02903532.

Ohgi, Y., Kaneda, K., and Takakura, A. (2014). Sensor data mining on the kinematical characteristics of the competitive swimming. *Procedia Eng.* 72, 829–834. doi:10.1016/j.proeng.2014.06.036.

Omae, Y., Kon, Y., Kobayashi, M., Sakai, K., Shionoya, A., Takahashi, H., et al. (2017). Swimming Style Classification Based on Ensemble Learning and Adaptive Feature Value by Using Inertial Measurement Unit. *J. Adv. Comput. Intell. Intell. Informatics* 21.

Opondo, M. A., Sarma, S., and Levine, B. D. (2015). The cardiovascular physiology of sports and exercise. *Clin. Sports Med.* 34, 391–404.

Osborough, C. D., Payton, C. J., and Daly, D. J. (2010). Influence of swimming speed on inter-arm coordination in competitive unilateral arm amputee front crawl swimmers. *Hum. Mov. Sci.* 29, 921–931. doi:10.1016/j.humov.2010.05.009.

Pan, M. S., Huang, K. C., Lu, T. H., and Lin, Z. Y. (2016). Using accelerometer for counting and identifying swimming strokes. *Pervasive Mob. Comput.* 31, 37–49. doi:10.1016/j.pmcj.2016.01.011.

Pansiot, J., Lo, B., and Yang, G. Z. (2010). Swimming stroke kinematic analysis with BSN. *2010 Int. Conf. Body Sens. Networks, BSN 2010*, 153–158. doi:10.1109/BSN.2010.11.

Payton, C., Baltzopoulos, V., and Bartlett, R. (2002). Contributions of rotations of the trunk and upper extremity to hand velocity during front crawl swimming. *J. Appl. Biomech.* 18, 243–256.

Payton, C. J., and Adrian Burden, E. (2017). *Biomechanical evaluation of movement in sport and exercise: the British Association of Sport and Exercise Sciences guide*. Routledge.

Payton, C. J., and Bartlett, R. M. (1995). Estimating propulsive forces in swimming from three-dimensional kinematic data. *J. Sports Sci.* 13, 447–454. doi:10.1080/02640419508732261.

Pendergast, D. R., Di Prampero, P. E., and Craig, A. B. (1980). Metabolic adaptations to swimming. *Exerc. Bioenerg. gas Exch. Ed by P. Cerreteli, BJ Whipp. Amsterdam*, 323–336.

Pendergast, D., Zamparo, P., di Prampero, P. E., Capelli, C., Cerretelli, P., Termin, A., et al. (2003). Energy balance of human locomotion in water. *Eur. J. Appl. Physiol.* 90, 377–386. doi:10.1007/s00421-003-0919-y.

Pereira, S. M., Ruschel, C., Hubert, M., Machado, L., Roesler, H., Fernandes, R. J., et al. (2015). Kinematic, kinetic and emg analysis of four front crawl flip turn techniques. *J. Sports Sci.* 33, 2006–2015. doi:10.1080/02640414.2015.1026374.

Peters, A., Galna, B., Sangeux, M., Morris, M., and Baker, R. (2010). Quantification of soft tissue artifact in lower limb human motion analysis: a systematic review. *Gait Posture* 31, 1–8.

Pla, R., Ledanois, T., Simbana, E. D., Aubry, A., Tranchard, B., Toussaint, J. F., et al. (2021). Spatial-temporal variables for swimming coaches: A comparison study between video and TritonWear sensor. *Int. J. Sport. Sci. Coach.* 16, 1271–1280. doi:10.1177/17479541211013755.

Psycharakis, S. G., and Sanders, R. H. (2010). Body roll in swimming: A review. *J. Sports Sci.* 28, 229–236. doi:10.1080/02640410903508847.

Pueo, B. (2016). High speed cameras for motion analysis in sports science. *J. Hum. Sport Exerc.* 11, 53–73.

Punchihewa, N. G., Yamako, G., Fukao, Y., and Chosa, E. (2019). Identification of key events in baseball hitting using inertial measurement units. *J. Biomech.* 87, 157–160.

Rana, M., and Mittal, V. (2021). Wearable Sensors for Real-Time Kinematics Analysis in Sports: A Review. *IEEE Sens. J.* 21, 1187–1207. doi:10.1109/JSEN.2020.3019016.

Robertson, E., Pyne, D., Hopkins, W., and Anson, J. (2009). Analysis of lap times in international swimming competitions. *J. Sports Sci.* 27, 387–395. doi:10.1080/02640410802641400.

Rocha, L. A., and Correia, J. H. (2006). Wearable sensor network for body kinematics monitoring. *Proc. - Int. Symp. Wearable Comput. ISWC*, 137–138. doi:10.1109/ISWC.2006.286364.

Ruschel, C., Araujo, L., Pereira, S. M., and Roesler, H. (2007). Kinematical Analysis of the Swimming Start : Block , Flight and Underwater Phases. *XXV ISBS Symp.*, 385–388.

Samson, M., Monnet, T., Bernard, A., Lacouture, P., and David, L. (2018). Comparative study between fully tethered and free swimming at different paces of swimming in front crawl. *Sport. Biomech.*

Sánchez, L., Arellano, R., and Cuenca-Fernández, F. (2021). Analysis and influence of the underwater phase of breaststroke on short-course 50 and 100m performance. *Int. J. Perform. Anal. Sport* 21, 307–323.

Särkkä, O., Nieminen, T., Suuriniemi, S., and Kettunen, L. (2016). Augmented inertial measurements for analysis of javelin throwing mechanics. *Sport. Eng.* 19, 219–227.

Schaffert, N., Engel, A., Schlüter, S., and Mattes, K. (2019). The sound of the underwater dolphin-kick:

developing real-time audio feedback in swimming. *Displays* 59, 53–62. doi:10.1016/j.displa.2019.08.001.

Schaffert, N., Oldag, B., and Cesari, P. (2020). Sound matters: The impact of auditory deprivation on movement precision in rowing. *Eur. J. Sport Sci.* 20, 1299–1306.

Schmidt, R., and Lee, T. (2019). *Motor Learning and Performance: From Principles to Application.* 6th ed. Human Kinetics Publishers, Champaign, US.

Seifert, L., and Carmigniani, R. (2021). Coordination and stroking parameters in the four swimming techniques: a narrative review. *Sport. Biomech.* 00, 1–17. doi:10.1080/14763141.2021.1959945.

Seifert, L., Chollet, D., and Bardy, B. G. (2004). Effect of swimming velocity on arm coordination in the front crawl: a dynamic analysis. *J. Sports Sci.* 22, 651–660.

Seifert, L., Chollet, D., and Mujika, I. (2011a). *World book of swimming : from science to performance*. Nova Science Publishers, New York, NY.

Seifert, L., L'Hermette, M., Komar, J., Orth, D., Mell, F., Merriaux, P., et al. (2014). Pattern recognition in cyclic and discrete skills performance from inertial measurement units. in *Procedia Engineering* (Elsevier B.V.), 196–201. doi:10.1016/j.proeng.2014.06.033.

Seifert, L., Leblanc, H., Herault, R., Komar, J., Button, C., and Chollet, D. (2011b). Inter-individual variability in the upper-lower limb breaststroke coordination. *Hum. Mov. Sci.* 30, 550–565. doi:10.1016/j.humov.2010.12.003.

Seifert, L., Schnitzler, C., Bideault, G., Alberty, M., Chollet, D., and Toussaint, H. M. (2015). Relationships between coordination, active drag and propelling efficiency in crawl. *Hum. Mov. Sci.* 39, 55–64. doi:10.1016/j.humov.2014.10.009.

Sewell, D., Griffin, M., Watkins, P., and Wilkinson, N. (2014). *Sport and exercise science: An introduction*. Routledge.

Shaw, G., Boyd, K. T., Burke, L. M., and Koivisto, A. (2014). Nutrition for Swimming. *Int. J. Sport Nutr. Exerc. Metab.* 24, 360–372. doi:10.1123/ijsnem.2014-0015.

Sheard, M., and Golby, J. (2006). Effect of a psychological skills training program on swimming performance and positive psychological development. *Int. J. Sport Exerc. Psychol.* 4, 149–169. doi:10.1080/1612197x.2006.9671790.

Shimadzu, H., Shibata, R., and Ohgi, Y. (2008). Modelling swimmers' speeds over the course of a race. *J. Biomech.* 41, 549–555. doi:10.1016/j.jbiomech.2007.10.007.

Shimojo, H., Sengoku, Y., Miyoshi, T., Tsubakimoto, S., and Takagi, H. (2014). Effect of imposing changes in kick frequency on kinematics during undulatory underwater swimming at maximal effort in male swimmers. *Hum. Mov. Sci.* 38, 94–105. doi:10.1016/j.humov.2014.09.001.

Sigrist, R., Rauter, G., Riener, R., and Wolf, P. (2013). Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review. *Psychon. Bull. Rev.* 20, 21–53. doi:10.3758/s13423-012-0333-8.

Siirtola, P., Laurinen, P., Roning, J., and Kinnunen, H. (2011). Efficient accelerometer-based swimming exercise tracking. *IEEE SSCI 2011 Symp. Ser. Comput. Intell. - CIDM 2011 2011 IEEE Symp. Comput. Intell. Data Min.*, 156–161. doi:10.1109/CIDM.2011.5949430.

Silva, A. F., Sousa, M., Willig, R., Sampaio, A. R., Vilas-boas, J. P., Figueiredo, P., et al. (2019). Relationship between strength , stroke efficiency and front crawl swimming performance. 24, 3–4.

Silva, A. S., Salazar, A. J., Correia, M. F., and Borges, C. M. (2011). WIMU: Wearable inertial monitoring unit - A MEMS-based device for swimming performance analysis. *BIODEVICES 2011 - Proc. Int. Conf. Biomed. Electron. Devices*, 87–93. doi:10.5220/0003172700870093.

Silveira, G. A., Araujo, L. G., Freitas, E. D. S., Schütz, G. R., de Souza, T. G., Pereira, S. M., et al. (2011). Proposal for standardization of the distance for analysis of freestyle flip-turn performance. *Brazilian J. Kinanthropometry Hum. Perform.* 13, 177–182. doi:10.5007/1980-0037.2011v13n3p177.

Slawson, S., Conway, P., Justham, L., Le Sage, T., and West, A. (2010). Dynamic signature for tumble turn performance in swimming. *Procedia Eng.* 2, 3391–3396. doi:10.1016/j.proeng.2010.04.163.

Slawson, S. E., Justham, L. M., Conway, P. P., Le-Sage, T., and West, A. A. (2012). Characterizing the swimming tumble turn using acceleration data. *Proc. Inst. Mech. Eng. Part P J. Sport. Eng. Technol.* 226, 3–15. doi:10.1177/1754337111428395.

Smith, D. J., Norris, S. R., and Hogg, J. M. (2002). Performance Evaluation of Swimmers. *Sport. Med.* 32, 539–554. doi:10.2165/00007256-200232090-00001.

Smith, P., and Bedford, A. (2020). Automatic classification of locomotion in sport: A case study from elite netball. *J. homepage http//iacss. org/index. php? id* 19.

Stamm, A. (2013). Velocity and arm symmetry investigations in freestyle swimming using accelerometry : Data Collection , Analysis and Feature Extraction by.

Stamm, A., James, D. A., Burkett, B. B., Hagem, R. M., and Thiel, D. V. (2013a). Determining maximum push-off velocity in swimming using accelerometers. *Procedia Eng.* 60, 201–207. doi:10.1016/j.proeng.2013.07.067.

Stamm, A., James, D. A., and Thiel, D. V. (2013b). Velocity profiling using inertial sensors for freestyle swimming. *Sport. Eng.* 16, 1–11. doi:10.1007/s12283-012-0107-6.

Stetter, B. J., Buckeridge, E., von Tscharner, V., Nigg, S. R., and Nigg, B. M. (2016). A Novel Approach to Determine Strides, Ice Contact, and Swing Phases During Ice Hockey Skating Using a Single Accelerometer. *J. Appl. Biomech.* 32.

Stewart, A. M., and Hopkins, W. G. (2000). Consistency of swimming performance within and between competitions. *Med. Sci. Sports Exerc.* 32, 997–1001. doi:10.1097/00005768-200005000-00018.

Stojmenova, K., Duh, E. S., and Sodnik, J. (2018). A Review on Methods for Assessing Driver's Cognitive Load. *Ipsi Bgd Trans. Internet Res.* 14.

Straeten, M., Rajai, P., and Ahamed, M. J. (2019). Method and implementation of micro Inertial Measurement Unit (IMU) in sensing basketball dynamics. *Sensors Actuators A Phys.* 293, 7–13.

Strohrmann, C., Harms, H., Kappeler-Setz, C., and Troster, G. (2012). Monitoring kinematic changes with fatigue in running using body-worn sensors. *IEEE Trans. Inf. Technol. Biomed.* 16, 983–990.

Takagi, H., Nakashima, M., Sato, Y., Matsuuchi, K., and Sanders, R. H. (2016). Numerical and experimental investigations of human swimming motions. *J. Sports Sci.* 34, 1564–1580.

Takagi, H., Nakashima, M., Sengoku, Y., Tsunokawa, T., Koga, D., Narita, K., et al. (2021). How do swimmers control their front crawl swimming velocity? Current knowledge and gaps from hydrodynamic perspectives. *Sport. Biomech.*, 1–20.

Tarasevicius, D., and Serackis, A. (2020). Deep Learning Model for Sensor based Swimming Style Recognition. in *2020 IEEE Open Conference of Electrical, Electronic and Information Sciences, eStream 2020 - Proceedings*, 38–41. doi:10.1109/eStream50540.2020.9108849.

Thng, S., Pearson, S., Rathbone, E., and Keogh, J. W. L. (2022). Longitudinal tracking of body composition, lower limb force-time characteristics and swimming start performance in high performance swimmers. *Int. J. Sport. Sci. Coach.* 17, 83–94. doi:10.1177/17479541211021401.

Toner, J., and Moran, A. (2015). Toward an explanation of continuous improvement in expert athletes: the role of consciousness in deliberate practice. *Int. J. Sport Psychol* 46, 666–675.

Toubekis, A. G., Drosou, E., Gourgoulis, V., Thomaidis, S., Douda, H., and Tokmakidis, S. P. (2013). Competitive performance, training load and physiological responses during tapering in young swimmers. *J. Hum. Kinet.* 38, 125.

Toussaint, H. M. (2002). Biomechanics of propulsion and drag in front crawl swimming. *ISBS-Conference Proc. Arch.*, 13–22.

Toussaint, H., and Truijens, M. (2005). Biomechanical aspects of peak performance in human swimming. *Anim. Biol.* 55, 17–40. doi:10.1163/1570756053276907.

Tsunokawa, T., Tsuno, T., Mankyu, H., Takagi, H., and Ogita, F. (2018). The effect of paddles on pressure and force generation at the hand during front crawl. *Hum. Mov. Sci.* 57, 409–416.

Ukai, Y., and Rekimoto, J. (2013). Swimoid: A swim support system using an underwater buddy robot. *ACM Int. Conf. Proceeding Ser.*, 170–177. doi:10.1145/2459236.2459265.

Vales-Alonso, J., Chaves-Diéguez, D., López-Matencio, P., Alcaraz, J. J., Parrado-García, F. J., and González-Castaño, F. J. (2015). SAETA: A smart coaching assistant for professional volleyball training. *IEEE Trans. Syst. Man, Cybern. Syst.* 45, 1138–1150.

Van der Kruk, E., and Reijne, M. M. (2018). Accuracy of human motion capture systems for sport applications; state-of-the-art review. *Eur. J. Sport Sci.* 18, 806–819. doi:10.1080/17461391.2018.1463397.

Vannozzi, G., Donati, M., Gatta, G., and Cappozzo, A. (2010). Analysis of Swim Turning, Underwater Gliding and Stroke Resumption Phases in Top Division Swimmers using a Wearable Inertial Sensor Device. *XIth Int. Symp. Biomech. Med. Swim.* 168, 178–180.

Vantorre, J., Chollet, D., and Seifert, L. (2014). Biomechanical analysis of the swim-start: A review. *J. Sport. Sci. Med.* 13, 223–231.

Vantorre, J., Seifert, L., Fernandes, R. J., Boas, J. P. V., and Chollet, D. (2010). Kinematical profiling of the front crawl start. *Int. J. Sports Med.* 31, 16–21. doi:10.1055/s-0029-1241208.

Verhagen, E. A. L. M., van Stralen, M. M., and Van Mechelen, W. (2010). Behaviour, the key factor for sports injury prevention. *Sport. Med.* 40, 899–906.

Wakayoshi, K., Yoshida, T., Udo, M., Kasai, T., Moritani, T., Mutoh, Y., et al. (1992). A simple method for determining critical speed as swimming fatigue threshold in competitive swimming. *Int. J. Sports Med.* 13, 367–371.

Wang, J., Wang, Z., Gao, F., and Guo, M. (2016a). SwimSense: Monitoring swimming motion using body sensor networks. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* 9864 LNCS, 45–55. doi:10.1007/978-3-319-45940-0_5.

Wang, Z., Shi, X., Wang, J., Gao, F., Li, J., Guo, M., et al. (2019). Swimming Motion Analysis and Posture Recognition Based on Wearable Inertial Sensors. *2019 IEEE Int. Conf. Syst. Man Cybern.*, 3371–3376. doi:10.1109/smc.2019.8913847.

Wang, Z., Wang, J., Zhao, H., Yang, N., and Fortino, G. (2016b). CanoeSense: Monitoring canoe sprint motion using wearable sensors. in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (IEEE), 644–649.

Washino, S., Mayfield, D. L., Lichtwark, G. A., Mankyu, H., and Yoshitake, Y. (2019). Swimming performance is reduced by reflective markers intended for the analysis of swimming kinematics. *J. Biomech.* 91, 109–113.

Wickström, G., and Bendix, T. (2000). The" Hawthorne effect"—what did the original Hawthorne studies actually show? *Scand. J. Work. Environ. Health*, 363–367.

Wilson, B. D. (2008). Development in video technology for coaching. *Sport. Technol.* 1, 34–40. doi:10.1080/19346182.2008.9648449.

Woodman, O. J. (2007). An introduction to inertial navigation. University of Cambridge, Computer Laboratory.

Worsey, M. T. O., Pahl, R., Thiel, D. V, and Milburn, P. D. (2018). A Comparison of Computational Methods to Determine Intrastroke Velocity in Swimming Using IMUs. 2, 1–4. doi:10.1109/lsens.2018.2804893.

Wright, B. V., and Stager, J. M. (2013). Quantifying competitive swim training using accelerometer-based activity monitors. *Sport. Eng.* 16, 155–164. doi:10.1007/s12283-013-0123-1.

Wulf, G., and Shea, C. H. (2002). Principles derived form the studies of simple motor skills do not generalize to complex skill learning. *Psychon. Bull Rev* 9, 185–211.

Yang, D., Tang, J., Huang, Y., Xu, C., Li, J., Hu, L., et al. (2017). TennisMaster: An IMU-based online serve performance evaluation system. in *Proceedings of the 8th augmented human international conference*, 1–8.

Yu, G., Jang, Y. J., Kim, J., Kim, J. H., Kim, H. Y., Kim, K., et al. (2016). Potential of IMU sensors in performance analysis of professional alpine skiers. *Sensors* 16, 463.

Zacca, R., Azevedo, R., Chainok, P., Vilas-Boas, J. P., Castro, F. A. de S., Pyne, D. B., et al. (2020). Monitoring age-group swimmers over a training macrocycle: energetics, technique, and anthropometrics. *J. Strength Cond. Res.* 34, 818–827.

Zamparo, P., Bonifazi, M., Faina, M., Milan, A., Sardella, F., Schena, F., et al. (2005). Energy cost of swimming of elite long-distance swimmers. *Eur. J. Appl. Physiol.* 94, 697–704. doi:10.1007/s00421-005-1337-0.

Zamparo, P., Cortesi, M., and Gatta, G. (2020). The energy cost of swimming and its determinants. *Eur. J. Appl. Physiol.* 120, 41–66.

Zatsiorsky, V. M., Bulgakova, N. Z., and Chaplinsky, N. M. (1979). Biomechanical analysis of starting techniques in swimming. *Swim. III*, 199–206.

Zihajehzadeh, S., Loh, D., Lee, T. J., Hoskinson, R., and Park, E. J. (2015). A cascaded Kalman filter-based GPS/MEMS-IMU integration for sports applications. *Measurement* 73, 200–210.

CURRICULUM VITAE

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Education

Doctoral candidate at EPFL — **Lausanne, Switzerland 2018-present**

EDRS - Robotic, Control and Intelligent Systems

Topics: motion tracking, machine learning, activity monitoring, sensor fusion, statistical analysis

Master of Science (hons.) at Sharif University of Technology — **Tehran, Iran 2014-2017**

Mechanical Engineering, Rehabilitation and Assistive Devices

Topics: dynamical modeling, robotic rehabilitation, system control and optimization

Bachelor of Science (hons.) at AmirKabir University of Technology — **Tehran, Iran 2010-2014**

Mechanical Engineering

Topics: mechanical design, CAD, FEA, system optimization and integration

Core experiences

Laboratory of Movement Analysis and Measurement (LMAM), EPFL, Lausanne — **Sep. 2018 - present**

Doctoral assistant and EPFLInnovators fellow

Data collection and analysis for assessment of swimming performance using wearable sensors

- Development of a novel method to evaluate swimming performance based on motion and technique analysis using a single sensor
  - Hands-on experience implementing neural network models for swimmer activity monitoring
  - Activity monitoring and automatic detection of swimming bouts and phases during the entire training session using signal processing techniques
  - Extraction and selection of technique-relevant parameters for performance evaluation
  - Machine learning modelling to quantify and classify swimmers' performance
- In-field test of the developed method with a swimming team of LausanneNatation club
  - Significant performance improvement of swimmers with 2.5 months of training with feedback

- Collaboration with the Swiss Swimming Federation and UNIL sports science professors
- Test organization and data management through collaboration with more than 60 swimmers and 10 coaches in Lausanne and Geneva in the limits of the pandemic

Gait Up S.A., Lausanne — **Jun. 2021 - present**

Algorithm researcher

- Ph.D. secondment in industry under the European EPFLInnovators fellowship for improving and adapting the algorithms to market needs
- Market analysis for the proposed swimming analysis system in Switzerland and feasibility study of the idea as a minimally viable product

PEDASYS Co., Tehran — **Jul 2016 - Mar 2018**

Mechanical engineering expert

- Simulation and design of an exoskeleton robot in the mechanical engineering team
- Months of testing and continuous communication with clinical partners, rehabilitation centres, patients and therapists for improving the device
- Conceptual and detail design, simulation, sensor manipulation, system identification and controller design of a body weight support system (M.Sc. thesis)

Mowafaghian Research Center, Tehran — **Jan 2015 - Jan 2017**

Research assistant

- Contribution to the design and implementation of several projects for stroke patients balance rehabilitation

Additional experiences

Evaluation of an entrepreneurial idea - Innosuisse business concept project — **Sep 2021 - Dec 2021**

- Teamwork to evaluate, write the business model and fund the idea
- Interviewing a large group of potential customers to analyze the market and adapt to their needs

Transferable skills training - EPFLInnovators fellowship — **Sep 2019 - Sep 2021**

- Following additional courses on identifying entrepreneurial opportunities, start-up environment, market analysis, lectures and presentations to engineers, and research ethics

Technical skills

Body motion tracking

Tracking the movement of body segments using inertial sensors and/or cameras

Activity monitoring

Long-term monitoring of athletic activity by detecting the key event in several days' worth of data

Programming

- Matlab (professional scripting and debugging, toolkits)
- Python (numpy, pandas, scipy, tensorflow, scikit-learn for data analytics and machine learning)

- R (statistical analysis with R Studio)

Sensors and devices

Accelerometer, gyroscope, barometer, magnetometer, force plate, servo system, Arduino, loadcell, encoder

Design and optimization

Optimized design of mechanical devices and products considering technical limitations and market requirements

Machine learning and classification

Data analysis and modelling based on supervised or unsupervised learning

Project management

Management and supervision of multiple students for semester projects

Teaching

Tutored undergraduate students and provided teaching assistance for several courses during the master's and doctoral programs

Languages

Persian (native), **English** (C2), **French** (B1)

Interests

- Basketball player - player at the local level during high school and bachelor
- Avid reader of Psychology books

Publications

- **Hamidi Rad, Mahdi**, et al. "SmartSwim, a Novel IMU-Based Coaching Assistance." Sensors 22.9 (2022): 3356.
- **Hamidi Rad, Mahdi**, et al. "Monitoring weekly progress of front crawl swimmers using IMU-based performance evaluation goal metrics." Frontiers in Bioengineering and Biotechnology (2022): 1352.
- **Hamidi Rad, Mahdi**, et al. "IMU phase-based performance evaluation sensitivity to the progress of young front crawl swimmers." ISBS Proceedings Archive 40.1 (2022): 251.
- **Hamidi Rad, Mahdi**, et al. "Coaching assistance by phase-based performance evaluation feedback obtained from a single sacrum IMU" ISBS Proceedings Archive 40.1 (2022): 255.
- **Hamidi Rad, Mahdi**, et al. "Swimming phase-based performance evaluation using a single IMU in main swimming techniques." Frontiers in bioengineering and biotechnology (2021): 1268.
- **Hamidi Rad, Mahdi**, et al. "Swimming phase-based performance evaluation using a single IMU in front crawl." ISBS Proceedings Archive 39.1 (2021): 61.
- **Hamidi Rad, Mahdi**, et al. "A Novel Macro-Micro Approach for Swimming Analysis in Main Swimming Techniques Using IMU Sensors." Frontiers in bioengineering and biotechnology (2021): 1511.
- **Hamidi Rad, M.**, et al. "A novel approach for swimming analysis in main swimming styles using a single sacrum-worn IMU sensor." 25th Annual Congress of the European college of sport science (ECSS). No. CONF. 2020.