

Inertial measurement unit and biomechanical analysis of swimming: an update

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Abstract

The biomechanical analysis of swimming always faced impeding factors of measurement in the aquatic environment. Our current knowledge of swimming locomotion is very much owing to employing video cameras to capture the body kinematics. Nevertheless, the recent improvements in wearable inertial sensor technology and signal processing techniques offer us a whole new range of measurement setups that were not realizable beforehand. The principal aim of this paper is to present the inertial sensor based systems that are used in the study of swimming biomechanics. In this manuscript we briefly introduce the other existing technologies used in analysis of swimming and the necessity of having an easy to use, reliable and affordable system. Then we highlight the application of inertial sensors in estimation of temporal phases of swimming and also estimation of performance metrics. The perspective of the inertial sensors applications in the swimming studies is eventually discussed. Our concluding remarks advocate the potentials of inertial sensors as a tool for coaches to design the optimal personal training plan for trainees.

Keywords:

Inertial measurement unit, Performance, Swimming, Coordination, Energy expenditure.

Résumé

L'analyse biomécanique de la nage a toujours été confrontée à des facteurs entravant la prise de mesures dans l'environnement aquatique. Nos connaissances actuelles de la locomotion en natation sont très documentées en raison de l'emploi de caméras vidéo pour capturer la cinématique du corps. Néanmoins, des récentes améliorations dans la technologie par l'utilisation de capteurs inertiels portables et dans le traitement du signal nous offrent une toute nouvelle gamme de possibilités de mesures qui n'étaient pas réalisables auparavant. L'objectif principal de cet article est de présenter les systèmes de capteurs inertiels qui sont utilisés dans l'étude de la biomécanique de natation. Dans ce manuscrit, nous présentons brièvement les autres technologies existantes utilisées dans l'analyse de la natation et le besoin d'un outil facile à utiliser, fiable et abordable. Par la suite, nous présenterons l'application des capteurs inertiels dans l'estimation des phases temporelles de la natation et aussi dans l'estimation des indicateurs de performance. Les résultats des applications de capteurs inertiels dans les études de natation sont finalement discutés. Nos conclusions préconisent l'utilisation des capteurs inertiels comme un outil idéal pour les entraîneurs afin de concevoir un plan d'entraînement personnalisé et même d'apporter des correctifs à d'éventuelles fautes techniques en natation.

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Introduction

Sport performance can be regarded as the interplay between morphology, maximal deliverable metabolic power, skill and race strategy. As sport science is taking more and more importance in the athlete's preparation, developing the systems that conform to the necessary measurement setup for experimental studies is crucial. Such a need is more pronounced by reviewing the shrinking gap between the top records in swimming. Reviewing the results of men's 50 meter freestyle semifinals at the 2012 summer Olympics it can be immediately noticed that the last ranked swimmer (16th) finished 76 hundredth of second after the first one. In order to unravel the technical difference in such a neck and neck event, the study of performance determinants should be upto a fine grained piece of information. At the same time, the improvement in accuracy, ergonomics and cost of wearable self-monitoring de-

vices in different on-land sport disciplines broadened the spectrum of individuals using these devices. Examples are Nike plus shoe worn sensor (Nike, Beaverton, OR) connected to an Apple iPod (Apple, Cupertino, CA) (Hanson, Berg, Deka, Meendering, & Ryan, 2011) and Polar heart rate monitoring belt (Polar Electro, Kempele, Finland) (Buchheit et al., 2009) for running.

An enhancement in the performance can be expected just after characterizing and then improving the efficiency of the motor pattern of the athletes. Sports biomechanics vastly benefited from classical movement analysis measurement systems such as optical motion capture, force and pressure measurement sensors, global positioning system (GPS) etc. However, when looking at movement in the water, difficulties arise rapidly as the water element hinders a straightforward deployment of those techniques. In consequence, the biomechanics of swimming has not been adequately explored.

The flourishing use of Inertial Measurement Unit (IMU) in out-of-laboratory studies of the human locomotion (Bergamini et al., 2012; Duc, Salvia, Lubansu, Feipel, & Aminian, 2013; Zeng & Zhao, 2011) suggested it as a powerful measurement system for swimming kinematics investigation. The aim of this article is to present the evolution in the application of IMUs in swimming studies used for motor pattern and performance related metrics assessment. Nevertheless, to realize the shortcomings that foster the application of IMUs, a review of other existing technologies used in the swimming biomechanics studies is inevitable.

Standard technologies in assessment of swimming locomotion

The omnipresent engineered systems to objectify swimmers' performance are chronometric devices that track the timing information and average velocity of the swimmers. In 1967, the Swiss-based watch manufacturer, OMEGA, developed the first electronic timing system for swimming with an accuracy of 0.01s (Smith, 2009). This new system placed touch pads at each lane of the pool, calibrated in such a manner that the incidental water movement could not trigger the pad sensors; the pad was only activated by the touch of the swimmer at the end of the race. As the length of the pool is known, the average velocity of swimming can be determined. Yet, it is not possible to retrieve any quantitative information about the athlete stroking technique during the course of training or competition.

Traditionally, quantitative assessment of swimming stroke has been carried out by analyzing the video sequence of motion. A big share of our understanding about swimming biomechanics has been formed using this technique especially as watching the video footage could be self-explanatory. Camera can be mounted on a trolley system to follow the swimmer (Seifert, Toussaint, Alberty, Schnitzler, & Chollet, 2010) or it can be fixed to focus on a specific phase e.g. dive or turning (Puel et al., 2012; Sanders & Psycharakis, 2009). The portable camera system is generally used for detecting the temporal descriptors of technique such as beginning and end of stroke phases (Chollet, Chalies, & Chatard, 2000; Chollet, Seifert, Leblanc, Boulesteix, & Carter, 2004), though it is not possible to reconstruct the trajectory of body segments. In the fixed setup, the 3D coordinates of key points on the body can be extracted using the Direct Linear Transform (DLT) method (Abel-Aziz & Karara, 1971). DLT determines the relationships between the object-space reference frame and the camera (image) reference frame. This requires a group of control points whose Cartesian coordinates are already known. The control points must form a volume called the control volume (not co-planar). These control points are typically fixed to a calibration frame (Kwon, Lindley, Sanders, & Hong, 1999) as illustrated in *Figure 1*. Using a small calibration frame that cannot well include the space of motion risks an extrapolation of coordinates and consequently, inaccurate coordinate computation. The trajectory reconstruction error for the typically used equipments is less than 1 cm (Callaway, Cobb, & Jones, 2009; Ceccon et al., 2013). Nonetheless, the video processing is problematic to be fully automated and therefore a common drawback of video-based systems is the manual post processing that needs exorbitant computation time. Recently a markerless 3D analysis method was proposed (Ceseracciu et al., 2011) based on extraction of swim-

mer's silhouette that reduces the video processing time. The application of all video-based methods is severely restricted by factors such as light refraction in water or bubbles generated around swimmers body (Callaway, et al., 2009). On top of that, the limited capture volume of fixed systems can capture a very limited number of cycles (*Fig.1*) that probably is not representative of the variability of motor pattern, the key to understand individual differences.

Since the ultimate goal of a competitive swimmer is to travel a given distance within the shortest time, the swimming velocity is the most intuitive index of swimming performance (T. M. Barbosa et al., 2010). Besides, it has been shown that variation of velocity adds up to the energy needed to swim a given distance at a constant velocity (Nigg, 1983). The tethered monitoring systems were devised to measure the velocity and its variations. Velocity is calculated by measuring the displacement of a nylon line attached to the swimmer waist. The line is tethered to a poolside shaft-encoder (Justham et al., 2008; Schnitzler, Seifert, Ernwein, & Chollet, 2008). Although instantaneous displacement, velocity and acceleration in direction of swimming can be monitored, the device disturbs the swimmer's technique when the cord touches swimmer's legs and measures the velocity only in one direction. Another shortcoming is the extra force that should be constantly applied to the swimmer in order to alleviate the nylon line's slack during the decelerations of the swimmer (Tella et al., 2008).

Highest performance in all forms of human locomotion including swimming, depends on the maximal metabolic power of the athlete (P. E. Di Prampero, 1986). The maximal metabolic power in swimming, can be estimated based on the aerobic, anaerobic lactic and anaerobic alactic energy contributions (Figueiredo, Zamparo, Sousa, Vilas-Boas, & Fernandes, 2011). The aerobic contribution in many studies was assessed by using Douglas bags or mixing chamber gas analyzer (Chatard, Collomp, Maglisco, & Maglisco, 1990; Pendergast, Di Prampero, Craig, & Rennie, 1978). The recent developments in breath-by-breath cardiorespiratory profiling allowed collection of gas exchange to calculate the aerobic contribution using a respiratory snorkel connected to a gas exchange indirect calorimetry module (T. Barbosa et al., 2006; P. Di Prampero, Pendergast, & Zamparo, 2011). The anaerobic lactic part is calculated by taking capillary blood samples to measure the lactate accumulation in blood (Figueiredo, Barbosa, Vilas-Boas, & Fernandes, 2012). The anaerobic alactic contribution is the energy produced by splitting phosphocreatine in the muscles ($416 \text{ J} \cdot \text{kg}^{-1} \cdot \text{s}^{-1}$) and increases with exercise duration with an empirical time constant of 23.4s (P. Di Prampero, et al., 2011). Keeping in mind that this framework is the only practical method of measuring the energy expenditure for the past decade, a big disadvantage is

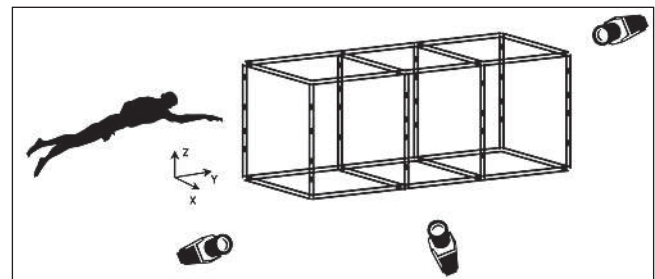


Figure 1: The calibration frame and reference points in a typical setup for 3D reconstruction of body key points in video-based analysis of swimming biomechanics. 3 to 4 cycles can be generally captured.

that the swimmers should modify several aspects of their technique, e.g. the breathing movement, tumble turning and underwater gliding are not possible anymore. Another downside is that the capillary blood sample collection is relatively invasive and athletes are usually disinclined to undergo the test.

The previous paragraphs suggest different areas of further development with two common characteristics: 1) the system should be easy-to-use and user-centric signifying that several athletes can be measured at a time without interfering with the other athletes' measurements; 2) the measurement capacity should be ubiquitous to allow assessing the variability of locomotion.

Wearable IMUs for assessment of swimming technique

The improvements in accuracy, size and cost of Micro-Electro-Mechanical-Systems (MEMS) introduce the IMUs as a credible option in the study of sport biomechanics such as running (Hanson, et al., 2011) and ski jump (Chardonnes, Favre, Cuendet, Gremion, & Aminian, 2013). IMU can encapsulate either of accelerometer, gyroscope and magnetometer. By reviewing the application of IMU-based systems in the study of swimming biomechanics, two prominent lines of developments can be noted: 1) assessment of temporal and coordinative parameters; 2) estimation of performance related parameters.

Assessment of temporal and coordinative descriptors of swimming stroke

In all the studies using IMU to extract the temporal events of a swimming cycle, a starting point is that there are common features in the stroke pattern that give rise to the extraction of stroke phases from inertial signals. In (Davey, Anderson, & James, 2008) and (Slawson et al., 2008) a sacrum mounted 3D accelerometer was used to automatically extract metrics such as lap time (based on wall push-off pattern on the acceleration signal) and stroke frequency (by detecting the signal peaks at every cycle). Their result suggested the improvement on the timing in comparison to the manual recording of the lap time. An IMU comprising a 3D accelerometer, 2D gyroscope and RF transceiver was used in (Chakravorti, Le Sage, Slawson, Conway, & West, 2013) to detect swimming phases i.e. glide phase, first stroke initiation and turn initiation in real time, though they did not provide any data on the system accuracy. The first automatic assessment of kick count and rate in front crawl was performed in (Fulton, Pyne, & Burkett, 2009) attaching a 3D gyroscope to thigh and shank where they found a typical error of approximately 4% for both parameters. SWiSS was a hybrid system composed of a 3D accelerometer on the back of the swimmer's head and an underwater camera to visualize the acceleration at each stroke in offline processing (Khoo, Lee, Senanayake, & Wilson, 2009). Nevertheless, without knowing the sensor orientation the gravity component cannot be separated from sensor readings to determine the movement acceleration.

Since around 90% of propulsive force in front-crawl is provided by arm strokes (Deschodt, Arzac, & Rouard, 1999), the investigation of arm stroke motor pattern can be demonstrative of race strategies and skill level (Alberty, Sidney, Pelayo, & Toussaint, 2009; Seifert et al., 2010). Using visual

scrutiny of video captured from front crawl, Chollet and co-workers (Chollet, et al., 2000), divided arm stroke into five distinct phases: 1) entry 2) catch 3) pull 4) push 5) recovery. Only, during the pull and push phases arm is propulsive. Therefore, by determining the beginning of pull phase and end of push phase the propulsive and non-propulsive phases of arm action can be determined. By calculating the lag time between the arms propulsive phases (Chollet, et al., 2000) quantified inter-arm coordination called the index of coordination (IdC). Similarly in breaststroke, a complete cycle of the arm and leg action can be divided into three main phases i.e. glide, propulsion and recovery (Seifert & Chollet, 2005). The coordination is defined based on the time gap between propulsive action of legs and arms shows the propulsive discontinuity that is called total time gap (TTG). Ohgi (Ohgi, 2002) was probably the first who used a wrist-worn IMU including a 3D accelerometer and a 3D gyroscope to characterize front crawl and breast stroke arm phases. He tried to qualitatively discriminate the stroke phases by matching some features from inertial signals with synchronized video footage of swimming trials. The study did not provide the statistical result to show how well the suggested features match the real events based on the video observation. Lee and co-workers (Lee, Burkett, Thiel, & James, 2011) used a wrist-worn IMU to detect when the arm entered or exited the water in the front-crawl, yet they simulated the movement on the swim-bench which considerably alters the normal swimming kinematics.

A missing point in the abovementioned studies is that in order to capture the common features in the studied population from IMUs' signals, the measurements should be insensitive to the placement of the IMUs on the body of different participants. Dadashi et al. (Dadashi, Crettenand, et al., 2013) introduced a novel approach for automatic temporal phase detection and IdC estimation in front crawl using two IMUs on the forearms and an IMU on the sacrum area (each IMU composed of a 3D accelerometer, 3D gyroscope as depicted in Fig. 2a). To guarantee that the method is not sensitive to the sensor placement, a functional calibration procedure was performed to align the sensors' axes to the body anatomical axes (Fig. 2b). The method was validated by comparison against a manual video analysis where a difference of $0.2 \pm 3.9\%$ between the two methods in assessment of the IdC was observed. The same group introduced a machine learning method for automatic detection of the breaststroke phases by using an IMU worn on the forearm and another IMU on the shank (Dadashi, Arami, et al., 2013). The method was validated against video footage and an average correct clas-

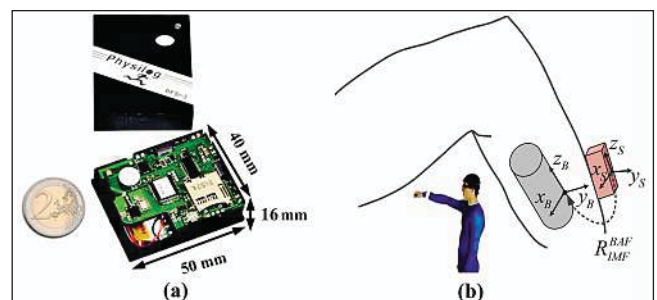


Figure 2: (a) The IMU used in (Dadashi, Crettenand, et al., 2013) and its dimensions. (b) The rotation matrix R_{IMF}^{BAF} transforms the sensor measurement to the segment movement that is computed using functional calibration. The functional calibration is composed of two uni-axial movements that allow aligning the IMU frame (IMF) to the bone anatomical frame (BAF).

sification of 93.5% for the arm phases, 94.4% for the leg stroke phases was obtained.

Assessment of swimming performance metrics

Velocity of swimming is the most intuitive hallmark of the performance. Other information such as variability of propulsion, duration of glide and stroke phase and symmetry of strokes can be acquired from instantaneous velocity monitoring. Besides, the study of other kinematics is a key to explain the difference of performance between skilled and less-skilled swimmers. Pansiot et al. (Pansiot, Lo, & Yang, 2010) used a 3D accelerometers attached to the swimming goggles strap to extract breathing pattern and stroke symmetry in front-crawl based on estimation of head orientation (Euler angles). Bächlin and Tröster (Bächlin & Tröster, 2012) used four 3D accelerometers on both wrists and upper and lower back to provide both swimming phase timing e.g. the wall-push-off, the wall-turns and the wall-strike events as well as body pitch and roll angle. They also proposed an audio-visual feedback to the swimmer through LEDs attached to the swimmer goggles and a piezo-electric beeper, though these feedbacks were not implemented in their system. Stamm et al. (Stamm, James, & Thiel, 2013) published a method using a 3D accelerometer on the lower back to measure the front crawl velocity. The main pitfall of all these methods that just use the 3D accelerometer is that the orientation information in the global frame of movement cannot be retrieved. Indeed, the projection of gravity on the acceleration in direction of movement is inseparable from movement acceleration that leads to serious inaccuracies. The instantaneous velocity of front-crawl swimming was estimated using a sacrum-worn IMU comprising a 3D accelerometer and a 3D gyroscope by applying the strap-down estimation of the IMU orientation using the angular velocity data (Dadashi, Crettenand, Millet, & Aminian, 2012). However, estimation of the velocity from the kinematics equation of motion requires an integration operation of IMU signals that leads to drifted velocity patterns due to intrinsic sensor noises. The proposed method attenuates the velocity drift by using a biomechanical constraint of front-crawl and prior knowledge about the pool length. The method was validated against a tethered reference system where an RMS error of 11.3 cm/s in instantaneous velocity estimation was observed that is in the range of the tethered system precision. Instantaneous velocity pattern can be used by coaches for subject-tailored training design. For instance, the velocity of the wall push-off exit, the velocity at first stroke initiation and also travelled distance at first stroke initiation can be calculated and then can be optimized as a race strategy for sprint events during training sessions (Fig. 3). Besides, the velocity variation around the average velocity can be assessed, that is an important classical determinant of swimming energy cost (Vilas-Boas, Fernandes, & Barbosa, 2010).

However, using the pool length for the velocity pattern offset correction restricts the application of the method to the full lap indoor conditions. A Gaussian regression framework in (Dadashi, Millet, & Aminian, 2013) was used to estimate the average cycle velocity of the front-crawl using a single sacrum worn IMU. The RMS error of the proposed system was 9.0 cm/s when compared with a commercial tethered reference. This system does not have limited capture volume and can be used even in open water. Potentially, once the model parameters are learnt, the model can be implemented

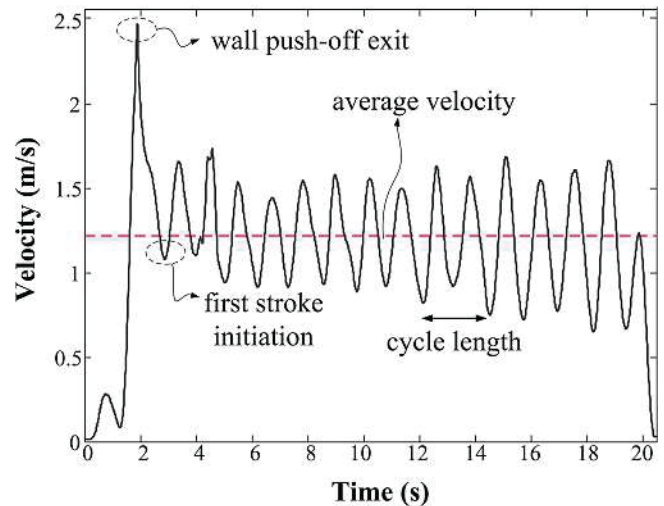


Figure 3: A typical instantaneous velocity profile provided by method in (Dadashi, et al., 2012). Different parameters extracted from the curve can be used to pinpoint the technical mistakes of the swimmer.

on a microprocessor for real-time velocity estimation. Real-time monitoring of cycle velocity can be effectively used to detect velocity anomaly as a sign of adverse condition that is a paramount to improve open-water safety.

Future perspective of IMUs in swimming biomechanics studies

By employing the wearable IMUs as explained in previous sections the study of technique variability becomes possible. In an attempt to sketch the future IMU-based developments for the study of swimming, two main research lines should be further investigated.

Firstly, skill progression can be effectively monitored through the study of both temporal and spatial inter-segmental coordination. Using underwater cameras, Seifert and co-workers (Seifert, Leblanc, Chollet, & Delignières, 2010) showed the application of continuous relative phase (CRP) to assess the inter-segmental coupling for evaluation of swimming technique. Although the recent works can pervasively track the temporal coordination (Dadashi, Arami, et al., 2013; Dadashi, Crettenand, et al., 2013), more developments in order to estimate inter-segmental kinematics are crucial. Estimation of inter-segmental angles using gyroscope signals suffers from integration drift. By, using movement constraints and/or complementary sensors like magnetometer in IMU this problem can be remedied.

Secondly, the estimation of energy expenditure using wearable IMU for different activities on-land has attracted several groups in the past decade (Sabatini, Martelloni, Scapellato, & Cavallo, 2004; Vathsangam, Emken, Schroeder, Spruijt-Metz, & Sukhatme, 2011). A recent work by our group showed the practicality of using wearable IMUs for the estimation of energy expenditure in front crawl (Dadashi, Millet, Crettenand, & Aminian, 2013). Three IMUs worn on the forearms and sacrum was used to extract IdC, velocity and velocity variability metrics to estimate the energy expenditure. The result was compared against the energy expenditure calculated based on using K4b2 telemetric gas exchange system (Cosmed, Italy) and taking blood lactate samples. The high relative precision of 9.7% is comparable to application of IMU for jogging and brisk walking (Panagiota, Layal, & Stefan, 2012). Yet, considering the contribution of leg kicks

to the energy expenditure can improve the results. Moreover, the methodology should be modified for other strokes.

Conclusion

The technical developments for assessment of swimming biomechanics are either too rudimentary or too complicated to deal with for a pervasive measurement of the athlete kinematics. The setup time, capturing volume, data processing time, resolution of measurement and number of swimmers that can be monitored at a time are the most critical problems that we face using the standard measurement systems in the pools. Wearable IMUs offer a user-centric and accurate solution to estimate temporal, coordinative and performance related parameters in swimming. Ensemble estimation of energy expenditure, coordination and velocity of the swimmer using wearable IMUs offers a convenient package to monitor the variability and also degradation of technique due to fatigue.

The bottom line is that wearable measurement systems are targeted to aid the coaches in designing an optimal personal training plan for athletes to improve their performance. More efficacious way to assist the coach intuition is designing an interface to superpose the parameters extracted from wearable IMU(s) (details of technique at stroke resolution) on the video recordings of the training sessions for a fast and comprehensible visualization.

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References

Abel-Aziz Y., & Karara H. (1971). Direct linear transformation from comparator coordinates into object space coordinates. Urbana, IL: American Society of Photogrammetry, 1–18.

Alberty M., Sidney M., Pelayo P., & Toussaint H.M. (2009). Stroking characteristics during time to exhaustion tests. *Medicine and Science in Sports and Exercise*, 41(3), 637–644.

Bächlin M., & Tröster G. (2012). Swimming performance and technique evaluation with wearable acceleration sensors. *Pervasive and Mobile Computing*, 8(1), 68–81.

Barbosa T., Fernandes R., Keskinen K.L., Colaço P., Cardoso C., Silva J., Vilas-Boas J.P. (2006). Evaluation of the energy expenditure in competitive swimming strokes. *International Journal of Sports Medicine*, 27(11), 894–899.

Barbosa T.M., Bragada J.A., Reis V.M., Marinho D.A., Carvalho C., Silva A.J. (2010). Energetics and biomechanics as determining factors of swimming performance: Updating the state of the art. *Journal of Science and Medicine in Sport*, 13(2), 262–269.

Bergamini E., Picerno P., Pillet H., Natta F., Thoreux P., & Camomilla V. (2012). Estimation of temporal parameters during sprint running using a trunk-mounted inertial measurement unit. *Journal of Biomechanics*, 45(6), 1123–1126.

Buchheit M., Al Haddad H., Millet G.P., Lepretre P.M., Newton M., Ahmadi S. (2009). Cardiorespiratory and cardiac autonomic responses to 30–15 intermittent fitness test in team sport players. *The Journal of Strength & Conditioning Research*, 23(1), 93–100.

Callaway A.J., Cobb J.E., Jones I. (2009). A comparison of video and accelerometer based approaches applied to performance monitoring in swimming. *International Journal of Sports Science and Coaching*, 4(1), 139–153.

Ceccon S., Ceseracciu E., Sawacha Z., Gatta G., Cortesi M., Cobelli C., Fantozzi S. (2013). Motion analysis of front crawl swimming applying CAST technique by means of automatic tracking. *Journal of Sports Sciences*, 31(3), 276–287.

Ceseracciu E., Sawacha Z., Fantozzi S., Cortesi M., Gatta G., Corazza S., Cobelli C. (2011). Markerless analysis of front crawl swimming. *Journal of Biomechanics*, 44(12), 2236–2242.

Chakravorti N., Le Sage T., Slawson S.E., Conway P.P., West A.A. (2013). Design and Implementation of an Integrated Performance Monitoring Tool for Swimming to Extract Stroke Information at Real Time. *Human-Machine Systems, IEEE Transactions on*, 43(2), 199–213.

Chardonens J., Favre J., Cuendet F., Gremion G., Aminian K. (2013). A system to measure the kinematics during the entire ski jump sequence using inertial sensors. *Journal of Biomechanics*, 46(1), 56–62.

Chatard J.C., Collomp C., Maglisco E., Maglisco C. (1990). Swimming skill and stroking characteristics of front crawl swimmers. *International Journal of Sports Medicine*, 11(2), 156–161.

Chollet D., Chaliès S., Chatard J.C. (2000). A new index of coordination for the crawl: Description and usefulness. *International Journal of Sports Medicine*, 21(1), 54–59.

Chollet D., Seifert L., Leblanc H., Boulesteix L., Carter M. (2004). Evaluation of arm-leg coordination in flat breaststroke. *International Journal of Sports Medicine*, 25(7), 486–495.

Dadashi F., Arami A., Crettenand F., Millet G., Komar J., Seifert L., Aminian K. (2013). A Hidden Markov Model of the Breaststroke Swimming Temporal Phases Using Wearable Inertial Measurement Units. Paper presented at the The 10th IEEE International Conference on Wearable and Implantable Body Sensor Networks (BSN), MIT, Cambridge, USA.

Dadashi F., Crettenand F., Millet G.P., Aminian K. (2012). Front-Crawl Instantaneous Velocity Estimation Using a Wearable Inertial Measurement Unit. *Sensors*, 12(10), 12927–12939.

Dadashi F., Crettenand F., Millet G.P., Seifert L., Komar J., Aminian K. (2013). Automatic front-crawl temporal phase detection using adaptive filtering of inertial signals. *Journal of Sports Sciences*, 31(11), 1251–1260.

Dadashi F., Millet G., Aminian K. (2013). Gaussian process framework for pervasive estimation of swimming velocity with a body-worn IMU. *Electronics Letters- IEE*, 49(1), 44–46.

Dadashi F., Millet G., Crettenand F., Aminian K. (2013). Towards Estimation of Frontcrawl Energy Expenditure Using the Wearable Aquatic Movement Analysis System (WAMAS). Paper presented at the The 10th IEEE International Conference on Wearable and Implantable Body Sensor Networks (BSN), MIT, Cambridge, USA.

Davey N., Anderson M., James D.A. (2008). Validation trial of an accelerometer-based sensor platform for swimming. *Sports Technology*, 1(4–5), 202–207.

Deschodt J.V., Arzac L.M., Rouard A.H. (1999). Relative contribution of arms and legs in humans to propulsion in 25-m sprint front-crawl swimming. *European Journal of Applied Physiology and Occupational Physiology*, 80(3), 192–199.

Di Prampero P., Pendergast D., Zamparo P. (2011). Swimming Economy (Energy Cost) And Efficiency. *World Book of Swimming: From Science to Performance*. Eds.: Seifert L., Chollet D., Mujika I, 297–312.

Di Prampero P.E. (1986). The energy cost of human locomotion on land and in water. *International Journal of Sports Medicine*, 7(2), 55–72.

Duc C., Salvia P., Lubansu A., Feipel V., Aminian K. (2013). Objective evaluation of cervical spine mobility after surgery during free-living activity. *Clinical Biomechanics*.

Figueiredo P., Barbosa T.M., Vilas-Boas J.P., Fernandes R.J. (2012). Energy cost and body centre of mass' 3D intracycle velocity variation in swimming. *European Journal of Applied Physiology*, 112(9), 3319–3326.

Figueiredo P., Zamparo P., Sousa A., Vilas-Boas J.P., Fernandes R.J. (2011). An energy balance of the 200 m front crawl race. *European Journal of Applied Physiology*, 111(5), 767–777.

Fulton S.K., Pyne D.B., Burkett B. (2009). Validity and reliability of kick count and rate in freestyle using inertial sensor technology. *Journal of Sports Sciences*, 27(10), 1051–1058.

Hanson N.J., Berg K., Deka P., Meendering J.R., Ryan C. (2011). Oxygen cost of running barefoot vs. running shod. *International Journal of Sports Medicine*, 32(6), 401–406.

Justham L., Slawson S., West A., Conway P., Caine M., Harrison R. (2008). Enabling Technologies for Robust Performance Monitoring (P10). *The Engineering of Sport* 7, 45–54.

Khoo B.H., Lee B.K.J., Senanayake S.M.N.A., Wilson B.D. (2009). System for determining within-stroke variations of speed in swimming (SWiSS). Paper presented at the IEEE AIM.

Kwon Y., Lindley S., Sanders R., Hong Y. (1999). Applicability of tour localized-calibration methods in underwater motion analysis. Paper presented at the Sci. Proc. of the XVII Inter. Symp. On Biomechanics in Sports.

Lee J.B., Burkett B.J., Thiel D.V., James D.A. (2011). Inertial sensor, 3D and 2D assessment of stroke phases in freestyle swimming.

Nigg B. (1983). Selected methodology in biomechanics with respect to swimming. *Biomechanics and medicine in swimming*, 72–80.

- Ohgi Y. (2002). Microcomputer-based Acceleration Sensor Device for Sports Biomechanics – Stroke Evaluation by using Swimmer's Wrist Acceleration. Paper presented at the Sensors.
- Panagiota A., Loyal S., Stefan H. (2012). Assessment of human gait speed and energy expenditure using a single triaxial accelerometer. Paper presented at the 9th International Workshop on Wearable and Implantable Body Sensor Networks.
- Pansiot J., Lo B., Yang G.Z. (2010). Swimming stroke kinematic analysis with BSN. Paper presented at the International Conference on Body Sensor Networks, Singapore.
- Pendergast D., Di Prampero P., Craig A., Rennie D. (1978). The influence of some selected biomechanical factors on the energy cost of swimming. *Swimming Medicine IV*, 367–378.
- Puel F., Morlier J., Avalos M., Mesnard M., Cid M., Hellard P. (2012). 3D kinematic and dynamic analysis of the front crawl tumble turn in elite male swimmers. *Journal of Biomechanics*, 45(3), 510–515.
- Sabatini A.M., Martelloni C., Scapellato S., Cavallo F. (2004). Energy expenditure rate in level and uphill treadmill walking determined from empirical models and foot inertial sensing data. *Electronics Letters*, 40(2), 95–96.
- Sanders R.H., Psycharakis S.-G. (2009). Rolling rhythms in front crawl swimming with six-beat kick. *Journal of Biomechanics*, 42(3), 273–279.
- Schnitzler C., Seifert L., Ernwein V., Chollet D. (2008). Arm coordination adaptations assessment in swimming. *International Journal of Sports Medicine*, 29(6), 480–486.
- Seifert L., Chollet D. (2005). A new index of flat breaststroke propulsion: A comparison of elite men and women. *Journal of Sports Sciences*, 23(3), 309–320.
- Seifert L., Komar J., Leprêtre P., Lemaitre F., Chavallard F., Alberty M., Hellard P. (2010). Swim Specialty Affects Energy Cost and Motor Organization. *International Journal of Sports Medicine*, 31(09), 624–630.
- Seifert L., Leblanc H., Chollet D., Delignières D. (2010). Inter-limb coordination in swimming: Effect of speed and skill level. *Human Movement Science*, 29(1), 103–113.
- Seifert L., Toussaint H.M., Alberty M., Schnitzler C., Chollet D. (2010). Arm coordination, power, and swim efficiency in national and regional front crawl swimmers. *Human Movement Science*, 29(3), 426–439.
- Slawson S., Justham L., West A., Conway P., Caine M., Harrison R. (2008). Accelerometer profile recognition of swimming strokes. *The Engineering of Sport*, 7, 81–87.
- Smith N. (2009). Olympic time [Electronic timekeeping]. *Engineering and Technology*, 4(6), 36–39.
- Stamm A., James D.A., Thiel D.V. (2013). Velocity profiling using inertial sensors for freestyle swimming. *Sports Engineering*, 16(1), 1–11.
- Tella V., Toca-Herrera J.L., Gallach J.E., Benavent J., González L.M., Arellano R. (2008). Effect of fatigue on the intra-cycle acceleration in front crawl swimming: A time-frequency analysis. *Journal of Biomechanics*, 41(1), 86–92.
- Vathsangam H., Emken A., Schroeder E.T., Spruijt-Metz D., Sukhatme G.S. (2011). Determining energy expenditure from treadmill walking using hip-worn inertial sensors: An experimental study. *Biomedical Engineering, IEEE Transactions on*, 58(10), 2804–2815.
- Vilas-Boas J., Fernandes R., Barbosa T. (2010). Intra-cycle velocity variations, swimming economy, performance and training in swimming. *World Book of Swimming: From Science to Performance*. Eds.: Seifert L., Chollet D., Mujika I, 119–134.
- Zeng H., Zhao Y. (2011). Sensing movement: Microsensors for body motion measurement. *Sensors*, 11(1), 638–660.
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