DOCTORAL THESIS

A Novel Approach for Aquatic Gait Analysis Using Wearable Inertial and Hydrodynamic Pressure Sensors

Cecilia Monoli

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CECILIA MONOLI

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TALLINN UNIVERSITY OF TECHNOLOGY
School of Information Technologies
Department of Computer Systems

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Supervisor: Assoc. Prof. Jeffrey A. Tuhtan, PhD
Department of Computer Systems, School of Information Technologies
Tallinn University of Technology
Tallinn, Estonia

Supervisor: Prof. Manuela Galli, PhD
Department of Electronics, Information and Bioengineering
Politecnico di Milano
Milano, Italy

Co-supervisor: Assoc. Prof. Alessandro Colombo, PhD
Department of Electronics, Information and Bioengineering
Politecnico di Milano
Milano, Italy

Opponents: Helena Gapeyeva, MD, PhD
Clinic of Medical Rehabilitation
East Tallinn Central Hospital
Tallinn, Estonia

Peter Wolf, PhD
Sensory-Motor Systems Lab, Department of Health Sciences and Technology ETH Zurich
Zurich, Switzerland

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the double doctorate degree at Tallinn University of Technology and at Politecnico di Milan, has not been submitted for a doctoral or equivalent academic degree.

Cecilia Monoli

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Uudne lähenemisviis veealuse kõnnaku analüüsiks, kasutades kantavaid inertsiaalseid ja hüdrodünaamilisi rõhuandureid

CECILIA MONOLI

POLITECNICO DI MILANO

DEPARTMENT OF ELECTRONICS, INFORMATION AND BIOENGINEERING
DOCTORAL PROGRAMME IN BIOENGINEERING

A NOVEL APPROACH FOR AQUATIC GAIT ANALYSIS USING WEARABLE INERTIAL AND HYDRODYNAMIC PRESSURE SENSORS

Doctoral dissertation of:

Cecilia Monoli

Supervisor:

Prof. Manuela GALLI

Supervisor:

Prof. Jeffrey A. TUHTAN

Co-Supervisor:

Prof. Alessandro COLOMBO

2024 – XXXVI Cycle

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Abstract

A Novel Approach for Aquatic Gait Analysis Using Wearable Inertial and Hydrodynamic Pressure Sensors

The lack of adequate technologies and protocols specifically developed and tailored for aquatic motion analysis hinders its evaluation and understanding. Therefore, knowledge of the impact of aquatic physical therapy on quality of life and motor skills remains limited. This Ph.D. thesis aims to address these deficiencies by developing, testing, and validating a method based on new wearable inertial and hydrodynamic pressure sensors for aquatic gait analysis. Four research objectives (RO) are defined and supported by peer-reviewed publications that provide valuable insight into aquatic motion analysis.

A systematic review of the literature (RO1) defined the state-of-the-art of aquatic motion analysis, with a focus on wearable technologies. The objective was to identify research gaps and deficiencies in methodologies and protocols. Only 23 of the 572 eligible papers used wearable technologies for aquatic motion analysis. The review also highlighted the absence of versatile and reproducible monitoring methods, limited whole-body or longitudinal research with wearables, and the overreliance on land-based measurements and assessment parameters. RO2 validated a wearable inertial measurement unit sensor system and processing method for gait analysis on land and in water. A proof-of-concept study compared the novel system with two gold standard methods, measuring knee angle during gait both in and outside water, showing reliability and portability ($r>0.8$ in all land tests, 93% in aquatic tests). An improved version of the technology, which integrates inertial and pressure sensors, was tested against an optoelectronic system in a motion laboratory, evaluating temporal gait and knee joint parameters, demonstrating good accuracy and reliability (RMSE for stride time $\sim$3% of the gait cycle). The sensors were further used in clinical trials to analyse differences in walking gait in and out of water (RO3). A novel pilot study was also conducted on backward aquatic walking with wearable sensors. The tests revealed a greater variability of the classical gait parameters in water (coefficient of variation 31.02% on land, 60.57% in water). Results of RO3 suggested that relying on parameters defined for overground walking may not provide an accurate description of aquatic motion. RO4 analysed the lateral hydrodynamic pressure on the lower extremities during aquatic gait, with the aim of exploring whether such parameter would give a better understanding of aquatic motion. It was observed a variation of hydrodynamic pressure at the foot (39.65%) comparable to the one measured for the knee angle on land (31.20%). These results suggest that hydrodynamic pressure might be a reliable metric to describe aquatic walking, enhancing our understanding of aquatic motion by characterizing the interaction between the submerged body and the fluid.

This dissertation aims to address the limited availability of wearable monitoring methods for aquatic motion analysis, as well as the predominant reliance on land-based parameters. By introducing new insights and methodologies, it contributes to the advancement of our knowledge on aquatic motion. The thesis proposes hydrodynamic pressure on the lower extremities as a novel way to describe aquatic locomotion. The developed wearable inertial technology, along with the use of hydrodynamic pressure, demonstrated to be a versatile and reproducible method for aquatic gait analysis. This work provides a more nuanced understanding of how the presence of water influences movements, potentially influencing the development of aquatic rehabilitation protocols in future studies.

Kokkuvõte

Uudne Lähenemisviis Veealuse Kõnnaku Analüüsiks, Kasutades Kantavaid Inertsiaal- ja Dünaamilisi Rõhuandureid

Veekeskkonnas liikumise hindamist ja mõistmist takistab spetsiaalselt selle valdkonna jaoks väljatöötatud asjakohaste tehnoloogiate ja protokollide puudumine. Seetõttu on teadmised vesifüsioteraapia mõju kohta elukvaliteedile ja motoorsetele oskustele endiselt piiratud. Käesoleva doktoritöö eesmärk on kõrvaldada need puudujäägid, arendades, katsetades ja valideerides meetodit, mis põhineb uutel kantavatel, veealuse kõnnaku analüüsiks mõeldud inertsiaal- ja dünaamilistel rõhuanduritel. Määratletakse neli uurimisülesannet (UÜ), mida toetavad eelretsenseeritud publikatsioonid, mis annavad väärtusliku ülevaate veealuse liikumise analüüsist.

Kirjanduse süstemaatilises ülevaates (UÜ1) määratleti veealuse liikumisanalüüsi hetkeseis, keskendudes kantavatele tehnoloogiatele. Eesmärgiks oli tuvastada teadusuuringute lüngad ning puudujäägid metoodika ja protokollide osas. Vaid 23 teadusartiklit 572-st kasutasid veealuse liikumise analüüsiks kantavaid tehnoloogiaid. Ülevaates toodi esile ka mitmekülgsete ja korratavate seiremeetodite puudumine, piiratud kogu keha või pikiuuringud kantavate seadmetega ning liigne tuginemine maismaapõhistele mõõtmistele ja hindamisparameetritele. UÜ2 valideeris kantava inertsiaalse mõõtmisseadmega andurisüsteemi ja töötlemismeetodi kõndimise analüüsiks maal ja vees. Kontseptsiooni valideerimisuuringus võrreldi uudset süsteemi kahe kuldstandardmeetodiga, mõõtes põlvenurka kõndimise ajal nii vees kui ka väljaspool vett, näidates usaldusväärsust ja kohandatavust ($r>0{,}8$ kõigis maismaa testides, 93% veekatsetes). Tehnoloogia täiustatud versiooni, mis sisaldab inertsiaal- ja rõhuandureid, testiti võrdluses optoelektroonilise süsteemiga liikumislaboris, hinnates ajalisi kõnni- ja põlveliigese parameetreid, näidates head täpsust ja usaldusväärsust (RMSE sammuajal $\sim$3% kõndimistsüklist). Andureid kasutati ka kliinilistes uuringutes, et analüüsida erinevusi kõndimises vees ja maal (UÜ3). Samuti viidi läbi uudne katse kantavate anduritega, vees tagurpidi kõndimise kohta. Katsed näitasid klassikaliste kõnni parameetrite suuremat varieeruvust vees (variatsioonikoefitsient 31,02% maismaal, 60,57% vees). UÜ3 tulemused näitasid, et maismaal kõndimiseks määratletud parameetritele tuginedes ei pruugi vees toimuvat liikumist täpselt kirjeldada. UÜ4 analüüsis alajäsemete külgsuunalist hüdrodünaamilist survet vees kõndimise ajal, et uurida, kas selline parameeter annaks parema ülevaate vees liikumisest. Täheldati hüdrodünaamilise surve muutumist jalalaba juures (39,65%), mis on võrreldav maismaal mõõdetud põlvnurga muutumisega (31,20 %). Need tulemused viitavad sellele, et hüdrodünaamiline surve võib olla usaldusväärne mõõdik veealuse kõndimise kirjeldamiseks, ning parandab meie arusaamist veealuse liikumise kohta, iseloomustades veealuse keha ja vedeliku vahelist vastastikmõju.

Käesoleva doktoritöö eesmärk on käsitleda veealuse liikumise analüüsiks kasutatavate kantavate seiremeetodite piiratud kättesaadavust ning valdavat tuginemist maismaapõhistele parameetritele. Uute arusaamade ja meetodite tutvustamisega aitab see kaasa meie teadmistele veealuse liikumise kohta. Doktoritöös pakutakse välja hüdrodünaamiline surve alajäsemetele kui uudne viis veealuse liikumise kirjeldamiseks. Välja töötatud kantav inertsiaalne mõõtetehnoloogia koos hüdrodünaamilise rõhu kasutamisega osutus mitmekülgseks ja korratavaks meetodiks veealuse kõnnaku analüüsiks. See töö võimaldab paremini mõista, kuidas vee olemasolu mõjutab liikumist ja võib mõjutada veealaste rehabilitatsiooniprotokollide väljatöötamist tulevastes uuringutes.

List of publications

This Ph.D. thesis is based on the following peer-reviewed publications that are referred to in the text by Roman numbers.

I C. Monoli, J. A. Tuhtan, L. Piccinini, and M. Galli, “Wearable technologies for monitoring aquatic exercises: A systematic review,” Clinical Rehabilitation, vol. 37, no. 6, pp. 791–807, 2023. PMID: 36437591. DOI: 10.1177/02692155221141039.

II C. Monoli, J. F. Fuentez-Pérez, N. Cau, P. Capodaglio, M. Galli, and J. A. Tuhtan, “Land and underwater gait analysis using wearable imu,” IEEE Sensors Journal, vol. 21, no. 9, pp. 11192–11202, 2021. DOI: 10.1109/JSEN.2021.3061623.

III C. Monoli, M. Galli, and J. A. Tuhtan, “Improving the reliability of underwater gait analysis using wearable pressure and inertial sensors,” PLOS ONE, vol. 19, pp. 1–15, 03 2024. DOI: 10.1371/journal.pone.0300100.

Conference abstracts

IV C. Monoli, I. Gasparini, L. Piccinini, J. A. Tuhtan, and M. Galli, “Comparing land and underwater gait characteristics with inertial measurement units.” 26th Congress of the European Society of Biomechanics - ESBiomech2021, July 11-14, 2021.

V C. Monoli, M. Galli, and J. A. Tuhtan, “In water and on land forward and backward spatiotemporal gait characteristics.” 28th Congress of the European Society of Biomechanics - ESBiomech2023, July 9-12, 2023.

Other related publications

1 L. Donno, C. Monoli, C. A. Frigo, and M. Galli, “Forward and backward walking: Multifactorial characterization of gait parameters,” Sensors, vol. 23, no. 10, 2023. DOI: 10.3390/s23104671.

2 C. Monoli, G. Simoni, J. A. Tuhtan, E. Palermo, M. Galli, and A. Colombo, “Motion analysis of therapeutic climbing: a rehabilitation tool for children with cerebral palsy.” 27th Congress of the European Society of Biomechanics - ESBiomech2022, June 26-29, 2022.

3 M. Gobbi, A. Aquiri, C. Monoli, N. Cau, and P. Capodaglio, Aquatic Exercise, pp. 35–50. Cham: Springer International Publishing, 2020. DOI: 10.1007/978-3-030-32274-8_3.

Author’s contributions to the publications

I In **Publication I**, the author led the investigation, defined the research questions, conducted literature search, filtered and selected the eligible papers for the qualitative synthesis, analysed and interpreted the results, and was main author of the manuscript.

II In **Publication II**, the author played a significant role in various aspects of the project, including the definition of the research problem, designing the protocol, overseeing subject recruitment, conducting experiments, and analyzing results. The author was the main contributor of the paper, wrote the manuscript, and was the corresponding author.

III In **Publication III**, the author directed the project, handling tasks such as defining the research problem, designing the protocol, recruiting participants, conducting experiments, and creating analysis algorithms. The author also analyzed and interpreted the results, wrote the manuscript, and served as the corresponding author for communication during the publication process.

IV In **Publication IV**, the author wrote the abstract and delivered the podium conference presentation, defined the research problem, protocol, and experiments. The author performed the tests, analyzed the data and interpreted the results.

V In **Publication V**, the author outlined the research problem, defined the research protocol, and carried out the experiments. The author performed the tests, analysed the data and explained what the results meant. The author created a summary and presented at the conference.

Abbreviations

A	Accelerometer
ACL	Anterior Cruciate Ligament
AHRS	Attitude and Heading Reference System
AKP	Anterior Knee Pain
BW	Backward Walking
COP	Center Of Pressure
CV	Coefficient of Variation
DL	Dry Land
EMG	Electromyography
FP	Force Plates
FW	Forward Walking
G	Gyroscope
GPR	Gaussian Process Regression
GRF	Ground Reaction Forces
H	Healthy
HR	Heart Rate
HS	Heel Strike
IMU	Inertial Measurement Unit
IQR	Interquartile Range
iSCI	incomplete Spinal Cord Injury
MoCap	Motion Capture
OPTO	Optoelectronic
PIMU	Pressure and Inertial Measurement Unit
Q1	First Quartile
Q2	Third Quartile
QOL	Quality of Life
ρ	Pearson's Correlation Coefficient
r	Spearman Correlation Coefficient
RMSE	Root Mean Squared Error
RO	Research Objective
ROM	Range Of Motion
ROP	Range Of Pressure
RPE	Rate of Perceived Exertion
S	Squats
SLS	Single Limb Squats
SS	Split Squats
TO	Toe Off
UW	Underwater

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1 Introduction

1.1 Background

Biomechanical motion analysis, as the study of human movement [11, 12], traces back to the XV century with Leonardo da Vinci's "Notes on the Human Body" [13]. Over time, the initial fascination with the mechanisms behind movement shifted to an accurate and quantitative evaluation of motion and the interpretation of its results and outcomes. Understanding motion became valuable in fields such as medicine (clinical, orthopedic, and rehabilitative), defining normality ranges, detecting abnormalities, and monitoring changes in individuals. Efficient mobility also plays a crucial role in daily activities for an acceptable quality of life and in sports performance, assisting with training design and performance monitoring.

Technological advancements have revolutionized biomechanical motion analysis (Figure 1.1), resulting in standardized methods for the systematic assessment of movement [14]. Initially (Figure 1.1*a*), observations and interpretations were only qualitative, limiting the description of movement to a subjective evaluation that showed poor cross-comparability between methods. The introduction of movie cameras (Figure 1.1*b*) improved the description of motion and allowed quantitative results such as body coordinate graphs, stick diagrams, and measurements of gait velocities, trajectories, and accelerations, load lifted, or jump height [11]. These, while easy to interpret, rely on the restricted field of view of the camera, which confines the analysis of wide gestures and allows only bidimensional planar observations, not corresponding to the true anatomical movements. With the development of computers (Figure 1.1*c*), motion analysis has become more accurate. Multiple cameras, with markers on anatomical landmarks, allow three-dimensional assessments, internal anatomical reconstruction, and the estimation of various quantitative parameters and performance indices. Despite these advances and high accuracy, video-based methods are still limited by a restricted field of view and a time-consuming setup. The latest development in biomechanical motion analysis involves the combination of computing and machine learning techniques (Figure 1.1*d*). Wearable wireless devices, mainly based on inertial measurement unit sensors (IMUs), with real-time data processing and interpretation, promise high accuracy and reliability in real-life contexts. Although still in development and with data processing limitations and constraints, wearable IMUs are gaining popularity in sports science.

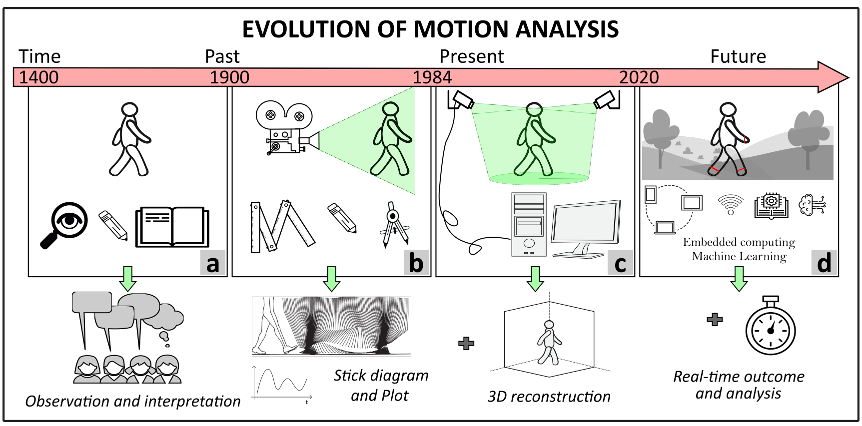


Figure 1.1: Evolution of biomechanical motion analysis.

1.1.1 Methods for motion analysis

Motion analysis methods can be broadly classified into quantitative and qualitative assessment tools [15]. *Quantitative methods* involve objective measures of kinematic and kinetic parameters, joint Range of Motion (ROM), centers of rotation, and ground reaction forces [16]. In contrast, *qualitative evaluations* are based on subjective evaluations through questionnaires and clinical scales, covering aspects such as mobility, perception of fatigue, and quality of life related to movement [17].

In the realm of *quantitative motion assessment*, different degrees of accuracy are achievable, and the most prevalent technique for kinematic assessments is ***camera-based motion capture*** (MoCap). MoCap employs traditional or infrared video cameras, offering both two-dimensional (using one camera) and three-dimensional (using more cameras) analysis of motion. Further categorization is possible between *marker-based* and *marker-less* MoCap depending on whether specific markers or tracers, which can be passive or active (usually LED lights), are used to track movement within video frames. When multiple infrared cameras are used, the MoCap is an ***optoelectronic system***, regarded the gold standard in biomechanical motion analysis due to its precision and accuracy [18]. Passive light reflecting markers are placed on the body surface following precise protocols based on anatomical landmarks [15]. The reflected brightness is recorded by the cameras, enabling reconstruction of the marker positions. Subsequently, the coordinates of the markers are extracted and the movement is tracked using recursive estimation and stereophotogrammetry, producing a three-dimensional reconstruction of the movement [19]. Although the optoelectronic system exhibits high accuracy, as with all MoCap systems, it faces limitations in terms of the investigated area, limited by the field of view and the volume captured by the cameras [20]. Furthermore, markers must be constantly visible to at least two cameras [21], and traditional video cameras may have insufficient sampling rates to accurately capture fast movements, such as running or jumping [22]. Finally, uncertainties and errors can also be caused by misplacement of markers and *soft tissue artifacts*, defined as the error that occurs when estimating bone motion through surface markers, caused by the relative motion between the skin and the underlying layers. Despite these limitations and its high cost and time-consuming setup, the optoelectronic system and marker-based MoCaps remain the most common techniques for motion analysis, known for their reliability and accuracy of about 63±5μm and a precision of 15μm [23]. Motion analysis through video cameras can also be carried out without the need for markers or special clothing on the subject's body, exploiting *marker-less MoCap* [24]. This approach reduces setup time and the need for trained operators to place the markers accurately. It is based on the use of computer vision systems and models, including convolutional neural networks for human recognition, pose estimation, and motion tracking [25]. Although markerless MoCap is user-friendly and convenient, especially in sport science and real-life settings, it currently does not reach the same level of accuracy as the optoelectronic system and is not suitable for clinical and diagnostic applications [26].

Alternatively to MoCap, there is a growing preference for employing ***inertial systems*** in motion analysis [27]. *Inertial Measurement Unit sensors* (IMUs) are small and lightweight devices that combine accelerometers, gyroscopes, and magnetometers to measure position, orientation, speed, and acceleration [28]. Acceleration is detected with accelerometers, gyroscopes measure the angular velocity, and magnetometers record the variability of the Earth's magnetic field in addition to the local field. The combination of these components enables the study of motion kinematics. Placing the IMUs directly onto the body segments allows one to assess their orientation relative to an Earth-fixed reference frame, from which kinematics can be investigated [29]. IMUs facilitate motion analysis in three dimensions, with high sampling rate, direct data streams, and without spatial constraint, which is especially useful in real-life contexts. Wearable inertial sensors find applications in fall prevention, posture analysis, rehabilitation, and sports science [30]. However, wearable IMU usage does come with challenges, including dealing with soft tissue artifacts, potentially uncomfortable sensor placement (especially in pathological cases), and complex data processing and parameter estimation [29].

Other methods and tools are often used for motion analysis, solely or in combination with MoCap and IMUs. *Electrogoniometers* use two potentiometers connected to body segments to measure the angles of the planar joint. Although it allows direct data analysis, the system can be cumbersome and uncomfortable [19]. *Electromyography* (EMG) quantifies the electric signals generated by muscle contraction and activation [31]. EMG uses surface or intramuscular electrodes, but has limitations in terms of placement, measurement errors, and potential discomfort or pain [32]. *Force plates* (FP) evaluate the interaction between the body in motion and the ground, namely, the reaction forces of the ground. FPs are generally mounted on the floor and are used in controlled environments [33]. Finally, *dynamometers* assess muscle strength, which is useful to track progress and standardization, although they lack specificity to identify task-specific weaknesses or imbalances [34].

The array of available motion analysis methods, their strengths and limitations, point out the importance of carefully considering both the specific type of movement to be analysed and the environmental conditions in which the investigation will be performed [35]. It is crucial to select the most suitable method to achieve the intended purpose that offers the highest reliability and comfort, with the fewest compromises possible. For example, for clinical and diagnostic investigations, the optoelectronic system is the preferred choice because of its reliability and accuracy. However, it comes with the drawback of necessitating a highly controlled laboratory environment. In such a controlled setting, awareness of being observed and evaluated can influence subjects to perform at their best, potentially introducing measurement bias, especially when involving pathological subjects. On the contrary, when measuring real-life movements or performing evaluations in natural settings (e.g., evaluating a soccer player during a game), IMU sensors become the preferred option. These sensors offer the advantage of freedom from environmental constraints. However, this choice may involve a trade-off, as it may come at the cost of slightly lower biomechanical accuracy.

1.1.2 Gait analysis

Walking is a fundamental aspect of daily life and is closely related to quality of life [36]. Many functional scales consider walking ability to be a key indicator of general health and autonomy, such as the Gross Motor Function Classification System, which assesses mobility in people with Cerebral Palsy [37].

Despite its apparent simplicity, walking involves intricate sensorimotor interactions [9], and gait analysis, the systematic assessment of walking, plays a crucial role in objectively measuring this motor task with applications in biomechanics, physiology, and human performance evaluations [38]. Gait analysis is valuable in clinics, as pretreatment assessment and postoperative follow-up, as well as for surgical or rehabilitative decision making. It is also crucial for the diagnosis and monitoring of motor pathologies, chronic conditions, and neuromuscular disorders, for the evaluation of prosthetic joint replacement, orthotics, and assistive devices, and for the study of athletic performance [39, 40].

Gait analysis follows an established nomenclature and classification with known characteristics and features, such as joint angles, angular velocities and accelerations, ground reaction forces, electromyographic activity, joint forces, moments and powers [9, 27, 41]. Walking, schematically reported in Figure 1.2, is divided into repeated ***gait cycles***, or *strides*, defined as movements occurring between two subsequent ipsilateral foot strikes. Between two foot strikes (or Heel strikes, HS), the other main gait event occurs, called toe-off (TO), identified as the moment of final contact. A gait cycle is divided into two main phases: the ***stance phase*** is the fraction of the gait cycle when the foot is on the ground, from HS to TO, taking up approximately 62% of the cycle; the ***swing phase***, is the remaining portion of the cycle (about 38%) in which the foot is not in contact with the ground, from TO to HS, when the contralateral limb is in the stance phase. Stance is further divisible into three sub-phases. *Early stance*, occurs from HS to the opposite leg TO. During this double-limb support, the ankle passes from heel contact to full foot contact and the knee flexes to absorb the shock of limb loading. *Mid stance* takes place from complete foot contact to opposite HS, where the opposite leg is not in contact with the ground and the trunk progresses over the stable limb. The stance phase ends with another double-limb support, called *late* or *terminal stance* in which the heel rises and prepares for TO. Similarly, the swing phase can be subdivided into sub-phases: *early swing* occurs from TO until the leg reaches the contralateral stationary leg (foot clearance); *mid-swing*, entails from foot clearance to tibia vertical; and *terminal swing*, defined from vertical tibia to HS.

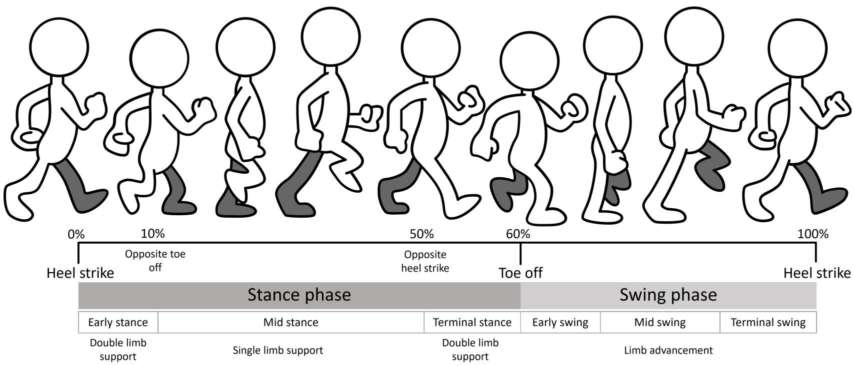


Figure 1.2: Sketch map of a complete gait cycle highlighting its phases and sub-phases, after [9].

1.1.3 Aquatic physical activity

Aquatic therapy encompasses different approaches, such as passive immersion in hot or cold water or active physical therapy, with the common goal of using the physical characteristics of water to promote health [8, 42, 43]. Specifically, the buoyancy provided by water results in a reduction in object weight, which implies a reduction in the strength applied to the joints, better cartilaginous irrigation, and posture control [44]. Hydrostatic pressure, distributed uniformly and orthogonally on a body immersed in water, helps support and stabilize, improving equilibrium and proprioception [45]. The density of water is made so that the submerged motion faces greater resistance, stimulating the muscoloskeletal, cardiovascular, and cardiocirculatory systems, and improving the reinforcement of muscles in terms of tone and flexibility, stability, and balance [46, 47]. Different water temperatures also influence metabolic and heart rate, resulting in anesthetic effects, reductions in edema, muscle relaxation, and vasodilation [48]. Finally, water is perceived as a safe and playful environment, which motivates patients to participate in activities that can be challenging in the air and can improve their commitment to long-term rehabilitation protocols [49].

Aquatic physical activity is aimed at various subjects, mainly affected by pathologies or injuries that limit the performance of the musculoskeletal system, the range of motion of the joints, balance, or daily activities related to movement [44, 50–52]. For example, in sport medicine and rehabilitation, aquatic therapy is used for muscle and task-specific training, endurance, to relax and avoid overtraining and injuries, and during injury recovery [53]. Water also shows positive effects in the treatment of neurological and musculoskeletal disorders, chronic and degenerative conditions such as fibromyalgia [54], osteoarthritis [55], Parkinson's disease [47], multiple sclerosis [56], asthma [57], hemophilia [58], chronic obstructive pulmonary disease [59] and chronic heart disease [60].

Although water is considered one of the most suitable environments for rehabilitation [47], classically used methods and protocols to investigate the kinematics of living organisms are hardly applicable in this environment. Electrical components constitute a strong limitation to the use in water of most of the methods seen in the previous section (Section 1.1.1). For example, the optoelectronic system is not suitable outside of motion capture laboratories, as it requires expensive and cumbersome cable-based instrumentation [61]. Infrared cameras are also not applicable to the water environment due to interference caused by water and other surfaces. The company Qualisys provides a commercial video system specifically designed for underwater measurements, but it is very expensive and still requires cables [62]. Finally, while traditional cameras can be used underwater using waterproof cases, the images recorded are heavily affected by the lens and colors distortion caused by the fluid, reducing the field of view even more. Therefore, portable IMU devices appear to be the most valuable method for aquatic biomechanical motion analysis due to their small dimensions, waterproofness, and absence of physical space restrictions.

1.1.4 Performance evaluation criteria

This dissertation envisions the development and validation of a novel IMU-based technology for aquatic motion analysis. Gait is the selected task due to its importance, known characteristics, apparent simplicity, and repeatability (Section 1.1.2). A summary of the parameters investigated and the analytical tools used for the validation is given to avoid misinterpretation and redundancy throughout the work.

Gait analysis: temporal gait parameters and knee kinematics

Investigating walking, the focus is on the temporal gait parameters and the kinematics of flexion-extension of the knee joint.

A gait cycle is defined identifying the gait events of HS ad TO (Section 1.1.2, Figure 1.2), allowing to estimate five **temporal gait parameters** for each gait cycle *k* [9]:

Stride time: time of a complete gait cycle, in seconds (s)

$$t_{cycle}(k) = HS(k+1) - HS(k) \tag{1}$$

Stance time: portion of the gait cycle in which the foot is in contact with the ground (from HS to TO), in seconds (s)

$$t_{stance}(k) = TO(k) - HS(k) \tag{2}$$

or as a percentage of the gait cycle, called *stance percentage*

$$p_{stance}(k) = \frac{t_{stance}(k)}{t_{cycle}(k)} * 100 \tag{3}$$

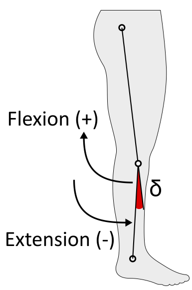
Swing time: portion of the gait cycle in which the foot is flying and progressing (from TO to HS), in seconds (s)

$$t_{swing}(k) = HS(k+1) - TO(k) \tag{4}$$

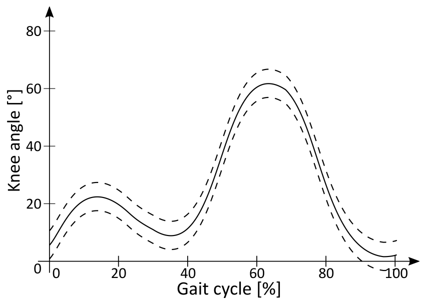
or as a percentage of the gait cycle, called *swing percentage*

$$p_{swing}(k) = \frac{t_{swing}(k)}{t_{cycle}(k)} * 100 \tag{5}$$

The **knee joint** during gait is investigated due to the fundamental role of this joint during locomotion, supporting body weight, absorbing shocks at heel strike and assisting the swing phase [63]. The main and most investigated movement is the **flexion-extension** on the sagittal plane (anterior-posterior), designated by convention as positive in flexion and negative in extension [10], as reported in Figure 1.3a. The physiological displacement of the knee joint during walking is commonly normalized throughout the gait cycle, as is visible in Figure 1.3b, and follows a standard behavior. During the stance phase (up to about 68% of the gait cycle), the knee joint is responsible for the shock damping mechanism to accept body weight, resulting in a maximum flexion at about 15% of the cycle during the loading phase and an extension peak at about 40% of the gait prior to the opposite heel strike. The swing phase is instead characterized by a maximum peak flexion at about 70% of the gait, when the knee assists flexion-extension, and by a maximal extension at the end of the cycle, for foot clearance and placement, in preparation for the next step.



(a) Knee convention angle.



(b) Knee flexion-extension curve.

Figure 1.3: Knee joint angle characteristics during walking: (a) convention used for the knee angle δ, where flexion is defined positive and extension negative; (b) flexion-extension curve over the gait cycle and Coefficient of Variation (CV =23%) during gait cycle at natural cadence, after [10].

In this dissertation, the knee kinematics during the gait cycle is characterized by estimating *maximum flexion* and *maximum extension*, and calculating the knee *range of motion* (ROM), as the difference between them. However, while the kinematic characteristics of the knee flexion-extension angle are generally preserved and comparable, each gait is specific and differs within and between subjects, for example, depending on the cadence [10, 11].

Gait variability estimates how consistent subjects are, between sessions within themselves or between subjects. Variability has significant clinical value, particularly in human locomotion [64], being an index of gait stability and complexity, and serving as a useful indicator of the risk of falls [65] and the ability to adapt to changing conditions. The loss of gait variability, reflecting stiffened motion, has been observed in advanced aging and in the presence of neurological pathologies such as Parkinson's disease [66]. In contrast, higher variability, the symptom of worsening gait consistency [67], is common in patients with knee osteoarthritis [68]. Therefore, it is important that a novel method for gait analysis is able to accurately measure the *average variability of the mean waveform* throughout different repetitions and subjects with the *Coefficient of Variation* (CV) [10, 11, 69].

CV is a variability to mean ratio ($CV = \sigma/X$, where σ is the standard deviation and X the sample mean) that, combined with the ensemble average, allows to calculate a variability score of the average standard deviation over the stride period. After normalization of the knee angle over the gait cycle, the stride period is divided into equal intervals (i.e. 1%, 2%, 5%) and for each the average angle and its standard deviation are evaluated. The CV is then calculated by taking the mean variability over the stride period and expressing it as a percentage of the mean value of the signal:

$$CV = \frac{\sqrt{\frac{1}{N}\sum\limits_{i=1}^{N}\sigma_i^2}}{\frac{1}{N}\sum\limits_{i=1}^{N}|X_i|} \tag{6}$$

where N is the number of intervals over the stride, X_i is the mean value of the variable at the i-th interval, σ_i is the standard deviation of the variable X about X_i.

CV is expected to be about 23% for natural cadence, 18% for faster walking, and 26% for slow walking, indicating that slower gait cycles are less consistent with each other and are generally more variable [10]. Additionally, in this dissertation, the z-scored coefficient of variation (CV_z) of knee flexion-extension is estimated. This, to compare the variability of different parameters, is calculated applying Equation 6 after the data have been z-scored by subtracting the mean and dividing by the standard deviation at each time-stamp.

Statistical measures and plotting tools

The following analytical tools are used to validate the proposed method and technology through a performance comparison.

1. **Root Mean Squared Error** (RMSE) is used to determine the distance between the paired measurements made with two different methods [70].

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}} \tag{7}$$

where $\hat{y}_i$ are the predicted values, y_i are the observed values and n is the sample size.

2. **Pearson's correlation coefficient** (*r*) is used to determine the strength of the linear relationship between two variables [71]. It ranges from -1 to +1, where +1 reflects a perfect positive, and -1 a perfect negative linear relationship. A correlation coefficient value $r > 0.8$ is considered to be suitable for clinical trial use, while $r < 0.5$ is considered to be too poor. For all trials, the comparisons are made using a significance level of α=0.05.

$$r = \frac{\sum\limits_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum\limits_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum\limits_{i=1}^{n}(y_i - \bar{y})^2}} \tag{8}$$

where n is the sample size, x_i and y_i are the sample points at time i, $\bar{x}$ and $\bar{y}$ are the sample means.

3. **Spearman correlation coefficient** (ρ) is a non-parametric measure of agreement between the ranks of two variables. It assesses the monotonic relationship without making assumptions about the distribution of data. It varies from 0 to 1 and quantifies the dependence between measurements.

$$\rho_s = 1 - \frac{6\sum_i D_i^2}{n(n^2 - 1)} \tag{9}$$

where D_i is the difference between observations ranks and n the number of observations.

4. **Bland-Altman plot** is a graphical tool for assessing the concordance between measurements of the same phenomena obtained from two distinct systems [72]. It allows to appraise effectiveness and eventual measurement bias of a novel measurement approach in comparison to a recognized gold standard [73]. The Bland-Altman plot is a scatter plot that reports on the horizontal axis the average of measurements ($(x_{1i}+x_{2i})/2$), and on the vertical axis the differences between measurements ($x_{1i} - x_{2i}$) made with the two methods. The plot typically also includes information on measurement bias, defined as the average of these differences ($\bar{b} = (\Sigma_{i=1}^{n} d_i)/n$), and the 95% confidence interval (evaluated as $bias \pm 1.96\sigma$), where σ is the standard deviation of the measurement differences. If a non-zero bias is observed, it may imply the presence of a significant systematic error in the measures of the novel method.

Throughout the dissertation, data processing, management, and statistical testing were carried out in MATLAB (R2018a, R2020a, R2022b, Mathworks Inc., USA, refer to each publication for the version used) and with XLSTAT (version 2019.2, Alladinsoft, France).

1.2 Research problem and research questions

Aquatic physical therapy holds significant importance in rehabilitation and wellness due to its unique therapeutic properties (Section 1.1.3). Conventional tools for motion analysis face significant limitations when applied underwater due to the complexity of aquatic environments (Section 1.1.1). An extensive review of the literature will support these claims (Chapter 2) pointing out the substantial deficit of evidence-based and standardized approaches [1]. Therefore, there is a pressing need for innovative technologies and methodologies tailored to aquatic motion analysis to overcome these challenges and optimize therapeutic results.

The new technology must be effective, easy to use, comfortable and have a convenient setup. Waterproofing, durability, and user safety are of paramount importance, together with adaptability and flexibility, to accommodate various testing situations. The method and protocol should be able to assess motion both overground and in water, without the need for complex adaptations. Additionally, the method for motion analysis should be reliable, accurate and able to precisely and consistently capture motion parameters over time and environments. Both the method and the technology should be compared against established gold standards to ensure that they can effectively capture aquatic motions. Finally, developing a novel parameter for aquatic motion analysis, customized to the characteristics of water, is crucial to gain deeper insights into human movement underwater, allowing better assessment and optimization of aquatic therapy and training programs.

The central *hypothesis* of this dissertation, substantiated by the literature review, is that ***a novel approach based on wearable inertial measurement unit and hydrodynamic pressure sensors will provide parameters tailored to the water environment to describe accurately aquatic motion***.

Testing this hypothesis, four research questions are defined:

1. What is the state-of-the-art method for aquatic motion analysis and what are notable research gaps on the use of inertial-based devices for aquatic exercise monitoring?
2. Can novel IMU-based wearable sensors, developed specifically for air and underwater motion analysis, provide an accurate assessment of kinematic gait characteristics?
3. Using these novel IMU-based sensors, what are the differences between aquatic and overground gait?
4. Can hydrodynamic pressure measured on the lower limbs describe underwater gait providing details on this motion and on the interaction between the body and the fluid?

1.3 Objectives and contributions of the thesis

Addressing the research problem and the questions introduced in the previous section, the main objective of this Ph.D. thesis is to ***create, evaluate, and validate an innovative method to measure aquatic motion based on wearable inertial and pressure sensors***. This goal is achieved through four *research objectives* (RO) that address the four research questions stated previously, which have resulted in valuable contributions to the field of aquatic motion analysis. These contributions have been supported by scientific peer-reviewed publications and conference presentations, which are summarized and discussed in this cumulative dissertation.

RO1: *Analyse the current state of the art on aquatic motion analysis through a systematic review of the literature to establish research gaps.* **Publication I**
a review of the literature was conducted that highlights research gaps and suggests potential avenues for improving future clinical studies on aquatic motion analysis. Two research questions were addressed. The first inquiry established the state-of-the-art, considering studies on aquatic physical therapy and reviewing the methods used to assess the efficacy of these rehabilitation protocols or to investigate aquatic activities. The second query focused solely on studies that used wearable devices for aquatic motion analysis, reporting their qualitative synthesis. This overview defined existing research gaps and proposed innovative means to address them and to generally improve aquatic motion analysis.

<u>Contribution:</u> An extensive review of the literature on aquatic physical activity was missing from the literature, limiting the awareness of the scientific community in this field. The focus on wearable devices and methods for monitoring aquatic exercise allowed for the identification of four research gaps and the definition of potential improvements for future studies. Overall, it was found thatthe lack of *flexible and reproducible monitoring methods and parameters* for the evaluation of aquatic physical activities was the most substantial gap.

RO2: *Develop and validate a novel technology and method based on Inertial Measurement Unit sensors for both overground and aquatic motion analysis.* **Publication II, III**
Designed to address the main limitation identified in RO1, wearable IMU loggers were developed for motion analysis both in on land and underwater. The reliability of the sensors and the proposed methodology were evaluated against gold standard systems. In a proof-of-concept study, **publication II**, the loggers were validated both on land, against an optoelectronic system and a marker-based video analysis, and underwater, using the marker-based MoCap as the gold standard reference. In this investigation, the focus was on the kinematics of the right knee along the gait cycle. The method was proven to be easy to use, wearable, portable, safe, and reliable for monitoring aquatic kinematics.
The encouraging results obtained from this preliminary investigation allowed us to go further both technologically and in terms of the adopted protocol. An improved version of IMU sensors and a more complete protocol for gait analysis, capable of estimating both knee kinematics and temporal gait parameters, were developed and tested in a clinical trial, **Publication III**. The validation of these innovative devices followed a validation protocol comparable to **Publication II**, estimating similar kinematic parameters and employing parallel analytical tools.

<u>Contribution:</u> In contrast to existing commercial sensors, the loggers used in both **Publication II** and **Publication III**, were specifically developed for both overground and aquatic motion analysis and do not require casing or foresight to be applied in water. A modified version of the Outwalk protocol [74] was proposed, focusing on the kinematics of the knee joint and the temporal parameters of gait. Unlike previous investigations that performed a

comparison between the overground and aquatic parameters, in **Publication II**, the technology and method have been validated through a performance comparison against gold standard methods in both environments. Additionally, a machine learning technique was used to enhance the estimate of knee angle made through the IMUs sensors that exploit the reference motion capture data.

RO3: *Conduct a clinical-size trial assessing the kinematic characteristics of walking on land and underwater.* **Publication III, IV, IV**
The IMU-based technology and method developed and validated in **Publication III** (RO2) was exploited in a clinical-size trial for the assessment of kinematic characteristics of aquatic and overground gait, considering temporal gait parameters and knee joint kinematics. The investigation pointed out the versatility of the developed system and the significantly higher variability of kinematic gait variables underwater. A pilot study was also conducted expanding the investigation to backward walking, in **Publication V**, assessing the differences that occur between the two tasks performed on land and in water.

<u>Contribution:</u> An original clinical-sized investigation with customized non-commercial IMU-based sensors has been conducted, providing benchmark data (about 1920 gait cycles for each environment), valuable as reference for future studies. In **Publication III, IV** temporal gait and knee joint parameters are considered and the lack of structured clinical procedures and methodologies for aquatic motion analysis via wearable devices is addressed, as noted in RO1. A modified Outwalk Protocol for sensor placement and customized data processing algorithms, for fast and accurate gait analysis were proposed. Additionally, in **Publication V** a novel investigation of underwater backward walking was illustrated through the use of the wearable sensors developed in this work.

RO4: *Propose and investigate the reliability of a new parameter for the characterization of aquatic physical activity.* **Publication III**
RO1 identified that current investigations are based on methods, technologies, protocols and parameters developed for land-based investigations, and mostly compare underwater and land-based observations. Although differences between the environments are identified, an overall understanding of the effects of the underwater environment and the interactions between the fluid and the body in motion remained lacking. Furthermore, the trials conducted addressing RO3, in **Publications III, IV, V**, determined a high degree of variability of underwater gait parameters, suggesting that using the same variables for land and water assessments may not be ideal to characterize underwater motion. In the study presented in **Publication III**, the IMUs were further equipped with pressure sensors. Accordingly, the feasibility and reliability of the lateral hydrodynamic pressure on the lower limbs was evaluated as a new motion parameter for aquatic gait analysis.

<u>Contribution:</u> In contrast to previous studies that relied on methods and parameters designed for land-based assessments, proven to give high variability in water, it is proposed a parameter tailored to the aquatic environment. Through a pressure sensor embedded in IMU loggers, the hydrodynamic pressure on the lower limb was measured during underwater walking and the effects of water on the body in motion were investigated. This pioneering study evaluated the fluid-body interaction and provided the basis for a new and more comprehensive understanding of how the presence of water changes the parameters used to study and evaluate walking gait.

1.4 Structure of the thesis

The main content of this dissertation is organized into chapters dedicated to each of four research objectives.

Chapter 2 addresses RO1, presenting and discussing the systematic analysis of the existing literature on aquatic physical activity, with a focus on the use of wearable IMU sensors for aquatic motion analysis. This section highlights the motivation and scientific importance of the experimental part of the dissertation, pointing out the research gaps in the field, and proposing solutions to address them.

Chapter 3 discusses RO2 by proposing and validating a novel wearable IMU-based technology and method for overground and aquatic motion analysis. Cross-comparison between the proposed method and two gold standard systems is performed both on land and in water, investigating knee joint kinematics and temporal gait parameters.

Assessing the reliability and trustworthiness of the proposed technology is a crucial step in the application of such devices to a clinical trial, and is summarized in Chapter 4. In this chapter, RO3 is targeted to conduct overground and aquatic gait analysis in healthy adults. Addressing a shortcoming of the existing literature, an aquatic backward walking analysis was conducted and the results are presented. These investigations allow to establish reliability and versatility of the technology proposed and validated, as well as highlight the variability of aquatic kinematic parameters. These, while regularly used for aquatic motion analysis, may not be optimal for a thorough assessment of motion in the water environment.

Chapter 5 focuses on RO4, and introduces a novel parameter tailored to underwater motion analysis. The hydrodynamic pressure on the lower extremities is discussed to quantitatively describe the interaction between the fluid and the body in motion during the walking gait.

Finally, the conclusions, limitations, future perspectives, and final remarks are presented and discussed in Chapter 6.

2 Systematic literature review

The methods commonly used for quantitative motion analysis have limited applicability for the investigation of aquatic physical activities, due to the presence of electrical components and general compatibility issues [61, 75]. Furthermore, the lack of a comprehensive and recent review of the methods used for aquatic motion analysis restrains the understanding of the field, its limitations and specific needs. Previous reviews have focused on specific conditions [44, 54, 57, 76], on the use of surface electromyography [77, 78], or examined gait characteristics in aquatic settings assessed through MoCap systems [79]. Only a single scientific publication reviewed the use of portable IMUs to monitor aquatic human motion during non-swimming activities [80] to-date, providing a limited evaluation of the existing literature.

Therefore, an up-to-date systematic review of the existing literature on aquatic physical therapy was conducted and presented in **Publication I**. The methodologies, tools and techniques used for assessing the efficacy of aquatic rehabilitation protocols and to perform aquatic motion analysis were considered. In this review, designated as **RO1**, the *focus is on the identification of significant research gaps in the field of aquatic motion analysis*, with an examination of two key research questions:

1. ***What are the most frequently employed methods for aquatic motion analysis over the past two decades?***

Taking into account the identified eligible articles, a comprehensive summary of the literature is provided, evaluting how the research community has investigated aquatic rehabilitation over the past two decades. The focus was on the general structure of the articles, the conditions addressed, and the assessment methods used.

2. ***What notable gaps exist in the current body of literature on the use of IMU wearable devices for aquatic exercise monitoring and how can our understanding of aquatic motion analysis be improved?***

Focusing solely on studies that used wearable IMU devices for aquatic motion analysis, a qualitative synthesis is reported. The analysis examines the structural characteristics, research methods and protocols employed in these studies, with the aim of elucidating the primary limitations within the field and delineating the prospective directions for future research.

2.1 Method of the systematic literature review

The review process followed the PRISMA guidelines [81] and was registered in the PROSPERO international database (CRD42022316782). A comprehensive search of relevant literature was conducted in four repositories: PubMed, IEEE Xplore, Web of Science, and Scopus. The eligible English-language peer reviewed articles were identified considering publications from 2000 onward, scanning the databases with the keywords listed in Table 2.1. For each database, the combination of terms used, additional filter criteria, the number of resulting papers and the number of publications included in the review after an initial screening based on the title were reported.

The PRISMA workflow was followed to establish eligible articles is reported in Figure 2.1. Potentially relevant articles from the database screening and additional papers discovered through citation searching were included in the review. After duplicate removal, two rounds of screening allowed identifying the eligible publications included in the comprehensive synthesis. In the final PRISMA stage, exclusive attention was given to those papers that utilized wearable IMU-based devices for aquatic motion analysis. Given the substantial heterogeneity among these studies, a qualitative synthesis was preferred to a meta-analysis. Furthermore, to evaluate the quality of the studies, a custom 19-question critical evaluation questionnaire was defined based on the assessment tools of STROBE [82], CASP [83] and McMaster [84] (see Table A2 in **Publication I**).

		PubMed[a]		**IEEE Xplore**		**Web of Science** [b]		**Scopus**[b]	
		Results	Incl	Results	Incl	Results	Incl	Results	Incl
((underwater) OR (aquatic) OR (water))	AND ((rehabilitation) OR(exercise) OR(kinematic) OR(therapy) OR(training) OR(hydrotherapy) OR (hydrokinesitherapy)) AND ((wearable) OR (sensor))	767	15	1176	8	2494	28	2500	26
	AND ((treadmill) OR (walk) OR (gait))	3135[c]	325	3289[c]	5	6980	651	5123	410
	AND (wearable)	295	10	318	4	2191	10	2454	12
	AND ((IMU) OR (accelerom*) OR (inertial))	453	18	1407	3	5967	28	7144	36
	AND ((emg) OR (electromyog*))	553	92	54	4	886	93	1269	133
	AND ((motion capture) OR (camera))	668	22	3641	4	2217[d]	10	1659[d]	8
	AND (force plat*)	343	36	481	0	8560	40	7199	52
	AND (dynamom*)	100	24	20	0	401	33	585	40
	AND (gonio*)	80	5	74	1	1062	11	1222	11
	Total	6394	547	10460	29	30758	904	29155	728

[a]: Additional filters used: English AND Human;
[b]: Additional filter: English;
[c]: Additional keyword run: ((underwater) OR (aquatic) OR (water)) AND ((treadmill) OR (walk) OR (gait) OR (run));
[d]: Only motion capture: ((underwater) OR (aquatic) OR (water)) AND (motion capture)

Table 2.1: Literature search databases, keyword combinations, and count of retrieved papers (Results). It is indicated the number of articles included (Incl) in the first step of the PRISMA flow chart.

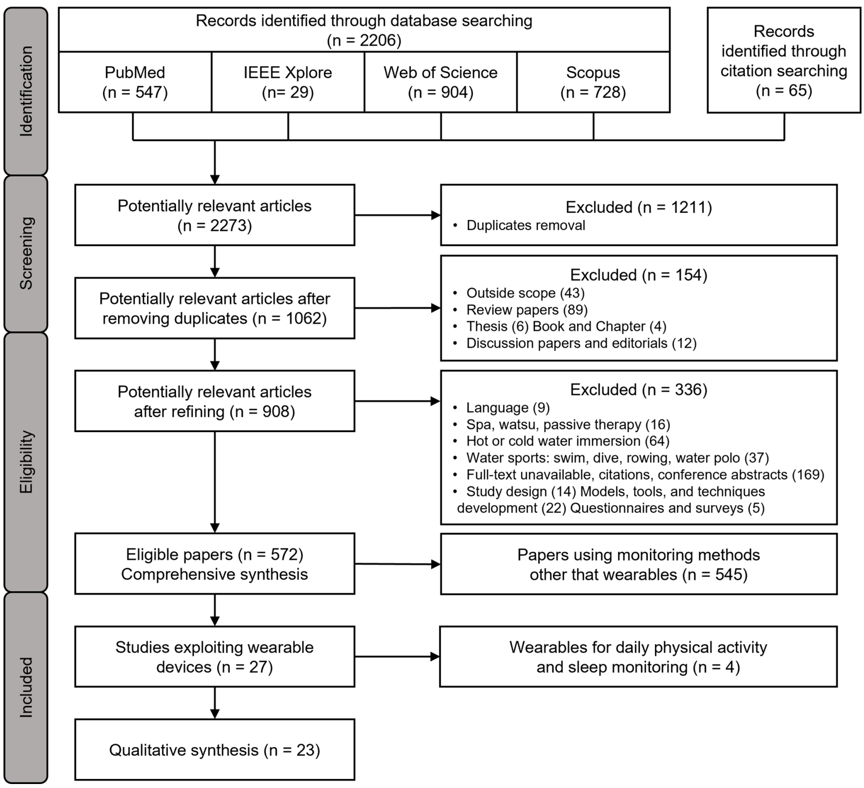


Figure 2.1: PRISMA flow diagram of the systematic review, with identification, screening, eligibility and inclusion steps, specifying reasons for papers exclusions.

2.2 Results

The initial search for articles yielded a total of 2,273 potentially relevant articles. By removing duplicates and performing two screening phases, 1,701 studies were excluded for various reasons reported in Figure 2.1, leaving 572 eligible articles that met the inclusion criteria. A comprehensive synthesis of these studies was conducted, addressing the first research question and defining the current state of knowledge, organizing the studies by publication year, demographics, general characteristics, and investigating the methods used for aquatic motion analysis. The second research question aimed to focus on the 23 articles among the eligible ones that utilized wearable IMU-based devices for aquatic motion analysis. Given the substantial heterogeneity of these works, a qualitative synthesis was conducted that gives an overview of the demographics and characteristics of the investigations, including the choice of protocol, the evaluation method, and the results.

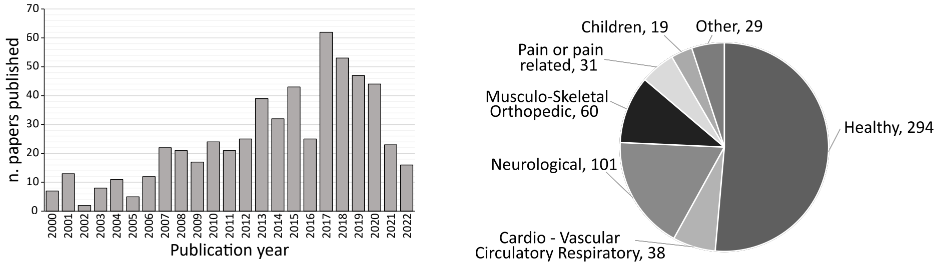
2.2.1 Preliminary synthesis of the eligible papers

Eligible papers are organized in Figure 2.2a by publication year showing a clear increase in the number of published papers on aquatic physical therapy in the last two decades. Between 2011 and 2022, 75% of the eligible articles were published, indicating a growing interest among researchers and clinicians in investigating aquatic motion.

Referring to the type of population involved, Figure 2.2b shows that slightly more than half (51%) of the eligible research engaged healthy individuals. The remaining papers were dedicated to examining various disorders and chronic conditions where neurological impairments were the most frequent (101 papers). Pain-related, orthopedic, and musculoskeletal disorders were involved in 91 works, 38 studies focused on cardiovascular or respiratory diseases, and 19 articles focused on children. The remaining 29 studies explored a diverse range of conditions, including, but not limited to, diabetes, obesity, and pregnancy. Furthermore, only 20 of these 278 works with a pathological population included a healthy control group.

Of the eligible articles, approximately 58% (333) examined the entire rehabilitation cycle using pre/post comparisons including the progression and effects of the proposed activities and protocols. The remaining 239 studies did not incorporate a full rehabilitation cycle, but focused on a single evaluation involving a limited number of repetitions of the investigated task (usually 3-5).

In relation to the methods used to assess aquatic motion or to monitor the outcomes of aquatic rehabilitation, one or more quantitative methods were used in 318 studies, while qualitative surveys and questionnaires were preferred in 447 researches, and 193 works opted for both quantitative and qualitative tools.



(a) Publication year of the eligible papers.

(b) Population involved in the eligible papers.

Figure 2.2: 572 eligible papers organized by (a) publication year and (b) population involved.

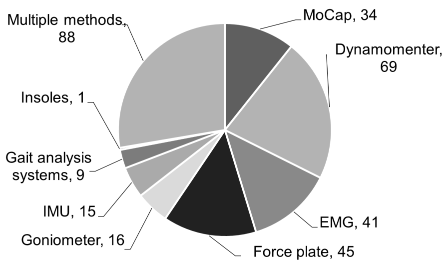


Figure 2.3: Quantitative methods used in the eligible papers, and their incidence.

MoCap, EMG	17	MoCap, IMU	5
FP, IMU	5	MoCap, IMU, FP	1
EMG, IMU	1	EMG, Dynamometer	3
Goniometer, MoCap	4	Goniometer, Dynamometer	5
Gait system, Dynamometer	1	MoCap, EMG, Goniometer	1
MoCap, FP, Dynamometer	2	EMG, MoCap, Dynamometer	3
EMG, FP, Dynamometer	1	EMG, Goniometer	2
Gait system, EMG	1	Gait system, FP	2
Goniometer, FP, EMG	1	Dynamometer, FP	1
MoCap, Dynamometer	1	EMG, Dynamometer, Goniometer	1

Table 2.2: Incidence of multiple quantitative methods in the eligible papers.

Figure 2.3 provides a concise summary of the quantitative methods employed in the studies, presenting the number of times each method was used. The methodology used most frequently was the dynamometer (94 studies). FP and pressure sensors were also very common (88 studies), MoCap technologies (84 studies), EMG (81 articles), and goniometers (34 studies). Wearable IMU devices were used in 27 papers, and 13 studies utilized other customized technologies. In particular, 88 studies used a combination of quantitative methods, where the most common combinations, reported in the Table 2.2, were MoCap and EMG (17 studies), MoCap and FP (10 studies) or MoCap, EMG, and FP (6 studies). Wearable devices were used in conjunction with MoCap, FP, and EMG in 12 investigations.

Alternatively or in addition to quantitative measures, 447 studies conducted metabolic assessments or adopted semi-quantitative and qualitative methods. These include tests, scales, and questionnaires to assess patient conditions, mobility, quality of life, and the overall effectiveness of water-based therapies. Seven distinct groups of tools can be identified: (1) metabolic tests, based on cardiovascular, cardiorespiratory, and ventilatory observations; (2) functional tests for motion-related evaluations, including kinematic and muscular assessments for gait, balance, and postural control, exercise-specific parameters, mobility, and muscular parameters; (3) pain assessment questionnaires; (4) ratings of perceived exertion and fatigue scales; (5) condition-specific tests and questionnaires, related to the population involved; (6) surveys on lifestyle, quality of life, mental health, and physical activity level; (7) patient self-evaluations and other related tests.

2.2.2 Wearables for aquatic motion analysis

The final stage of the PRISMA workflow identified 27 articles that used wearable inertial sensors to monitor aquatic physical activities. Four of these were excluded as they used accelerometers to quantify daily physical activities [85, 86], quality of life [87], and quality of sleep [88] of subjects undergoing hydrotherapy protocols.

The main characteristics of the remaining 23 articles are summarized in Table 2.3. Interestingly, most studies were published during 2017, 2019 and 2020. Most of the articles (17) involved healthy adults or elderly subjects, while the remaining investigated anterior cruciate ligament injury [89, 90], anterior knee pain [91], and incomplete spinal cord injury [92–94]. The sample sizes ranged from 10 to a maximum of 50 subjects, four articles having a balanced gender distribution [91, 95–97] and three involving a healthy control group [89–91]. Three main study purposes are identifiable: the investigation of a specific aquatic task, the comparison between land and aquatic motion, and the development and validation of methods or technologies. Concerning exercises, protocols, and evaluation metrics, there is considerable variability, with gait being the most common task and task-specific parameters generally estimated. With the exception of four studies [98–101] that only considered the water environment, motion analysis was typically performed on either land or in water. Interestingly, nine studies preferred a pool with adjustable depth, while the remaining used a pool with fixed depth.

Various wearable methods were used, with IMU sensors being the most popular, exploited in 13 studies. Three works used a combination of accelerometer and gyroscope, five a stand-alone accelerometer, and one a smartphone. The number of devices and their positioning on the subject varied from one to eight, placed most commonly on the trunk and laterally on the lower limbs. Additional quantitative tools were used to support inertial sensors in 15 works, such as MoCap, optoelectronic systems, force plates, and electromyography. Five papers also explored metabolic, cardiovascular, and cardiorespiratory parameters. With the exception of Chien et al. [102] that used the Borg scale to assess perceived exertion rate and Marinho-Buzelli et al. [92, 93] who performed a clinical examination on balance and perception through International Standards for Neurological Classification of Spinal Cord Injury, Berg's Balance Scale, Mini-BESTest and perception interviews, no other studies included functional tests, pain assessment, or quality of life questionnaires.

Finally, the customized critical evaluation tool was applied to evaluate the overall quality of the articles; the results are reported in Table A3 of **Publication I**. Although the articles were generally of satisfactory quality, only four studies specified the study design [89, 92, 95, 98], and only two [91, 101] indicated clear inclusion/exclusion criteria. Additionally, no study involved multiple measurements over a rehabilitation protocol or discussed the management of missing data.

Table 2.3: Summary of the articles included in the qualitative synthesis. Organized by publication year, are reported: investigation purpose, demographics (population involved, gender distribution (M-F) and age), exercise protocol adopted and testing environment, monitoring methods and measurable outcome. The type of inertial sensor used, their number and positioning are also specified.

Author Year	Purpose	Part (M-F) Age	Protocol	Monitoring methods	Outcome measured
Kaneda 2014 [98]	Developed a model for energy expenditure water-walking	50 H (29-21) 27 to 73	Gait UW	A (1: head), Gas analyzer	Energy expenditure estimation (acceleration, velocity, O2 and CO2 exchange)
Fantozzi 2015 [103]	Compared land and water lower limb and thorax-pelvis joints kinematics	11 H (6-5) 27.0±3.4	Gait DL + UW	IMU (8: thorax, pelvis, laterally on thighs, shanks, feet)	Outwalk protocol (temporo-spatial param, joints kinematics), Linear Mixed Model
Cortesi 2016 [89]	Method for land and water gait for joints kinematics analysis of an ACL injured	1 ACL (NA) NA	Gait DL+UW	IMU (8: thorax, pelvis, laterally on thighs, shanks, feet)	Outwalk protocol (temporo-spatial param, joints kinematics)
Chien 2017 [102]	Estimated impacts of land and water knee extension	17 H (0-17) 22.1±0.7	Knee flexion-extension, DL+UW	A (1: below malleolus of the ankle), HR monitor, Near-Infrared Spectroscopy, RPE Borg scale, EMG	HR, Blood flow, Total Saturation Index, RPE, Muscular activity, Knee extension kinematic
Macdermid 2017 [104]	Evaluated effects of different depth water treadmill running	6 H (NA) 29.8±13.0	Treadmill running, DL+UW	A (3: lateral right tibia, lower back, forehead), Gas analyzer, HR monitor, MoCap (reference)	Transfer function, Temporo-spatial param, Oscillation, shock attenuation, loading rate, Physiological data
Macdermid 2017 [99]	Evaluated effects of different depth water treadmill running	8 H (NA) 25±12	Treadmill running, UW	A (1: lateral right tibia), HR monitor	Temporo-spatial param, Rate of impact loading, Acceleration features (slope, peak at impact)

Author Year	Purpose	Part (M-F) Age	Protocol	Monitoring methods	Outcome measured
Mangia 2017 [90]	Instrumental validation of IMUs in water, test in clinical and sport settings	5 Elderly (3-2) 71.6±2.2 1 ACL (1-0) 39	Gait DL+UW	IMU (8: thorax, pelvis, thighs, shanks, feet)	Outwalk protocol (temporo-spatial param, joints kinematics)
Buzelli 2017 [105]	Influence of water on COP parameters and on trunk acceleration during quiet standing	10 H (6-4) NA	Stand still, eyes opened or closed, DL+UW	IMU (2: lower and upper trunk), FP	COP param (time- and frequency-domain), Trunk acceleration param (postural sway)
Buzelli 2017 [95]	Investigated posture kinematics and kinetics during water gait initiation	10 H (5-5) 19 to 35	Standing and gait initiation, DL+UW	IMU (3: upper and lower trunk, shank), FP	COP trajectories, GRF components, Trunk acceleration param (postural sway)
Severin 2017 [106]	Quantified differences between land and water S, SS, SLS	25 H (14-11) 22.1±4.0	S, SS, SLS, DL+UW	IMU (3: upper and lower trunk, shank), FP	Joints kinematics (ROM, movement depth), Peak velocities
Severin 2017 [91]	Assessed kinematics and asymmetry during land and water S and SLS in AKP	2 AKP (10-10) 22.8±4.0	S and SLS, DL+UW	A+G (6: laterally on thighs and shanks, trunk, sacrum)	Joints kinematics, Asymmetry index score (shank, thigh, thorax)
Buzelli 2019 [92]	Influence of water on quasi-static posture after iSCI	6 iSCI (4-2) 42 to 69	Stand still with eyes opened and closed, DL+UW	IMU (2: upper and lower trunk), FP, Clinical examination, perception interviews	COP parameters, % Body weight offloading, Trunk acceleration param (postural sway), Perception questionnaire
Buzelli 2019 [93]	Influence of water on gait initiation in iSCI	5 iSCI (4-1) 42 to 69	Standing and gait initiation, DL+UW	IMU (2: upper and lower trunk), FP, Clinical examination, perception interviews	COP parameters, Trunk acceleration param (postural sway), Perception questionnaire
Severin 2019 [107]	Impacts of water on ROM and peak velocities during S and SS	24 Elderly (7-17) 71.4±5.4	S and SS, DL+UW	IMU (6: trunk, sacrum, laterally on thighs, shanks)	ROM trunk, hip, knee, Velocities, Squat depths
Souza 2019 [108]	Analysed walking inside and outside water	1 H (NA) NA	Gait DL+UW	A + G (4: inner side calf, medial malleoli)	Temporo-spatial param
Fantozzi 2020 [109]	Land and water walking kinematics of elderly and young adults	9 Elderly (4-5) 73.5±5.8	Gait DL+UW	IMU (5: trunk, pelvis, laterally on thigh, shank, foot)	Outwalk protocol (temporo-spatial param, joints kinematics), Linear mixed models
Gandolla 2020 [96]	Designed a biofeedback for aquatic movement analysis	2 H (1-1) 20	Soulder movements, DL+UW	IMU (3: trunk, upper and lower arm), Optoelectronic (land validation)	Measurement uncertainty and algorithm validation, System usability
Kaneda 2020 [110]	Compared land and water walking using IMU and video camera	10 H (6-4) 30±6	Gait DL+UW	IMU (1: thigh midpoint front), MoCap	Stance ratios and joints kinematics, Acceleration, angular velocity
Pacini 2020 [97]	Water performance of 17 algorithms for land gait events estimation	10 H (5-5) 26.2±3.3	Gait DL+UW	IMU (5: trunk, shanks, dorsal feet), MoCap, FP	Quality algorithms, Temporo-spatial param, GRF
Monoli 2021 [2]	Tested and validated developed underwater wearable IMUs	7 H (4-3) NA	Gait DL+UW	IMU (2: laterally on thigh and shank), MoCap, Optoelectronic (land validation)	Knee angle, Gaussian Process Regression enhancement
Chien 2022 [100]	GRF measured and predicted different accelerometer positions and jump intensities	12 H (0-12) 23.6±1.8	UW countermovement jumps	A (3: right ankle, lumbar, neck), FP, HR monitor	Acceleration, GRF, GRF predicted via accelerometer data
Lee 2022 [101]	Reliability of leg segment and joint angles measurements with smartphones	19 H (7-12) 22.0±1.9	Gait UW	IMU (3 smartphones: frontal on trunk, thigh, and shank), MoCap	Joints kinematics and ROM (hip, knee)
Fantozzi 2022 [94]	Compared DL+UW gait initiation in iSCI	10 iSCI (9-1) 65±8	Gait initiation DL+UW	IMU (4: upper and lower trunk, left and right shanks)	Anticipatory Postural Adjustment time, First-step characteristics

UW: Underwater. DL: Dry Land. NA: Not Applicable. A: Accelerometer. G: Gyroscope. IMU: Inertial Measurement Unit. ROM: Range of Motion. S: Squats. SS: Split Squats. SLS: Single Limb Squats. HR: Heart Rate. EMG: Electromyography. MoCap: Motion Capture. FP: Force Platform. RPE: Rate of Perceived Exertion. COP: Center Of Pressure. GRP: Ground Reaction Forces. AKP: Anterior Knee Pain. iSCI: incomplete Spinal Cord Injury.

2.3 Research gaps and conclusions on RO1

The systematic review of the literature conducted in **Publication I** focused on aquatic physical activities, considering articles published in the last two decades. No distinction was made between studies that evaluated aquatic motion, on land or in both environments, but all research was included in the context of aquatic physical therapy. The main limitations of the review carried out are the keywords and inclusion criteria selected and the exclusion of swimming and other water-related activities.

The synthesis of the 572 eligible papers identified following the PRISMA workflow addressed the first research question by highlighting that the most common methods used for aquatic motion analysis are dynamometers, force plates, and motion capture. Two major methodological categories emerged: quantitative methods for objective assessment and qualitative or semi-quantitative methods to assess motion quality and the impact of water exercise.

To target the second research question and identify existing research gaps, a qualitative summary of the 23 articles used IMU-based wearable devices for monitoring aquatic motion was carried out. This allowed the determination of four main research gaps:

1. **Lack of standardized clinical protocols for aquatic motion analysis.** The studies varied significantly in their methods, making cross-comparison challenging. Future research should establish clear protocols for underwater wearables to improve the comparability of water-based activities.

2. **Inadequate coverage of whole-body studies with IMU devices.** The technical challenges of analysing inertial data in water limited the focus mainly to specific parts of the body, neglecting the whole body system and the unique forces of buoyancy and drag that act in aquatic environments.

3. **Insufficient longitudinal studies monitored by wearable devices.** Limited data due to logistical challenges hindered insights into the effects of water on kinematics and the long-term benefits of hydrotherapy.

4. **Over reliance on land-based measurement and assessment methods.** Most studies used methods developed and commonly used for overground assessment. Furthermore, few investigations exploited other monitoring methods in combination with IMUs, while the adoption of multiple quantitative methods and specific tests and questionnaires could improve the understanding of aquatic exercise and its impact on kinematics.

In conclusion, **RO1** lead to the identification of a substantial deficit in evidence-based approaches. Most notably, there are no existing protocols and methods tailored specifically for water rehabilitation studies. The need for standardized protocols, whole-body monitoring, longitudinal studies, and a more comprehensive approach to wearable monitoring in aquatic exercise research was highlighted.

3 Development and validation of the method

The literature review presented in the previous chapter identified the lack of standardized methodologies and technologies suitable for both over-ground and underwater motion analysis as the main research gap (Chapter 2). To address this, **RO2** *aims at developing and validating a novel technology and method based on IMUs, suitable for the evaluation of aquatic and overground motion.* Two investigations were carried out, in which the IMU-based technology was validated by a performance comparison with gold standard methods for motion analysis to test the reliability, trustworthiness, and eventual measurement bias and systematic errors.

An initial proof-of-concept study, reported in **Publication II** and presented in Section 3.1, validated an IMU-based prototypical technology both on land and in water, against optoelectronic and marker-based MoCap. Gait analysis was performed, involving a small cohort of healthy adults and focusing on the estimation of knee joint kinematics. The results of this preliminary investigation allowed for technological and methodological improvements and for a larger scale application, presented and discussed in **Publication III**. Given the novelty of the technology, validity and reliability of these IMUs and protocol were tested overground through performance comparison against the gold standard optoelectronic system, considering the knee kinematics over the gait cycle and gait temporal parameters (Section 3.2).

The two studies followed similar validation protocols, estimating kinematic parameters, and using analytical tools introduced in Section 1.1.4. In contrast to existing literature that exploited wearable IMUs developed for overground assessments, the devices used in these two studies have been specially developed for air and aquatic body-mounted kinematic measurements. The sensors do not require additional casing for clinical application and both power and data storage are self-contained, eliminating the need for cables and allowing versatility and easy use in both environments. If these validations prove to be effective, the developed technology and method could offer a reliable approach to monitoring aquatic rehabilitation, addressing the technological limitations that currently challenge conventional optoelectronic and motion tracking methods.

3.1 Proof of concept study

The initial proof-of-concept study, detailed in **Publication II**, is designed to test and validate a wearable IMU system through a comprehensive multi-method performance comparison in both terrestrial and aquatic conditions. Reliability and repeatability of the proposed IMU technology were assessed focusing on the flexion-extension knee angle (sagittal planar component) throughout a complete gait cycle.

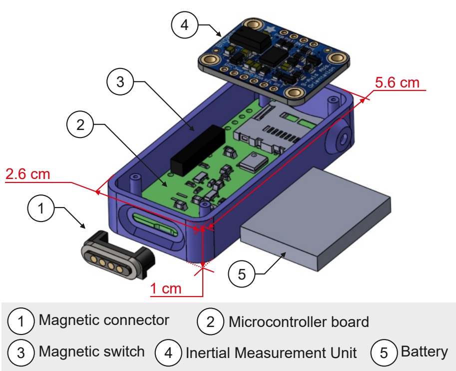
The investigation consisted of two trials. *Trial 1* was performed in a traditional land-based rehabilitation setting, involving an optoelectronic system and a marker-based MoCap system as reference methods for motion analysis. The trial was carried out in the Clinical Laboratory for Gait Analysis and Posture of the Piancavallo Auxological Center (Italian Auxological Institute, Italy). *Trial 2* tested the IMU system in the aquatic environment, comparing its performance with an underwater MoCap system. These tests were conducted in the indoor swimming pool at the Keila Health Center (Keila, Estonia).

3.1.1 Technology and protocol

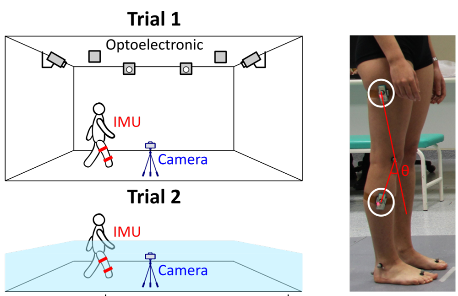
Two **IMU-based waterproof sensors**, designed for aquatic and overground motion tracking at Tallinn University of Technology, were used (Figure 3.1a). The outer dimensions of the loggers (5.6x2.6x1.0cm) and their lightweight (22g) allow them to interfere as little as possible with the human motion. The sensing unit (BNO055) is an IMU that records, through accelerometer and gyroscope, sampling at 100Hz, and magnetometer, sampling at 20Hz, the absolute orientation using an attitude and heading reference system (AHRS). The loggers use a CortexM0 processor, have 16GB memory for data storage, and a 100mAh rechargable battery.

The same protocol was adopted for the two trials, although each differed in the number of participants and repetitions executed (Figure 3.1b). Following the Outwalk protocol [74], two sensors were placed on the shank of each subject and on the outer thigh of the right leg, at the approximate height of the center of mass [11], as shown in Figure 3.1. To validate the system, two reference systems were used, and kinematics parameters were cross-compared. During Trial 1, Vicon-460 (Oxford Metrics Ltd) **optoelectronic** system, consisting of 6 infrared cameras (sampling at 100 Hz), was used as the gold standard. Subjects were outfitted with passive light-reflective markers on anatomical landmarks, following the Davis protocol [38]. Infrared cameras identified and tracked the marker positions; the recorded three-dimensional coordinates of the markers, enabled motion reconstruction within a defined space. **Marker-based MoCap** analysis (referred to as Camera) was conducted in both trials, using an ASUS ZenFone 3 (ZC520TL, 13 MP, autofocus, 30 fps) in Trial 1, and a Sony Alpha A5000 (20MP, continuous autofocus, 25 fps) in Trial 2. The camera was oriented orthogonally to the gait direction at 0.8m from the ground. The focal distance between the camera and the subjects was 2.8m for Trial 1 and 4.3m for Trial 2. This was needed to record a complete aquatic gait cycle, since the refractive index of water is 33% higher than that of air, reducing the field of view of the camera. The camera calibration was carried out following the *MATLAB camera calibration toolbox* [111].

Prior to any data acquisition, anthropometric measurements were collected to establish the location of the wearable sensors. For each repetition of the task, subjects were asked to perform a static two-pose calibration, similar to [112], to identify the trial and grant post-processing synchronization between the measurement systems. The participants were told to stand straight (pose one) and then lift their right leg, bending the hip and knee comfortably (pose two) for at least 2 seconds. The subjects were then asked to walk along a straight line, starting with the right leg, while wearing the IMU and simultaneously recorded by the optoelectronic and/or MoCap system.



(a)



	Systems			Characteristics	
	IMU	OPTO	CAMERA	Subjects	Rep
Trial 1	x	x	x	3 (2F 1M)	6
Trial 2	x		x	4 (1F 3M)	11

(b)

Figure 3.1: Proof of concept study. (a) Breakdown of the IMU loggers used. (b) Protocol and summary of the two trials conducted, including the methods used, the subjects involved and the repetitions made.

3.1.2 Method and data processing

Data collected with the three methods was processed to obtain the knee flexion-extension angle during the second complete right-leg gait cycle.

The **IMU sensors** return in a comma-delimited *. txt* file the *n* row-wise entries of timestamp (ms), accelerometer readings (x,y and z m/s^2) and absolute orientation (quaternions). The knee angle in each direction was estimated using a custom MATLAB script following [113]:

$$\text{Knee}_i(t) = \tan^{-1}\left(\left\|V_i^1(t) \times V_i^2(t)\right\|, V_i^1(t) \cdot V_i^2(t)\right) \tag{10}$$

where $Knee_i(t)$ is the knee angle in the axis of interest i (x,y,z) at each time stamp, t, calculated as the *four-quadrant inverse tangent* (tan^{-1}) between the cross product and the dot product of the rotated vectors of the two sensors along the axis V_i^a. With i the body frame axis of interest and a (1 or 2) the index of the two sensors.

Gaussian Process Regression (GPR), is a robust non-parametric method for both human and robotic gait analysis [114] was applied using MATLAB to improve IMU assessments. The predictor variable, IMU estimates of the knee angle, was ameliorated through a 10-fold cross-validation using optoelectronic and camera-based observations as the target variable. Data from all subjects from Trials 1 and 2, including both reference methods, were concatenated into a single ensemble data set, and the predictor and target data were normalized by subtracting the means and dividing by the standard deviations. The predictor variable was then converted to a time-shifted vector of length n = 40 lags, chosen because it represented the mean of the zero crossing of the knee angle autocorrelation. The Matern 5/2 kernel covariance function $k(x_i, x_j)$, defined as follows, was found to exhibit the best RMSE performance for latent variables $f(x_i), f(x_j)$, having a Euclidean distance r between them.

$$k(x_i, x_j) = \sigma_f{}^2 \left(1 + \frac{\sqrt{5}r}{\sigma_l} + \frac{5r^2}{3\sigma_l^2}\right) \exp\left(-\frac{\sqrt{5}r}{\sigma_l}\right) \tag{11}$$

where σ_f = 0.8568 was the empirically derived standard deviation of the IMU-derived knee angle during the gait, and σ_l = 2.2084 was the characteristic length scale.

The *Plug-in Gait body model* [115] was used to calculate the knee joint kinematics from the **optoelectronic system** marker positions, obtaining a standard 3D Biomechanics Data files *.c3d* [116, 117]. Mokka software (3D Motion Kinematic & Kinetic analyser, Biomechanical ToolKit) was used for data visualization and export into *.csv* files.

The **marker-based MoCap** (Camera) recordings were analysed using Kinovea (version 0.8.26) [118] to obtain the knee angle. Optoelectronic markers were tracked in Trial 1, while for Trial 2, circular black and yellow markers were used, placed on the thigh, knee, and shank. After tracking, a *.txt* file was exported with the knee angle estimates (rad).

3.1.3 Results and conclusions of the proof of concept

Trial 1 validated the IMU-based measurements (IMU) overground by cross-comparing them with both the marker-based MoCap (CAMERA) and the optoelectronic system (OPTO). Three subjects were involved and the task was repeated six times. An execution for Subject 1 was faulty, leaving a total of 17 valuable experiments. Trial 2 applied the IMU-based system in water (IMUw), comparing its performance against the MoCap (CAMERAw), considering 11 repetitions for each of the four subjects involved. Two executions were dismissed due to camera malfunction (from Subject 4 and Subject 7) leaving 42 available experiments. In both trials, the IMU estimations of knee angle were improved by applying GPR (referred to GPR and GPRw, respectively, for Trial 1 and Trial 2).

An example of the estimated knee flexion-extension angle, obtained during Trial 1 for

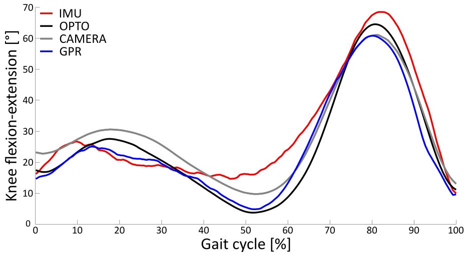


Figure 3.2: Knee angle over the gait cycle, estimated by the different systems used in Trial 1.

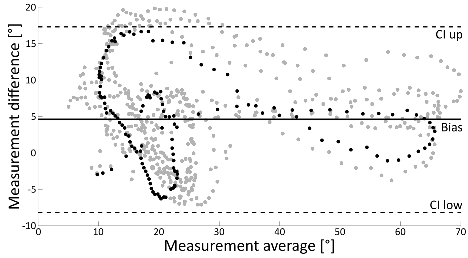
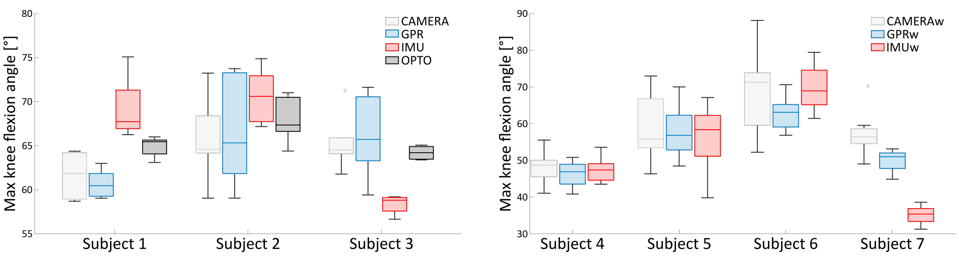


Figure 3.3: Example of a Bland-Altman plot of the 6 repetitions of Trial 1, Subject 1.

the three methods and the GPR is shown in Figure 3.2. The data are presented normalized over the gait cycle, and the improvement prompted by the GPR is noticeable. Figure 3.3 reports, as an example, the Bland-Altman plot of the six repetitions of a subject during Trial 1. One repetition is highlighted in black and are also reported the bias (black line, average of the differences) and the confidence interval (dashed lines, $bias \pm 1.96\sigma$).

Maximum knee flexion for each measurement system and subject involved in Trial 1 and Trial 2 are presented as boxplots in Figure 3.4. A one-way ANOVA test with confidence 95% did not reveal significant differences (p = 0.7) for Trial 1, while for Trial 2 there were statistically significant differences between the measurement methods for all subjects ($p < 0.05$). This observation aligns with our hypothesis that the IMU-based method is applicable in both air and aquatic studies of knee angles during gait, although large differences are noticeable between subjects and the limited sample size restricts the generalization of the findings.

Table 3.1 provides the summary mean and standard deviation of the RMSE and the correlation coefficient r of the comparison between measurement methods, for all sub-



(a) Trial 1, on land. Methods: optoelectronic (OPTO), camera-based (CAMERA), inertial sensors (IMU), and Gaussian Process Regression (GPR).

(b) Trial 2, in water. Methods: camera-based (CAMERAw), inertial sensors (IMUw), and Gaussian Process Regression (GPRw).

Figure 3.4: Box and whisker plots of the maximum flexion angle for each subject and measurement methods used during Trial 1 (a) and Trial 2 (b).

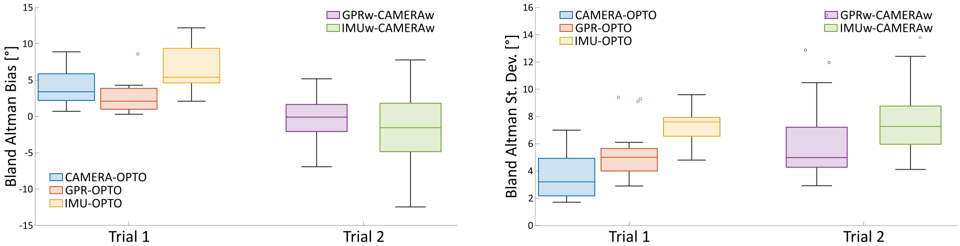
Trial 1	IMU-OPTO	IMU-CAMERA	GPR-OPTO
RMSE [°]	10.1 ± 2.7	8.1 ± 2.1	6.3 ± 2.2
r [unitless]	0.90 ± 0.03	0.90 ± 0.03	0.95 ± 0.05

(a) Trial 1

Trial 2	IMUw-CAMERAw	GPRw-CAMERAw
RMSE [°]	8.8 ± 2.6	6.6 ± 2.6
r [unitless]	0.88 ± 0.06	0.91 ± 0.08

(b) Trial 2

Table 3.1: Mean and standard deviation of the Root Mean Squared Error (RMSE) and correlation coefficient (r) obtained comparing measurement methods in Trial 1 and Trial 2.



(a) Bland-Altman bias, average of the differences.

(b) Bland-Altman standard deviation of the differences.

Figure 3.5: Bland-Altman coefficients of bias (a) and standard deviation of the differences (b), for Trial 1 and Trial 2, obtained from the pair-wise comparison between different measurement systems.

Trial 1	IMU	OPTO	CAMERA	GPR
Subject 1	11.6	14.0	14.6	13.1
Subject 2	20.0	28.4	22.4	23.6
Subject 3	6.5	10.5	12.5	12.7

(a) Trial 1

Trial 2	IMUw	CAMERAw	GPRw
Subject 4	20.1	23.8	18.6
Subject 5	24.9	21.3	23.0
Subject 6	14.5	16.7	12.8
Subject 7	16.3	18.3	24.8

(b) Trial 2

Table 3.2: Coefficient of Variation from Trial 1 and Trial 2 for each measurement system used.

jects involved in Trial 1 and Trial 2. During Trial 1, the IMU-based system reported an error marginally larger than the camera-based measurements, compared to the optoelectronic system, while the GPR model reduced the RMSE to about 2°. During aquatic validation, Trial 2, the error was found to be slightly higher when comparing inertial and camera-based systems (from 8.1° to 8.8°); while, similarly to Trial 1, the RMSE after GPR was smaller. The Pearson correlation coefficient was found acceptable (above 0.8) in all the repetitions of Trial 1, and in 93% of the cases of Trial 2; while also reporting that the GPR improved the estimates increasing r for both trials. One-way ANOVA tests (95% confidence) found significant differences ($p < 0.001$) between the correlation coefficients of the three groups for Trial 1.

Bland-Altman plots were drawn for each subject and trial, reporting the bias coefficients and standard deviation in the box plots of Figure 3.5. For Trial 1, the Bland-Altman plot was evaluated with the optoelectronic system as reference (OPTO); while in Trial 2, the camera-based system (CAMERAw) was considered as ground truth. During Trial 1, the bias was always greater than zero, indicating that the IMU systematically overestimated the knee angle. The standard deviation remained consistent between all test subjects and the measurement technologies, while the GPR results show that the regression model reduced both the bias and standard deviation. During Trial 2 a reduced bias was detected and indicates that there is a low probability of a systematic error, although a larger number of test subjects are needed to thoroughly substantiate this claim. The coefficients of variation (CV) calculated for Trial 1 and Trial 2, are reported in Table 3.2. In general, CV tends to be highly subject-specific and always higher than the values reported in the literature [11]. This could be due to the small number of repetitions utilized, the modest cohort involved, or slow walking speed. Although it does not allow for comprehensive statements, it is also important to note that in both trials GPR did not consistently reduce CV.

The proof-of-concept study conducted shows that the developed IMU-based method assesses the knee angle throughout the gait cycle, in agreement with previous land-based performance comparisons between IMU and motion tracking systems [119, 120]. It is the first work to perform both overground and aquatic validation against optoelectronic and MoCap systems and to apply a GPR model to underwater gait data to improve IMU performance. The main result of this investigation is that 93% of the aquatic experiments using IMU and motion tracking showed a high cross-correlation threshold, while the land-based experiments comparing IMU with optoelectronic and motion capture systems resulted in a cross-correlation, r >0.8 in all experiments.

The main limitations of this study were: (1) the assumption and investigation of a two-dimensional knee angle, although it is considered as an appropriate simplification [121]; (2) the number of subjects and repetitions were not sufficient for comprehensive clinical inference but adequate for the purpose of validating and testing a novel device and protocol; (3) the execution of the two trials at different locations and with different subjects, due to logistic constraints; (4) soft tissue disturbances were ignored, as well as the subjects' comfort during the testing. Finally, the Kinovea software required considerable manual adjustment during marker tracking between frames, resulting in a high uncertainty of measurement. However, this experience also mirrored comments found in a previous study [118]. While not free from limitations, the findings in this study are sufficient to warrant future application of the proposed IMU system for testing in clinical trials.

3.2 Clinical study, PIMU validation

Acknowledging the results of the proof-of-concept study, an improved version of the sensors was developed and tested in a clinical-size trial presented in **Publication III**. New wearable loggers, including IMU and pressure sensors (PIMU) [122], were designed at Tallinn University of Technology specifically to monitor aquatic kinematics. Similarly to the investigation presented in the previous section and before applying PIMUs to the water environment, the validation of these devices was necessary to establish the eventual measurement bias and systematic errors. Gait analysis was conducted overground using PIMU sensors to estimate the temporal gait and knee joint parameters, comparing them with those obtained from the optoelectronic system for performance validation. In contrast to the proof-of-concept investigation, a relatively large cohort of healthy adults was involved and three sensors were placed on the right lower limb to allow estimation of both the knee joint and temporal gait parameters.

3.2.1 Technology and protocol

Three PIMU sensors [122] were used for gait analysis, their schematics and positioning on the lower limb are reported in Figure 3.6. The wearable devices are smaller (35 x 13 x 13.55mm) and lighter (6.9g) than the ones used in the proof-of-concept study (Section 3.1.1), to further minimize the discomfort of the patients. PIMU sensors log data at 100 Hz and include a triaxial IMU (BMX160, Bosch Sensortec, Germany) with accelerometer, gyroscope and magnetometer. A pressure sensor (MS5837-2BA, TE Connectivity, Switzerland) is also included to measure the hydrodynamic pressure (discussed in Chapter 5). Data are stored as a comma-separated values (*.csv*) file on an onboard memory module (SD card) with 2 GB of storage, and are retrieved via a USB connection. The loggers are powered by a Lithium-Polymer battery (3.7V, 40mAh), include a microprocessor (32-bit ARM Cortex-M0+ SAM D21G) and were waterproofed with epoxy resin.

Sixteen healthy young adults participated in the study (see Section 4.1 for their demographics), wearing three PIMU sensors laterally on the right leg, as visible in Figure 3.6. Sensors were fixed with self-adhesive medical tape at the approximate center of mass of the thigh, shank, and foot [11], following a modified version of the Outwalk protocol [74].

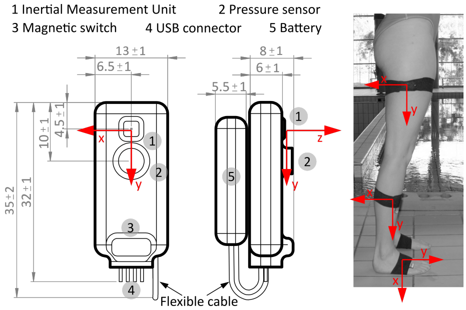


Figure 3.6: Technical drawing and placement of the PIMU sensors on a test subject.

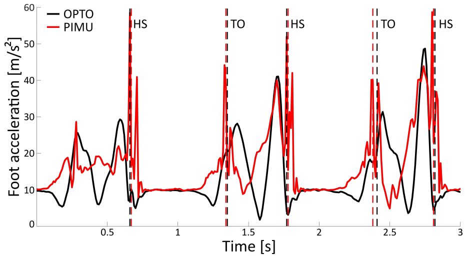


Figure 3.7: Foot COM acceleration data from the optoelectronic system (OPTO) and PIMU sensors.

Validation was carried out in the Laboratory of Posture and Movement Analysis "Luigi Divieti" of Politecnico di Milano (Milan, Italy), where the 8 camera BTS-SmartDX 400 **opto-electronic system** (BTS Bioengineering S.p.a., Italy), sampling at 100Hz, was used simultaneously with PIMUs. Light-reflecting optoelectronic markers were placed on test subjects following the Davis protocol [38]. Anthropometric measurements were taken to establish the location of the wearable sensors and the optoelectronic markers. Before each trial, to synchronize the optoelectronic system and the sensors, a static calibration of two posts was performed after [112]. Subjects were asked to stand upright (pose one) and then lift their right leg, in hip flexion with the knee flexed to a comfortable angle (pose two) for at least 2 seconds. Following the calibration procedure, the experimental protocol encompassed ten walking tasks, starting with the right leg, at subjects' preferred self-selected speed, with arms folded across the chest. Each subject performed ten walking tasks. A task was repeated in case of optoelectronic malfunctioning (e.g. lost marker, markers not visible during the trial ecc).

3.2.2 Method and data processing

Standard gait analysis was performed considering the second stride of the right leg. The PIMUs data were processed in MATLAB with an algorithm developed by the authors to automatically detect gait events based on the acceleration magnitude of the foot-mounted sensor. The knee angle was estimated from gyroscope and accelerometer data, applying the Madgwick filter to calculate the relative angle between the sensors mounted on the thigh and the shank, following Song et al. [123]. Optoelectronic data was processed using the BTS Smart Clinic software (BTS Bioengineering S.p.a., Italy) by manually identifying gait events and, through anthropometric data, reconstructing motion kinematics and internal center of rotation of the knee [124].

Figure 3.7 shows an example of the data obtained with the optoelectronic system (OPTO) and the PIMUs. The COM acceleration of the right foot estimated by the opto-electronic system (black) is reported against the magnitude acceleration of the PIMU positioned on the right foot (red). The vertical lines indicate the gait events of HS and TO identified with the two methods.

The temporal gait parameters of stride time, stance and swing times, stance and swing percentages were estimated, as well as the angle of flexion-extension of the knee throughout the gait cycle and the knee parameters of maximal flexion, maximal extension, ROM, CV, and CV_Z. All parameters (160 samples per parameter: 16 participants, 10 repetitions) were normalized over the gait cycle to allow cross-comparison between repetitions, subjects, and methods. The validation of the PIMU-based method against the optoelectronic system focused on descriptive statistics and the estimation of RMSE, ρ, and Bland-Altman plots. Brunner-Munzel test was also used for a pairwise comparison between measurements [125]. This non-parametric test method is a generalized and more robust version of the Mann-Whitney U test, which does not require the assumption of equal variances between sample populations [126]. The use of this test is key, as there were substantial differences between parameters when considering the land and underwater test environments.

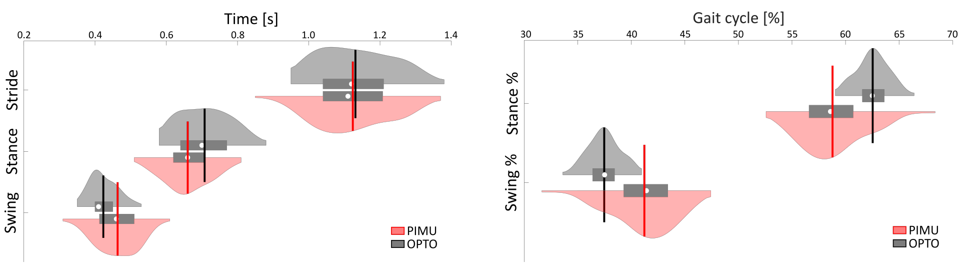
3.2.3 Results and conclusions of PIMU validation

A total of 159 samples were obtained, since one subject had only nine acceptable trials due to non-detected optoelectronic malfunction during data collection (missing a knee marker throughout the recording). These were used to assess the reliability and measurement errors of the PIMUs. Data were tested for normality using a Kolmogorov-Smirnov test and were not found to be normally distributed for the majority of trials. Therefore, results reporting median and interquartile ranges (IQR) are discussed.

Temporal gait parameters estimated by the optoelectronic system and the PIMU sensors are summarized in Table 3.3 and in the violin plots of Figure 3.8. It is appreciable that the stride time estimations were consistent between the methods, while PIMU underestimated the stance time (median difference of 4% of the gait cycle), resulting in an overestimation of the swing time by the same amount. This difference might be attributable to an imprecise definition of the TO event that divides the gait cycle into the stance and swing

		Optoelectronic		PIMU	
		Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
Temporal gait parameters	Stride time [s]	1.12 (1.04, 1.21)	0.17	1.11 (1.04, 1.21)	0.17
	Stance time [s]	0.70 (0.64, 0.77)	0.13	0.66 (0.62, 0.71)	0.09
	Swing time [s]	0.41 (0.40, 0.45)	0.05	0.46 (0.42, 0.51)	0.09
	Stance phase [%]	62.50 (61.61, 63.59)	1.98	58.59 (56.60, 60.69)	4.09
	Swing phase [%]	37.50 (36.41, 38.39)	1.98	41.41 (39.31, 43.40)	4.09
Knee joint parameters	ROM [°]	62.70 (58.54, 67.32)	8.79	60.79 (57.41, 65.47)	8.06
	Max flexion [°]	66.44 (61.38, 69.01)	7.63	63.93 (59.47, 69.36)	9.89
	Max extension [°]	1.76 (-2.11, 5.40)	7.51	2.34 (0.45, 5.18)	4.73
	CV [%]	27.84		31.02	
	CV_z [%]	20.97		31.20	

Table 3.3: Temporal gait and knee joint parameters obtained with the optoelectronic system and PIMU sensors. For each parameter are reported median, first (Q1) and third (Q3) quartiles in parenthesis, and interquartile range (IQR = Q3-Q1).



(a) Temporal gait parameters in seconds.

(b) Gait phases in % of the gait cycle.

Figure 3.8: Violin plot of the temporal gait parameters in seconds (a) and of the gait phases in percentage of the gait cycle (b), obtained by the PIMU sensors (red) and optoelectronic system (OPTO, black). The violin plots graphically represent the data distribution while also reporting its mean value (whole lines), median (white circle), and interquartile range (gray boxplot).

phases. The Brunner-Munzel test found that there were no statistically significant differences between the two methods (p =0.6); while, both stance and swing times demonstrated significant disparities (p <0.001).

The average and standard deviation patterns of the knee flexion-extension angle during the gait cycle obtained by the optoelectronic system and the PIMU are shown in Figure 3.9. The knee angle of the PIMU exhibited a reduced peak value during the stance phase (0 to 20% of the stride) and was found to have a higher residual flexion angle at the end of the gait cycle, around 18°, while approximately 6° for the optoelectronic system. Furthermore, in agreement with the results obtained for the temporal gait parameters, the PIMU slightly anticipated the estimation of maximum knee flexion and TO, represented by the vertical dashed lines. Table 3.3 reports the knee flexion-extension parameters, while Figure 3.10 summarizes the distributions of knee ROM and maximum flexion estimated by two systems. The PIMU underestimated the ROM on average by 1.91° and the maximal flexion by 2.51°, although when looking at the violin plots, the ROM distributions appear similar between methods and, for both parameters, generally more variable for the PIMU system. When comparing CV, it is also noticeable that the variability of the knee joint of PIMU was slightly higher, although both values were in agreement with the reference CV between subjects for a slow cadence of 26% [10]. The differences between optoelectronic and PIMU knee parameters, tested with the Brunner-Munzel test, revealed statistically significant differences in knee ROM (p =0.02) and maximal extension (p =0.02), while no significant differences were observed in maximum flexion (p =0.67).

The validation parameters in Table 3.4 revealed a modest RMSE (up to approximately 5% of the gait cycle for stance time) and an acceptable Spearman correlation coefficient (>0.8) for the temporal gait parameters, consistent with similar studies [127]. The Bland-Altman measurement biases for stride and stance times were small, respectively 0.05s and -0.04s, suggesting a slight underestimation by the PIMU method. Bland-Altman plots

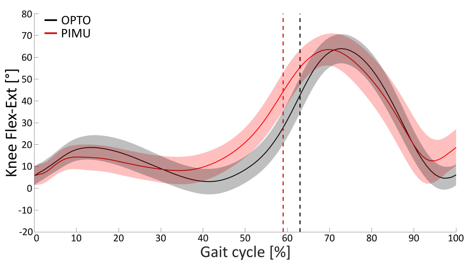


Figure 3.9: Average and standard deviation of the knee angle over the gait cycle for the optoelectronic (OPTO, black) and PIMU (red) system.

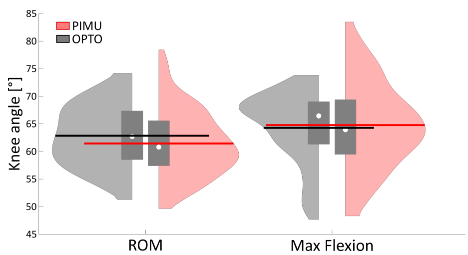


Figure 3.10: Violin plots of ROM and maximal flexion of the knee angle measured by the optoelectronic (OPTO, black) and PIMUs (red).

	RMSE	ρ	Bland-Altman plot coefficients			
			bias	σ	CI low	CI up
Stride time [s]	0.03	0.95	0.01	0.03	-0.06	0.07
Stance time [s]	0.06	0.84	0.05	0.04	-0.03	0.12
Swing time [s]	0.05	0.80	-0.04	0.04	-0.11	0.03
Knee angle [°]	10.96	0.74	-2.94	10.56	-23.64	17.76
Knee ROM [°]	3.81	0.81	1.40	3.55	-5.56	8.36

Table 3.4: Validation parameters used to compare the optoelectronic and the PIMU systems: Root Mean Squared Error (RMSE), Spearman coefficient (ρ), and Bland-Altman bias (average of the differences), standard deviation (σ) and confidence interval boundaries (CI low, CI up).

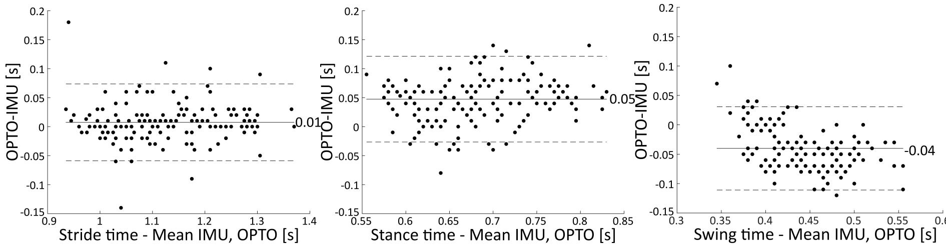


Figure 3.11: Bland-Altman plots of stride time, stance and swing times (in seconds) comparing optoelectronic and PIMU assessments. The whole line is the measurement bias (average of the differences, OPTO-PIMU), and the dashed lines the confidence interval (bias$\pm$ 1.96σ, with σ the standard deviation of the differences).

of the gait temporal parameters of stride, stance, and swing times are provided in Figure 3.11. Additionally, the validation parameters of the knee joint indicated a relatively high RMSE, with respect to the optoelectronic, but a low Bland-Altman bias, comparable to [128].

The improved pressure and IMU loggers developed for aquatic and overground motion analysis were validated through performance comparison against the optoelectronic system. This allowed for the assessment of the system's reliability and to explore the presence of systematic measurement errors. The PIMU system was found to have good accuracy and reliability for motion analysis (RMSE for stride time around 3% of the gait cycle) and was capable of measuring both temporal and joint parameters with a reasonable trade-off between precision and ease of application. However, an underestimation of stride and stance parameters is acknowledged by the PIMUs (respectively, Bland-Altman bias of 0.01s and 0.05s).

The main limitations of this study were the algorithms used to identify gait events. Indeed, solely the planar superficial flexion-extension knee angle were considered, rather than the fully three-dimensional motion around the anatomical internal center of rotation. This limits understanding of the overall motion [129] and may be responsible for the measurement bias and recorded RMSE. On the other hand, the differences in temporal gait parameters observed between PIMU and optoelectronic estimates are presumably a consequence of the method and algorithm used for the identification of the gait events. The definition of HS and TO, based on the detection of acceleration peaks of the foot-mounted sensor, has effects on the estimates of knee angle and is likely to be responsible for the anticipated behavior of the joints and the observed RMSE [130]. Finally, magnetometers are susceptible to local ferromagnetic disturbances and gyroscopic drift that limited the synchronization of the three PIMUs, resulting in time-consuming manual data post-processing required for the final estimation of the kinematic parameters [131, 132].

3.3 Conclusions on RO2

Previous studies [80, 90] have demonstrated the potential of IMU-based systems for aquatic quantitative motion analysis. However, the systematic review presented in Chapter 2 and **Publication I**, revealed a lack of suitable wearable IMU-based technologies, methods, and parameters specific to aquatic motion analysis. To address these gaps, a technology and method for gait analysis is developed and validated that is suitable for both land and underwater investigations. The sensors, based on IMUs measurements, provide a simple and relatively affordable way to quickly and easily perform motion analysis. The development of this technology included two validation steps, presented in **Publication II** and **Publication III**. Considering locomotion, performance cross-comparison of the proposed technology, method and algorithm for data processing was performed against gold standard methods to assess reliability and eventual measurement bias [133].

The proof-of-concept study presented in **Publication II** investigated the kinematics of the knee joint during walking in a small population, using two sensors placed on the thigh and shank of the right leg. Cross-correlation and coefficient of variation indicated strong similarities between the camera-based system and the developed IMU system, and no statistically significant differences were found. The proposed technology was also validated in water, with a marker-based MoCap as a reference, observing an error similar to that observed on land. These findings suggest that the presence of water does not interfere with IMU measurement and that the proposed IMU-based system is suitable for the study of knee kinematics both on land and in water. **Publication II** was the first investigation to validate an IMU-based wearable method on both land and water. Additionally, Gaussian Progress Regression was applied successfully for the first time to improve IMU-based estimates of the kinematics of the knee joint in water.

The results obtained allowed for a technological and methodological improvement of the IMU-based system, presented and discussed in **Publication III**. Three pressure and inertial-based sensors, smaller, lighter, and more versatile than the ones used for the proof-of-concept study, were used to estimate both temporal gait and knee joint parameters. The validation was performed against an optoelectronic system solely overground since the technology and waterproofing methods were similar to those proposed in the proof-of-concept. The findings were aligned with the earlier study, affirming satisfactory precision and reliability. The algorithm used in this study to estimate knee flexion-extension [123] improved RMSE and CV, while the use of three sensors allowed the estimation of gait events and temporal gait parameters, although a slight underestimation of the latter was observed.

The validation carried out in both **Publication II** and **Publication III** relied on three assumptions: (1) the gait pattern of each test subject is considered equally repeated through iterations, neglecting the effects of fatigue and psychological state; (2) the commercial optoelectronic system is assumed to be the most accurate method to record human gait kinematics; (3) the knee flexion extension angle is assumed planar, ignoring lateral variations of body motion and skin artifacts, allowing to compare MoCap, IMU and optoelectronic measures.

Although these assumptions somewhat limit the estimation of the kinematic parameters, to the best of the author's knowledge, the studies conducted to address **RO2** are the first to exploit non-commercially available wireless and cableless inertial sensors for air and aquatic gait analysis. The physical characteristics of the sensors minimize potential movement restrictions, allowing for the continuous monitoring of sports- and rehabilitation-specific movements. The results obtained during the validation study encourage future applications to investigate aquatic gait kinematics, compare it with overground assessments, and analyse more complex tasks and exercises.

4 Aquatic gait analysis

To address **RO3**, the PIMU sensors detailed and validated in the preceding chapter (Section 3.2) were tested in an aquatic setting. The objective is to *systematically characterize aquatic walking*, addressing the gap in structured clinical procedures and methodologies tailored for underwater motion analysis, highlighted in the literature review in Chapter 2.

The clinical-size trial, detailed in **Publication III**, characterizes the primary kinematic features of aquatic walking, encompassing both temporal and knee joint parameters. Preliminary results of this study are also presented as a podium discussion in **publication IV**. The study involved healthy young participants introduced in the PIMU validation study (Section 3.2). Aquatic results are juxtaposed with PIMU land-based data from the validation trial to discern and quantify the kinematic differences that occur between the two environments.

A subset of these participants was enrolled in an additional trial designed to *investigate backward walking in water*, as showcased in the podium presentation in **Publication V**. Although a prevalent component in aquatic rehabilitation protocols [134], objective investigations of backward walking in water through wearable IMU devices were lacking, as indicated by the systematic literature review. This pilot study, which uses the PIMU devices and methods developed for **publication III**, tested the versatility of the sensors and the reliability of the data processing algorithms.

The experimental tests on land and underwater were conducted in compliance with the World Medical Association Declaration of Helsinki and were approved by the Ethics Committee of Politecnico di Milano (Decision 22/2021 on June 14th, 2021. Milan, Italy).

4.1 Instrumentation, method and protocol

To investigate the kinematic peculiarities of aquatic walking, in **Publication III**, sixteen healthy young adults were enrolled (9 Females: 24.8 ± 1.1years, 1.66 ± 0.06m, 59.2 ± 6.7kg; 7 Males: 25.4 ± 2.9years, 1.78 ± 0.05m, 73.6 ± 11.6kg). All subjects had no functional impairments, no neurological or orthopedic conditions, and were free from musculoskeletal injury or pain at the time of data collection. The volunteers had no previous experience with water rehabilitation exercises.

Instrumentation, protocol, and methods were presented in Section 3.2 for the validation portion of **Publication III**. Briefly, the Outwalk protocol [74] was adopted, placing three PIMU sensors on the right lower limb, on the thigh, shank, and foot, and was used to perform gait analysis. The tests were carried out within one week from the validation trial presented in the previous chapter, at the rehabilitative swimming pool of the Enjoy Sport Center (Cernusco sul Naviglio, Milan, Italy). The pool has a fixed depth of 1.20m, is 3m long, and the water temperature remained at 31°C throughout the trials. The same validation trial testing procedure was adopted to allow cross-comparison between environments. Subjects were asked to perform 10 walking tests, initiated with the right leg and anticipated by a two-pose calibration [112].

The data processing methods presented in Section 3.2.2 were adopted to handle aquatic PIMU data and estimate the temporal gait parameters of stride time, stance, and swing times and percentages, as well as to evaluate the knee joint flexion-extension angle and joint parameters. From the magnitude of the acceleration of the PIMU sensor mounted on the foot were identified the gait events of heel strike (HS) and toe off (TO), to determine each gait cycle and temporal gait parameters. From the PIMUs on the thigh and shank, the knee flexion-extension angle was estimated during walking by processing accelerometer and gyroscope data [123]. The second complete gait cycle of the right leg was considered, producing a total of 159 parameters per environment (16 subjects x 10 repetitions, one subject had only 9 valid trials). Characteristics of aquatic walking and differences with land locomotion were observed through descriptive statistics, reporting median and IQR range, and applying the Brunner-Munzel test for non-parametric populations. A subset of this population, further described in Section 4.4, participated in **publication V**, where the same protocol, method, and data processing procedures were adopted and ten repetitions of backward walking were performed after the ten forward walking trials.

4.2 Land and aquatic temporal gait parameters

The acceleration magnitude recorded by the foot-mounted PIMU is used to identify the gait events of HS and TO. An illustration of the raw accelerometer data throughout a complete gait cycle is presented in Figure 4.1, where the stance and swing phases for both land and water environments are highlighted. Notably, underwater gait exhibited a stride time duration almost 2.5 times longer than that observed on land. Furthermore, the acceleration magnitude is observed to be higher on land.

Violin plots in Figure 4.2 show the distributions of temporal gait parameters of the stride, stance, and swing times, in seconds, for land (green) and underwater (blue) walking. These parameters in water increased both in magnitude and variability. Stride increased by a factor of 172%, stance of 162% and swing of 167%, with long distribution tails. All temporal gait parameters are reported in Table 4.1, where despite the substantial increase observed in water, the subdivision into the stance and swing phases remained similar to the on land assessments, respectively, about 58% and 42% of the gait cycle. In good agreement with previous investigations [135], these results confirm that walking in

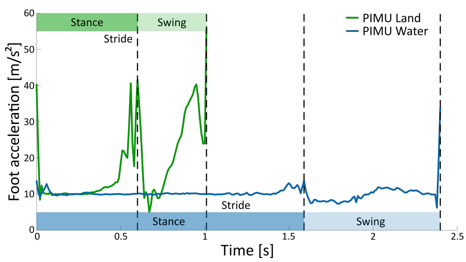


Figure 4.1: Foot-mounted accelerometer magnitude time series during a single gait cycle on land and in water, with highlighted gait phases.

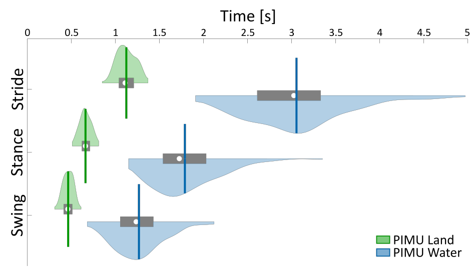


Figure 4.2: Violin plots of the temporal parameters of stride, stance and swing times for land (green) and aquatic (blue) gait analysis.

		PIMU Land		PIMU Water	
		Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
Temporal gait parameters	Stride time [s]	1.11 (1.04, 1.21)	0.17	3.02 (2.61, 3.33)	0.72
	Stance time [s]	0.66 (0.62, 0.71)	0.09	1.73 (1.54, 2.03)	0.49
	Swing time [s]	0.46 (0.42, 0.51)	0.09	1.23 (1.06, 1.43)	0.38
	Stance phase [%]	58.59 (56.60, 60.69)	4.09	58.18 (56.09, 61.27)	5.18
	Swing phase [%]	41.41 (39.31, 43.40)	4.09	41.82 (38.73, 43.91)	5.18
Knee joint parameters	ROM [°]	60.79 (57.41, 65.47)	8.06	60.19 (50.07, 71.68)	21.60
	Max flexion [°]	63.93 (59.47, 69.36)	9.89	65.71 (55.00, 77.91)	22.91
	Max extension [°]	2.34 (0.45, 5.18)	4.73	6.37 (1.00, 11.80)	10.80
	CV [%]	31.02		60.57	
	CV_z [%]	31.20		67.69	

Table 4.1: Temporal gait and knee parameters estimated with the PIMU system in water and on land, reporting median, first (Q1) and third (Q3) quartiles in parenthesis, and interquartile range (IQR).

water encompasses longer gait cycles, but the presence of water does not alter the subdivision into phases. Finally, temporal gait parameters on land and in water were found to be significantly different ($p < 0.001$) according to the Brunner-Munzel test.

4.3 Knee joint parameters in water and on land

Aquatic knee flexion-extension angle, together with the overground assessment, are presented in Figure 4.3. The mean and standard deviation envelopes, normalized over the gait cycle, showed higher variability (shaded area) in water and few differences between environments. During aquatic walking, an average 18° knee flexion angle was observed at 0% of the gait cycle, while the classical flexion peak was absent at the beginning of the stance phase (around 10% of the gait cycle). Knee joint parameters are reported in Table 4.1, where the higher qualitative variability appreciable in Figure 4.3 is confirmed by the superior IQR and a nearly double CV in water, compared to the land-based results. It was also found that the median values of maximal flexion and extension were higher in water,respectively 1.78° and 4.03°. While a similar ROM was observed between the two environments, the IQR was found to be 2.5 higher in water. The Brunner-Munzel test on underwater and overground knee joint parameters were not statistically significant for ROM ($p = 0.46$) and maximal flexion ($p = 0.47$), while maximal extension was statistically significant ($p < 0.001$).

These results, aligned with similar camera-based observations [103, 136, 137], conclude that aquatic gait kinematics is likely to be inherently less repeatable than those on land. The variations in knee flexion-extension observed in water, such as the lack of flexion during load acceptance and the decreased maximum flexion, may be associated with a slower walking pace [10].Previous work has pointed out that these discrepancies may be partially explained by different experimental conditions, such as the depth of the water and the age of the participants [103]. To account for the effect of the height of the participants on the estimated indexes, we also calculated the CV of the knee angle after z-scored normalization (CV_z). Similarly, this parameter more than doubled during the water trials.

The properties of water and the resistance offered to the movement can lead to slower, less controlled and therefore less repeatable motions and overall different motor strategies [103]. These factors limit the cross-comparison of results between subjects and studies on land and underwater.

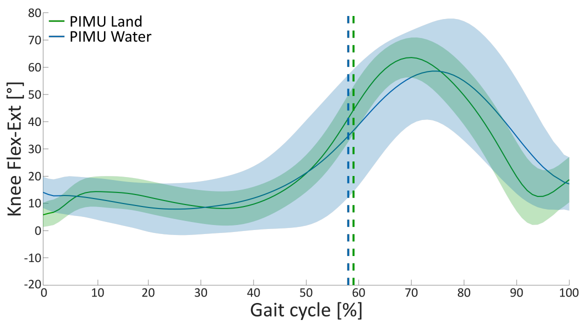


Figure 4.3: Mean and standard deviation envelopes (shaded regions) of the knee joint angle over the gait cycle, calculated on land (green) and in water (blue) with PIMUs. Vertical dashed lines highlight the toe off.

4.4 Backward gait on land and in aquatic setting

Backward Walking (BW) is often overlooked in rehabilitation protocols [6], despite its proven benefits for balance, muscle strength, pain reduction, joint mobility, and overall stability [138, 139], being particularly well suited for people unable to perform high-impact exercises [140]. Backward walking training has shown positive effects on spatio-temporal gait parameters and balance ability [141], also in pathological populations [138]. Previous investigations noted greater variability in temporal parameters, joint angles, and muscular activation compared to forward walking (FW) [142], reduction in knee joint loading [139], and overall differences in balance, coordination, cognitive function, proprioception and spatial awareness [143].

Despite the known benefits of backward walking in water [134, 144], from the review presented in Chapter 2, it is noticeable that no previous studies have investigated the kinematic differences between forward and backward walking in water using wearable IMU sensors. Addressing this research gap, a subset of the participants in the clinical study presented in **Publication III** were involved in a pilot study.

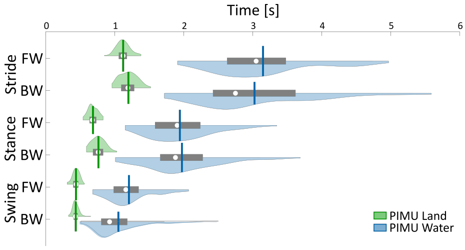
The aim of the study was to assess and compare the characteristics of forward and backward gait, both in and out of water, using PIMU sensors. Specifically, the focus was on spatial-temporal parameters and the kinematics of the knee joint. Five females (24.5 ± 0.6 years, 1.62 ± 0.06 m, 58.8 ± 5.4 kg) were involved and walked 10 times forward and backward in and outside the water. The pool was the same used in the clinical study (3m long, 1.20m deep), and the sensors' positioning, protocol and data processing followed the one described in Section 3.2. Given the small sample size involved, the first two complete gait cycles or the right leg were analysed, providing 100 samples for each parameter and environment (5 participants x 10 times, two gait cycles each).

The median and IQR of the temporal gait parameters and the knee joint measures are

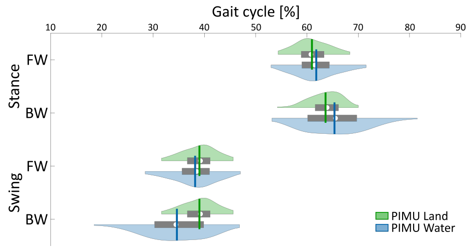
		PIMU Water			
		Forward walking		Backward walking	
		Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
Temporal gait parameters	Stride time [s]	3.05 (2.63, 3.48)	0.85	2.75 (2.43, 3.62)	1.19
	Stance time [s]	1.91 (1.58, 2.24)	0.66	1.88 (1.66, 2.28)	0.62
	Swing time [s]	1.16 (0.99, 1.35)	0.36	0.93 (0.81, 1.18)	0.37
	Stance ph. [%]	61.52 (59.01, 64.36)	5.35	65.56 (60.14, 69.71)	9.57
	Swing ph. [%]	38.48 (35.64, 40.99)	5.35	34.44 (30.29, 39.86)	9.57
Knee joint parameters	ROM [°]	79.91 (61.14, 102.88)	41.74	75.62 (62.27, 95.25)	32.98
	Max Flex. [°]	79.68 (62.13, 102.17)	40.04	75.91 (56.87, 100.38)	43.51
	Max Ext. [°]	5.47 (-4.10, 12.39)	16.49	0.30 (-7.95, 6.84)	14.79
	Knee CV [%]	73.32		90.59	
	Knee CV_z [%]	82.79		84.83	

		PIMU Land			
		Forward walking		Backward walking	
		Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
Temporal gait parameters	Stride time [s]	1.12 (1.06, 1.18)	0.12	1.19 (1.09, 1.28)	0.19
	Stance time [s]	0.68 (0.63, 0.73)	0.10	0.76 (0.69, 0.83)	0.14
	Swing time [s]	0.44 (0.40, 0.47)	0.07	0.43 (0.40, 0.46)	0.06
	Stance ph. [%]	60.77 (58.88, 63.33)	4.45	63.91 (61.60, 66.15)	4.55
	Swing ph. [%]	39.23 (36.67, 41.12)	4.45	36.09 (33.85, 38.40)	4.55
Knee joint parameters	ROM [°]	61.38 (58.24, 63.75)	5.51	50.08 (48.12, 52.43)	4.31
	Max Flex. [°]	62.54 (59.12, 65.38)	6.26	55.13 (48.71, 57.96)	9.25
	Max Ext. [°]	1.22 (-2.29, 3.19)	5.48	3.04 (-1.08, 8.01)	9.09
	Knee CV [%]	32.43		40.04	
	Knee CV_z [%]	35.27		35.49	

Table 4.2: Temporal and knee joint parameters estimated with the PIMU system in water and on land during forward and backward walking. For each parameter are reported median, first (Q1) and third (Q3) quartiles in parenthesis, and interquartile range (IQR = Q3 - Q1).



(a) Temporal gait parameters in seconds.



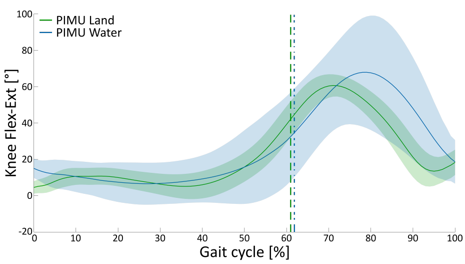
(b) Gait phases in % of the gait cycle.

Figure 4.4: Temporal gait parameters (a) and subdivision into gait phases (b) during Forward (FW) and Backward (BW) walking on land (green) and in water (blue).

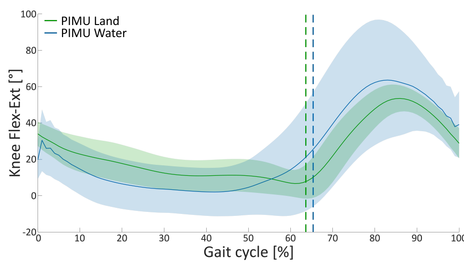
reported in Table 4.2 for the two environments and tasks considered. Figure 4.4 shows the violin plot for the temporal gait parameter, on land and in water for forward (FW) and backward (BW) walking, while the values are reported in Table 4.2. Similarly to what was observed in the previous section, when moving from land (green) to underwater (blue) assessments, the parameters increased in magnitude and variability. The duration of stride in water tripled during forward walking and doubled for backward walking. Interestingly, when moving from FW to BW walking, a longer stride time was observed on the ground and a reduced one in the water (Figure 4.4a). Taking into account the gait phases of FW, expressed as a percentage of the cycle (Figure 4.4b), when in water, the variance of all distributions increased, but the subdivision into stance and swing phases remained in general similar to the land-based walking values. Unlike BW, a longer stance phase was appreciable, on land and even more in water, resulting in shorter swing phases.

The kinematics of the knee, normalized over the gait cycle for walking on land and underwater, forward and backward, is shown in Figure 4.5. During backward walking, the stance phase is characterized by higher flexion at the beginning of the gait cycle and a generally more extended knee angle during the midstance (from 20% to 50% of the gait cycle). In both tasks, the knee joint reaches a higher maximum flexion in water, although with greater variance. The angle coefficients of the knee joint in Table 4.2 confirm these qualitative observations, also supported by CV, much higher in water and during backward walking.

This preliminary study was successful in assessing forward and backward walking in



(a) Forward walking.



(b) Backward walking.

Figure 4.5: Mean and standard deviation envelope (shaded regions) of the knee joint angle normalized over the gait cycle, calculated on land (green) and in water (blue) during Forward and Backward walking. Vertical dashed lines highlight the toe off.

water with the proposed wearable PIMU sensors, with results in agreement with previous camera-based investigations of land-based walking [6]. The results pointed out a much higher variability of both temporal and knee joint parameters for backward walking both in water and on land, while the overall kinematics is preserved between the two environments.

4.5 Conclusions on RO3

To address **RO3**, the PIMU sensors were applied to the water environment to investigate and quantify the main kinematic characteristics of aquatic walking. **Publication III** encompassed a clinical-size trial involving 16 healthy adults that addressed the lack of structured procedures and methodologies based on wearable IMU devices specifically tailored for underwater motion analysis. WearablePIMU sensors were used without any adjustment on land and underwater, with results in agreement with previous IMU-only studies [103, 109]. The kinematic differences between land and underwater gait and knee joint parameters can be justified by the slower walking speed in water [137]. All parameters reported higher variability in water, compared to land-based walking. For example, the stride time on land reported an IQR of 0.17s, while underwater it was 0.72s, which is about 15% and 24% of the gait cycle, respectively. Similarly, the knee angle coefficient of variation after normalization (CV_z), was 67.69% in water, a result far from the standard CV defined by Winter of 26% [10].

In **Publication V** a pilot study on backward aquatic walking was recommended. The purpose was to examine the adaptability of the PIMU that was developed in evaluating a different task that is somewhat similar. The results were promising, although they involved a small population. While in agreement with a similar previous analysis on backward walking on land [139], a greater variability of all kinematic parameters was observed, which may be linked to the absence of visual feedback during backward walking [6].

Focusing on the water environment, the higher volatility of the kinematic gait parameters has been justified by previous investigations by the properties and resistance of the fluid medium [103]. The density of water increases the resistance to movement, resulting in slower, less controlled, and less repeatable motions. This suggests that different motor strategies may have been utilized. Additionally, the act of walking in water presented a novel form of exercise for the participants, leading to a lack of ability to replicate and maintain consistency across different attempts. The study did not anticipate a trial for adaptation, which could have impacted the variability of the findings. Future studies should consider an adaptation period and might investigate the learning effect and changes in gait variability across trails and repetitions. Furthermore, the studies conducted only involve sensors being placed on the right leg. This limitation restricts the examination of the overall body movements and symmetry of walking, resulting in a lack of comprehensive understanding regarding the strategies employed for walking in water.

The results obtained have validated the flexibility and dependability of PIMUs for aquatic gait analysis. However, the significant variability raises concerns about the appropriateness of using the standard kinematic gait parameter to analyse and describe underwater motion. Although the comparison between walking on land and underwater is undoubtedly valuable, using terms that are specific to land-based movement overlooks the presence of water and may not be sufficient for accurately describing underwater motion and the impact of the medium.

5 Hydrodynamic pressure during aquatic walking

The review discussed in Chapter 2 (**Publication I**) highlighted that previous research on aquatic motion relies on methodologies, technologies, and parameters that were originally developed for assessing land-based movements. As a consequence, there is a requirement for strategies to modify traditional technology for underwater use, such as employing waterproof casings that may sacrifice accuracy or investing in costly technologies that resemble the optoelectronic method for use in water. Moreover, in Chapter 3 and Chapter 4 (**Publication II, III, IV, V**), it has been observed that the estimation of traditional land-based gait parameters in water exhibits higher variability and uncertainty compared to overground estimates.

Despite the acknowledgement of the lower repeatability of aquatic motion and the challenges associated with the task, these findings raise doubts about the suitability of these parameters for characterizing underwater motion. Furthermore, the use of conventional overground parameters fails to account for the presence of water and its unique properties, limiting the investigation to the kinematics resulting from the interaction with the fluid. Consequently, our understanding of the interaction between a moving body and the fluid, as well as the characterization of water's buoyancy, drag, and resistance, remains limited.

In order to overcome these limitations, the PIMU sensors that have been previously presented, validated, and tested in previous chapters are utilized. This is done to evaluate the reliability of the hydrodynamic pressure on the lower limbs as a new parameter for analysing aquatic motion (RO4). By using this measure, which is specifically tailored for water environments, a more accurate understanding of the interaction between the body and the fluid can be obtained. It provides insights into the hydrostatic pressure of water, which is responsible for supporting and stabilizing the submerged body (pressure) [45]. Additionally, quantifying the pressure on the lower body allows for the consideration and description of the resistance encountered during aquatic motion. This is important for assessing the effects of aquatic training on the musculoskeletal, cardiovascular, and cardiocirculatory systems [46, 47].

In **Publication III**, the hydrodynamic pressure was recorded during typical forward walking. Additionally, the data collected for **Publication V** was used to quantify the hydrodynamic pressure during both forward and backward walking. In doing so, this author was able to characterize the hydrodynamic pressure time series at the thigh, shank, and foot during a gait cycle. Afterwards, this allowed for the comparison of the variability and trustworthiness of these pressure measurements with the knee angle measurements, as presented in Chapter 4 using the z-scored Coefficient of Variation.

5.1 The method and data processing

During both **Publication III and V**, three PIMU sensors were placed laterally on the right lower limb (see Section 3.2 and Figure 3.6). Each PIMU included a MS5837-02BA (TE Connectivity) pressure sensor, with operating range 300-1200 mbar between -20 to +85°C and accuracy of ±4 mbar.

The hydrodynamic pressure recorded by each sensor, later referred to as thigh, shank, and foot, was processed by subtracting the median value for each dataset to account for the different heights and submersion levels of the subjects, and was subsequently normalized over the gait cycle. The hydrodynamic pressure parameters similar to the knee angle were estimated: maximal and minimal pressure, as well as the Range Of Pressure (ROP), calculated as their difference and coefficients of variation (CV and CV_z). Descriptive statistics of the results are given reporting average time series and standard deviation envelopes for each sensor, median, and IQR per each parameter estimated.

5.2 Hydrodynamic pressure during forward walking

The 16 healthy participants involved in **Publication III** resulted in 159 hydrodynamic pressure measures per sensor location. The mean time series and standard deviation envelopes of the hydrodynamic pressure over the gait cycle are shown in Figure 5.1 for each sensor location, where the vertical dashed line highlights the average toe off. Distinctive patterns can be observed in the gait cycle. Approximately 40% of the gait cycle, specifically during the stance phase, showed minimal signals. At 40% of the gait cycle, during the mid-stance phase, the pressure on the shank started to decrease, indicating the arrival of the contralateral swinging leg and the upward movement of the leg towards the water surface. In contrast, the pressures on the thigh and foot remained relatively constant until 50% of the gait cycle, which corresponds to the heel-off phase. This phase marks the initiation of the foot detaching from the ground in preparation for the swing phase. A reduction in thigh and foot pressure was noted during the preswing and initial swing phases of the gait cycle, which occurred after 50% of the cycle. During this phase, the thigh, shank, and foot come closer to the water surface, resulting in a decrease in hydrodynamic pressure. The magnitude of these fluctuations was found to be directly related to the degree of movement, with smaller variations observed in the thigh, intermediate changes in the shank, and larger fluctuations in the foot. During the final stages of the gait cycle, specifically the mid- and terminal swing phases (80% to 100%), the hydrodynamic pressure steadily rose until returning to its original level. As the lower limb approached the ground in anticipation of heel strike, the leg moved away from the water surface, resulting in an increase in hydrodynamic pressure. Notably, the average pressure on the thigh and shank exhibited two clear patterns around the 60% and 80% points of the gait, corresponding to the initial swing and mid-swing phases.

The violin plots in Figure 5.2 report the ROP distributions for the three locations, while all estimated parameters are summarized in Table 5.1. The pressure measured on the thigh exhibited the smallest ROP in terms of both the median (7.68 mbar) and the IQR (5.60 mbar), along with the highest CV at 138 35%. In contrast, the foot location recorded the largest ROP (19.97 mbar with an IQR of 11.78 mbar) and the lowest CV (80.06%). Finally, the shank location displayed intermediate values for both ROP (13.98 with an IQR of 8.34) and CV (98.99%). Normalization of CV (CV_z) confirms that the hydrodynamic pressure on the foot (CV_z = 39.65%) exhibits greater repeatability between subjects and trials.

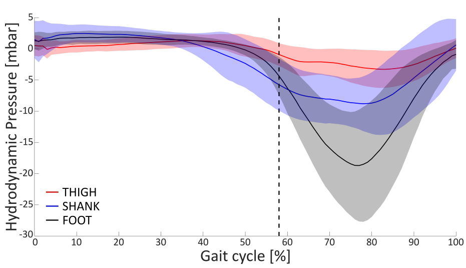


Figure 5.1: Mean and standard deviation envelopes (shaded) of the hydrodynamic pressure over the gait of thigh, shank and foot PIMUs.

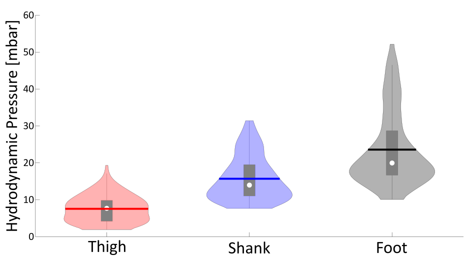


Figure 5.2: Range of pressure violin plots, reporting mean value (whole lines), median (white circle), and interquartile range (gray box).

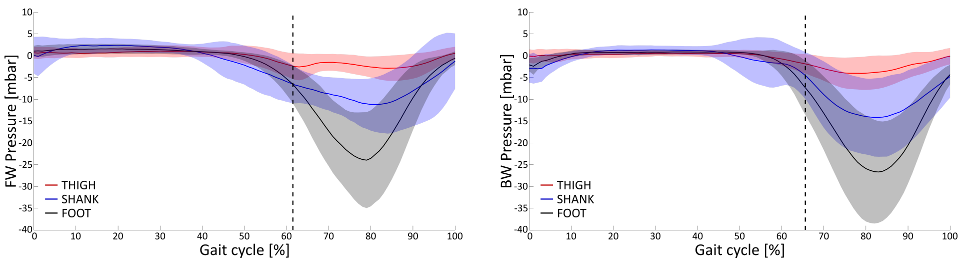
	Thigh		Shank		Foot	
	Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
ROP [mbar]	7.68 (4.20, 9.81)	5.60	13.98 (11.04, 19.39)	8.34	19.97 (16.75, 28.53)	11.78
Max pressure [mbar]	2.50 (1.67, 3.29)	1.63	3.13 (2.32, 4.10)	1.78	2.43 (1.80, 3.27)	1.47
Min pressure [mbar]	-4.54 (-7.00, -2.52)	4.49	-11.35 (-15.75, -7.80)	-14.20	-17.64 (-26.61, -14.20)	12.41
CV [%]	138.34		98.99		80.06	
CV_z [%]	126.88		70.15		39.65	

Table 5.1: Hydrodynamic pressure parameters of underwater gait, reporting median, first (Q1) and third (Q3) quartiles in parenthesis and interquartile ranges (IQR = Q3-Q1) of Range of Pressure (ROP), maximal and minimal pressure and coefficient of variation (CV and CV_z).

5.3 Hydrodynamic pressure during backward walking

Publication V investigated the characteristics of forward and backward aquatic walking. As introduced in Section 4.4, five healthy young women were asked to walk ten times forward and backward in and outside a rehabilitation swimming pool. The tasks were performed while wearing three PIMUs on the right lower limb, as described in Section 3.2. The first two complete gait cycles of the right leg were considered, obtaining 100 hydrodyamic time series per PIMU location.

The mean and standard deviation envelopes of the hydrodynamic pressure for the location of the three sensors are reported in Figure 5.3 for forward and backward walking. The hydrodynamic pressure of the thigh sensor during backward walking does not exhibit the two distinct curves observed during forward walking in Figure 5.3 (around 60% and



(a) Forward walking. *(b) Backward walking.*

Figure 5.3: Mean and standard deviation envelope (shaded regions) of the hydrodynamic pressure over the gait cycle during Forward and Backward walking.

		Thigh		Shank		Foot	
		Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
Forward walking	ROP [mbar]	8.48 (6.71, 10.76)	4.05	18.8 (14.02, 25.03)	11.01	25.37 (19.32, 39.84)	20.52
	Max pressure [mbar]	2.91 (2.20, 3.64)	1.44	2.73 (1.96, 4.49)	2.53	1.98 (1.38, 3.06)	1.68
	Min pressure [mbar]	-5.70 (-7.46, -3.63)	3.83	-15.53 (-20.47, -11.57)	8.90	-24.20 (-37.03, -17.97)	19.06
	CV [%]	155.93		105.24		82.43	
	CV_z [%]	63.64		13.56		5.71	
Backward walking	ROP [mbar]	7.74 (4.58, 10.22)	5.64	20.43 (14.29, 26.55)	12.26	28.22 (21.30, 36.88)	15.58
	Max pressure [mbar]	1.96 (1.45, 2.58)	1.13	2.27 (1.67, 2.81)	1.14	1.37 (1.00, 1.75)	0.75
	Min pressure [mbar]	-6.01 (-8.01, -2.67)	5.34	-17.56 (-23.99, -12.44)	11.55	-27.13 (-35.06, -20.01)	15.05
	CV [%]	163.80		114.43		81.23	
	CV_z [%]	67.66		14.11		5.00	

Table 5.2: Hydrodynamic pressure parameters of underwater forward and backward walking, reported as the median, first (Q1), third (Q3) quartiles in parenthesis and interquartile ranges (IQR) of the Range of Pressure (ROP), maximal and minimal pressure, and coefficient of variation (CV and CV_z).

80% of gait). The hydrodynamic pressure on the shank started to decrease around 50% of the gait cycle for FW, while for BW this decrease occurred around 60% of the stride, probably for the longer stance phase observed. Finally, the pressure on the foot does not show major differences between FW and BW. Table 5.2 summarizes the pressure parameters estimated for forward and backward walking. The median ROP decreased in BW for the thigh, but increased in both median and IQR for the shank and foot. Both maximal and minimal pressure were reduced during backward walking, while CV and CV_z increased for the thigh and shank and decreased for the foot.

5.4 Conclusions on RO4

Provided the high variability in water of traditional gait analysis parameters, **RO4** proposed and investigated the use of pressure sensors for the characterization of aquatic walking. Wearable PIMUs were used to describe the interaction between water and the body in motion in an unprecedented way. Unlike previous studies that relied on methodologies and parameters designed for terrestrial assessments, this work introduces a parameter specifically tailored to the underwater environment. The unique characteristics of water are therefore considered and their effects on the body in motion.

The hydrodynamic pressure exerted on the moving body during underwater locomotion was investigated at three locations of the lower limb (thigh, shank, and foot). Data were processed similarly to knee angle estimates, involving z-score normalization to account for height variations amoung the human test subjects. **Publication III** pointed out interesting features of hydrodynamic pressure during the gait cycle, with peculiar time series sequences, especially at the thigh. The z-scored Coefficient of Variation of pressure and knee joint angle were compared, observing that CV_z of the hydrodynamic pressure at the foot (39.65%) was comparable to the one observed for the knee on land (31.20%). These results imply that foot hydrodynamic pressure might serve as a less variable parameter for evaluating underwater walking gait compared to knee angle that reported in water a CV_z of 67.69%.

A preliminary pilot study measured the hydrodynamic pressure on the lower limb during forward and backward locomotion. Differences were observed between tasks and, while the small number of subjects involved does not allow for comprehensive statements, the smaller CV_z at the foot suggested a more controlled movement during backward walking. These results could be justified by the fact that when walking backwards in water subjects are more dependent on buoyancy force at the pelvis level, allowing for more controlled foot placement and greater thigh motion (higher CV_z). The hydrodynamic pressure CV_z during backward walking were also significantly smaller than those observed in **Publication III**, possibly because of the reduced number of subjects involved and of the consideration of the first two gait cycles, rather than relying on only one step per repetition.

The PIMU sensors were placed on the lower limb following the Outwalk protocol in both studies. This positioning provided hydrodynamic pressure data specifically for the lateral part of the leg. Although this approach restricts the comprehension of the overall interaction between the lower limb and the surrounding fluid, it enables a more accurate comparison with the CV_z of the knee angle. However, it is still unknown if there are more appropriate locations for evaluating the hydrodynamic pressure.

The proposed device and method enhance our understanding of how the existence of water influences the walking gait in water. It is recommended to utilize hydrodynamic pressure as a measurement in order to obtain a thorough understanding of the interaction between the human test subject and the water environment.

6 Conclusions and future outlook

This dissertation achieved the *objective of developing, validating and testing a novel wearable technology for the assessment of aquatic motion*. Four main research objectives were defined and addressed, providing significant contributions to the field and to the state of the art. The systematic literature review (RO1), provided a much-needed up-to-date assessment on the state of wearable aquatic motion analysis research. Focusing on methods for monitoring aquatic exercise and on the use of wearable IMU-based devices, four research gaps were identified, providing a foundation for future studies to improve monitoring methods and parameters. The core deficiency highlighted was the lack of versatile and reproducible methods and parameters developed specifically for underwater monitoring. This was addressed through the three subsequent research objectives in this dissertation by developing and validating (RO2) a novel technology for aquatic assessment, testing it underwater (RO3), and developing, testing and validating the hydrodynamic pressure on the lower limbs as a new parameter for aquatic motion analysis and gait characterization (RO4).

The proposed technology used custom-designed loggers suitable for motion analysis both on land and underwater. These small and lightweight loggers encompass the hardware requirements for use underwater. They are safe, simple to attach to the body and cause as little discomfort as possible to movement. The devices incorporate an inertial measurement unit and a pressure sensor and were validated for gait analysis in both environments (RO2). This sets the research apart from existing commercial sensors, which are often unsuitable for aquatic use and come with limited versatility and trustworthiness, due to proprietary processing algorithms. The Outwalk protocol was modified to focus on knee joint kinematics and gait temporal parameters, allowing for a comprehensive assessment of locomotion on land and underwater. The integration of Gaussian Process Regression further improved the accuracy of knee angle estimates. Validation against gold standard systems for motion analysis demonstrated the prototype PIMU system's high versatility and reliability. PIMU loggers were also used in a clinical-sized investigation to characterize aquatic locomotion (RO3). This addressed the lack of structured clinical procedures for aquatic motion analysis. The modified Outwalk protocol and the custom data processing algorithms facilitated fast and accurate gait analysis. An exploratory study on aquatic backward gait analysis through wearable IMU was also carried out. In all cases investigated, thekinematic parameters displayed greater variability in water than on land, exhibiting larger uncertainties and overall lower task repeatability. Finally, the use of hydrodynamic pressure as new parameter for evaluating the walking gait in the water environment (RO4) was explored. This innovative parameter is well-suited for the aquatic environment and provides insight into how water influences body movement. The results highlighted unique characteristics of the hydrodynamic pressure on the thigh, shank and foot throughout the gait, providing a detailed description of the interaction between the body in motion and the surrounding fluid.

It is crucial to acknowledge the limitations of the investigations carried out in this work, both in terms of the protocol used and the methods adopted. The number of subjects involved, especially in the proof-of-concept study and in the pilot study on backward walking were insufficient for a comprehensive generalization of the findings. Although the number of subjects was sufficient for the preliminary nature of these analyses, only healthy young adults were involved, and therefore a large question remains as to the suitability of the technology and protocol for pathological populations. Similarly, the walking gait cycle was the focal task of this work, and the transferability of the proposed technology and processing algorithms to other locomotive activities remains to be tested. Due to environmental constraints, a pool with fixed depth was used, reducing the understanding of aquatic gait kinematics and of the effects of hydrodynamic pressure at different submersion depths. Another limitation of this work was the choice to equip only the right leg with sensors during study to limit the amount of data processing. This restricted the analysis to a single limb, where a more comprehensive understanding of aquatic locomotion, bilateral movement, and symmetry patterns require follow-up studies including sensors applied to the whole body. The algorithms and processing methods adopted may also have influenced the accuracy and applicability of the developed technology. By focusing on a few well-established parameters, the investigation of the knee joint was primarily planar, neglecting the incidence of mediolateral 3D components. Therefore, the broader spectrum of potential kinematics gait parameters influenced by the presence of water remains unexplored. Finally, it should be mentioned that the studies carried out in this work did not evaluate measures related to subjective experiences, such as fatigue, adaptation to the task and general comfort.

To broaden the applicability of the PIMU technology, future studies should consider exploring a variety of aquatic exercises beyond walking and extending to pathological populations. Understanding how the technology performs across different activities and conditions, such as squat, lunges, leg lifts, and aqua-cycling, which will further serve to enhance its versatility. Additionally, investigating how individuals with specific conditions or impairments interact with water, such as elderly, post-stroke, and Parkinson's patients, could open new possibilities for therapeutic interventions. Incorporating qualitative questionnaires along with the proposed methodology could provide insight into the subjective experiences and perceptions of individuals engaging in aquatic activities, offering a more holistic understanding. While alternative processing techniques and algorithms could enhance the robustness of the assessment system, prospective research should delve into a more detailed characterization of water forces. Distinguishing between resistance components (pressure and drag) and buoyancy represents a crucial avenue for refinement. This nuanced understanding will contribute to refining the assessment of aquatic motion.

This work contributed to the field of aquatic locomotion by proposing, validating, and critically discussing the application of the proposed PIMU technology. It did so by systematically addressing gaps identified in the literature. The customized PIMU sensors were validated against gold standard methods on land and underwater and were evaluated in clinical investigations. Kinematic gait characteristics and differences between aquatic and overground motion were given special attention. Finally, the validation of the hydrodynamic pressure provides a new parameter for aquatic motion analysis by incorporating and characterize fluid-body interaction over the gait cycle. The contributions of this work thus enable a new, versatile and comprehensive wearable technology for aquatic motion assessment.

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Appendix 1

Publication I
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Wearable technologies for monitoring aquatic exercises: A systematic review

Cecilia Monoli[1,2], Jeffrey A Tuhtan[1], Luigi Piccinini[3], and Manuela Galli[2]

Abstract

Objective: To review methods for aquatic exercise monitoring using wearables.

Data sources: Database search of PubMed, IEEEXplore, Scopus and Web of Science based on keywords, considering articles from the year 2000. The last search was performed on 26 October 2022.

Review methods: Following the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) protocol, eligible articles on water exercises were selected and summarized. Further screening process concentrated on studies exploiting wearable devices, organized according to demographics, purpose, protocols, outcomes and methods. A custom critical appraisal questionnaire was applied.

Results: Out of the 1062 articles identified, 572 were considered eligible and subjected to preliminary synthesis. The final review focused on 27 articles featuring wearable devices applied to aquatic exercises. Four studies were disregarded as they applied wearable devices to determine daily physical activity or for sleep monitoring after training. Summary tables of 23 studies exploiting wearable devices for underwater motion analysis are provided, specifying the investigated parameters, major outcomes and study quality. This review identified four research gaps: (a) the absence of clinical protocols for underwater motion studies, (b) a deficit of whole-body studies, (c) the lack of longitudinal studies monitored via wearable devices and (d) the reliance of underwater studies on measurement and assessment methods developed for land-based investigations.

Conclusions: This review emphasizes the need for both technological and methodological improvements for underwater motion analysis studies using wearables. We advocate for longitudinal clinical investigations with wearables to substantiate water exercise as an addition or replacement for land-based physical activity.

Keywords

Aquatic exercises, water, hydrotherapy, wearables, IMU, systematic review

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[1]Department of Computer System, Tallinn University of Technology, Tallinn, Estonia
[2]Department of Electronics, Information and Bioengineering, Politecnico di Milano, Milano, Italy
[3]Scientific Institute "E. Medea" Ass. La Nostra Famiglia, Bosisio Parini, Italy

Corresponding author:
Cecilia Monoli, Department of Computer Sysytem, Tallinn University of Technology, Tallinn 12616, Estonia.
Email: cecilia.monoli@taltech.ee

Introduction

Aquatic exercises and hydrotherapy are especially well suited where traditional land-based physical therapies are known to be potentially harmful,[1] due to the weight-reducing and stabilizing forces of buoyancy and drag that water provides.[2] Systematic reviews of aquatic motion analysis have focused on specific dysfunctions or conditions, such as neurological diseases,[1,2] fibromyalgia,[3] asthma,[4] spinal cord injury,[5,6] haemophilia[7] and stroke[8–10.] Additional reviews have also investigated the physiological effects of water,[11] evaluated the use of aquatic exercise for healthy subjects[12,13] and for glycaemia[14] and studied the biophysical differences between aquatic and land-based treatments.[15] The presence of water generally constrains the application of classical investigative tools for motion analysis, including motion capture and electromyography.[16,17] Currently, systematic investigations of underwater motion remain scarce: two reviews explored the literature on surface electromyography for exercises and gait in water, and for deep water running,[18,19] while Heywood et al.[20] focused on spatiotemporal and kinematic parameters in water. Lastly, Marinho et al.[21] surveyed the use of wearable Inertial Measurement Units (IMUs) for underwater human monitoring for non-swimming activities.

The objective of this review is to identify major research gaps and determine potential improvements for future clinical studies by addressing two research questions. First, what are the most frequently applied methods for aquatic motion analysis over the past two decades? Second, what major gaps remain when considering the existing body of literature using IMU wearable devices for monitoring of underwater exercises, and what can be done to improve the understanding of aquatic motion analysis?

The current review provides a systematic assessment of the state of the art of aquatic exercises and hydrotherapy studies, following the Preferred Reporting Items for Systematic Review and Meta-Analyses[22] (PRISMA) method.

Methods

The review protocol was registered in the international database PROSPERO (CRD42022316782). The selected literature repositories were searched using specific keywords and considering only peer-reviewed articles published from 2000 onward. The final search was performed on 26 October 2022 by two independent reviewers.

The identification of candidate English-language literature was performed on *PubMed*, *IEEE Xplore*, *Web of Science* and *Scopus* databases. The complete list of keywords and filters applied is reported in Appendix (Table A1), as well as the number of articles selected per database. Due to the large number of potentially significant studies, the terms underwater, water and aquatic were used to refine the field of interest. The keyword combinations used for screening concerned general exercise terms including rehabilitation, training, hydrotherapy and kinematic. In addition, the exercise-specific keywords treadmill, gait and walk were included to improve the specificity of the filtering stage of the review. The keywords IMU, electromyography, motion capture, force plate and wearable devices were also included as they represent the most current aquatic exercise monitoring methods.

Potentially relevant articles and additional articles identified through citation searching were screened following PRISMA after removing duplicates (Figure 1). To reduce errors and avoid risk of bias, the identified articles were filtered, sorted, examined and evaluated by two independent authors. Based on the title and abstract, articles outside the scope of the research questions, review articles, publications featuring animals or robots, book chapters and theses, discussion articles and editorials unrelated to aquatic exercises were excluded. Subsequently, further works were omitted which were unrelated to active hydrotherapy including shower massages, spa therapies or passive water immersion, swimming, diving or other recreational water sports. In addition, articles developing mathematical models, works which provided guidelines for clinical study designs, physical activities surveys or publications testing novel waterproofing methodologies and tools were also excluded. A preliminary synthesis was conducted on the remaining eligible articles. The synthesis was used to define the state of the art, organize the studies by publication year, demographics, general characteristics and the methods used to investigate motion.

Finally, PRISMA stage was considered solely the eligible articles exploiting wearable devices. A qualitative synthesis of works using wearable technologies for underwater motion analysis was conducted because a meta-analysis was considered inappropriate due to the substantial heterogeneity of the remaining studies. Articles using wearable devices to quantify daily physical activity or for sleep monitoring were disregarded from the qualitative synthesis.

An overview of the demographics and characteristics of the investigation, choice of protocol, evaluation method and estimated outcomes was generated. A custom critical appraisal questionnaire of the studies was created based on STROBE,[23] CASP[24] and McMaster[25] assessment tools. The custom questionnaire consists of nineteen questions and is provided in Table A2. Articles were evaluated according to positive, negative, partial answer or not applicability of the inquiry.

Results

Preliminary synthesis of the eligible articles

After removing duplicates, a total of 1062 potentially relevant articles were identified and filtered producing 572 eligible articles (Figure 1). In the period ranging from 2000 to 2010, 142 (25%) articles were published on water exercise and from the years 2011 to 2022, 430 (75%) articles were identified, indicating a growing interest of researchers and clinicians in aquatic activities.

Examining the structure of the eligible studies, 333 (58%) works analysed the whole rehabilitation cycle over multiple weeks to evaluate the effect of the long-term protocols through pre/post comparison. The remaining 239 (42%) studies investigated the subjects once, and generally presented results based on 5–10 repetitions of the investigated task to estimate the differences between water and land-based exercises.

Slightly more than half of the eligible articles (293, 51%) involved healthy subjects. The remaining 279 focused on patients with disorders and chronic conditions, 20 of which included a healthy control group. The most common conditions investigated were neurological impairments (100) including Parkinson's disease, stroke, multiple sclerosis, incomplete spinal cord injury and intellectual disabilities. The second most common conditions pain-related disorders including arthritis, osteoporosis, fibromyalgia and non-specific back pain (75). A total of 39 studies considered cardiovascular or respiratory diseases. Twenty articles involved children and 16 considered orthopaedic conditions. The remaining 29 works focused the investigation on various pathologies and conditions as diabetes, obesity and pregnancy.

The outcomes of water activities were monitored in 318 of the 572 eligible studies with quantitative methods. Among them, 88 works exploited two or more of these tools. The most common methodology exploited was the dynamometer (94), which was applied to estimate strength and muscular endurance. Force plates and pressure sensors were used in 88 studies to investigate the dynamic component of motion as ground reaction forces or to evaluate balance ability and proprioception. Kinematics were investigated with motion capture in 84 articles using optoelectronic[26] systems based on infrared cameras or video analysis using standard commercial cameras and smartphones. Electromyography was used in 81 articles to record the electric signals generated by muscle contraction via surface or intramuscular electrodes. A total of 34 studies exploited goniometers to measure joints' range of motion, 27 articles used IMU devices to investigate motion using small, lightweight data loggers outfitted with a combination of triaxial accelerometer, gyroscope and magnetometer sensors. The remaining set of 13 studies made use of other highly customised technologies. The most common combinations of monitoring systems were motion capture and electromyography (17) or force plates (10) or both (6). Wearables were used in combination with motion capture, force plates and electromyography in 12 studies.

The other main category of techniques employed to monitor aquatic exercises are methods for metabolic assessments. The most common methods were heart rate and respiratory gas analysis. Semi-quantitative and qualitative methods for motion analysis included tests, scales and questionnaires, and were focused towards determining patient conditions, mobility and the overall effectiveness of water-based therapies. Furthermore, these methods can be categorized into seven distinct groups: (a) functional tests of motion-related, kinematic and muscular evaluations for gait specific tests, balance and postural control, exercise-specific parameters, mobility tests and muscular parameters; (b) metabolic tests based on cardiovascular, cardiorespiratory and/or ventilatory observations; (c) pain assessment; (d) rates of perceived exertion and fatigue; (e) condition-specific tests and questionnaires; (f) lifestyle and quality of life tests, mental health tests and / or physical activity level; (g) patient self-evaluation and other related tests. Of the 572 eligible articles, 447 (78%) utilized semi-quantitative and qualitative methods while 193 studies combined quantitative analysis with at least one of these 7 groups.

Qualitative summary on wearables for water motion analysis

Only 27 of 572 eligible articles exploited inertial-based wearable devices in studies on aquatic physical activity. The following tables synthesize 23 works in which inertial sensors assessed underwater motion, four remaining studies were excluded from the qualitative synthesis as they exploited accelerometers to evaluate the amount of daily physical activities[27,28] and the quality of sleep[29,30] of subjects undergoing hydrotherapy protocols (Figure 1).

Table 1 summarizes the characteristics and demographics of the included articles, showing that the majority of studies were published between 2017,[31–38] 2019[39–42] and 2020[43–46] and no articles were found before 2014. Most of the articles[31–33,35–37,42,44–51] involved healthy adults or elderly subjects,[41,43] while the remaining investigated anterior cruciate ligament injury,[34,52] incomplete spinal cord injury[39,40,53] and chronic anterior knee pain.[38] Three studies involved a healthy control group,[34,38,39] and one[52] exploited previously published data of a healthy reference group. The sample size was typically 10 or more subjects, up to a maximum of 50, and 4 articles[36,38,44,46] had a balanced gender distribution. One article included both the validation of the developed system as well as observational studies in the clinical field and in sport biomechanics.[34] All studies included observations of motion both on land and underwater, with the exception of [33,47,50,51] in which only underwater motion was investigated.

Table 2 outlines the study purpose, experimental protocols, measured outcomes, wearable technology, a description of additional methods and major study outcomes. The 23 analysed articles encompass a wide variety of study purposes concerning movement analysis, compare land and underwater motion or focus solely on methodological development and validation. This variety is also reflected in the adopted protocols, exercises and evaluation metrics. Gait analysis is performed on dry land and underwater in nine studies,[34,42,43,45–49,51,52] following in four[34,43,48,52] cases the Outwalk protocol.[54] In all of these works, as well as in studies evaluating running on a treadmill,[32,33] the measured outcomes are focused on temporo-spatial parameters, joint kinematics and range of motion. In three studies[37,38,41] squats, split squats and single limb squats have been performed to estimate joint kinematics, range of motion and asymmetries. In the remaining articles, gait initiation,[36,40,53] balance during standing[35,39] and counter-movement jumps[50] were included to assess centre of pressure parameters and ground reaction forces. Exercise-specific parameters have been estimated when knee flexion-extension[31] and shoulder movements[44] were performed. Additionally, linear mixed models were developed[43,48] to approximate the effects of water on the observed kinematic parameters. Ground reaction forces were quantified by accelerometer data in[50] and in two studies, quality and validation of algorithms were assessed.[44,46]

Considering wearable methods, 13 studies made use of IMU sensors (gyroscope, magnetometer and accelerometer),[34,35,36,39–41,43–46,48,49,52] 3 used a sensor with accelerometer and gyroscope[37,38,42] and 5 studies applied a stand-alone 3D accelerometer[31–33,47,50]; lastly, Lee and Han[51] explored the novel use of smartphones for underwater gait analysis. The number of devices and their positioning on the subject varied from one to eight, placed most commonly on the trunk and laterally on the lower limbs and in one case on the occipital

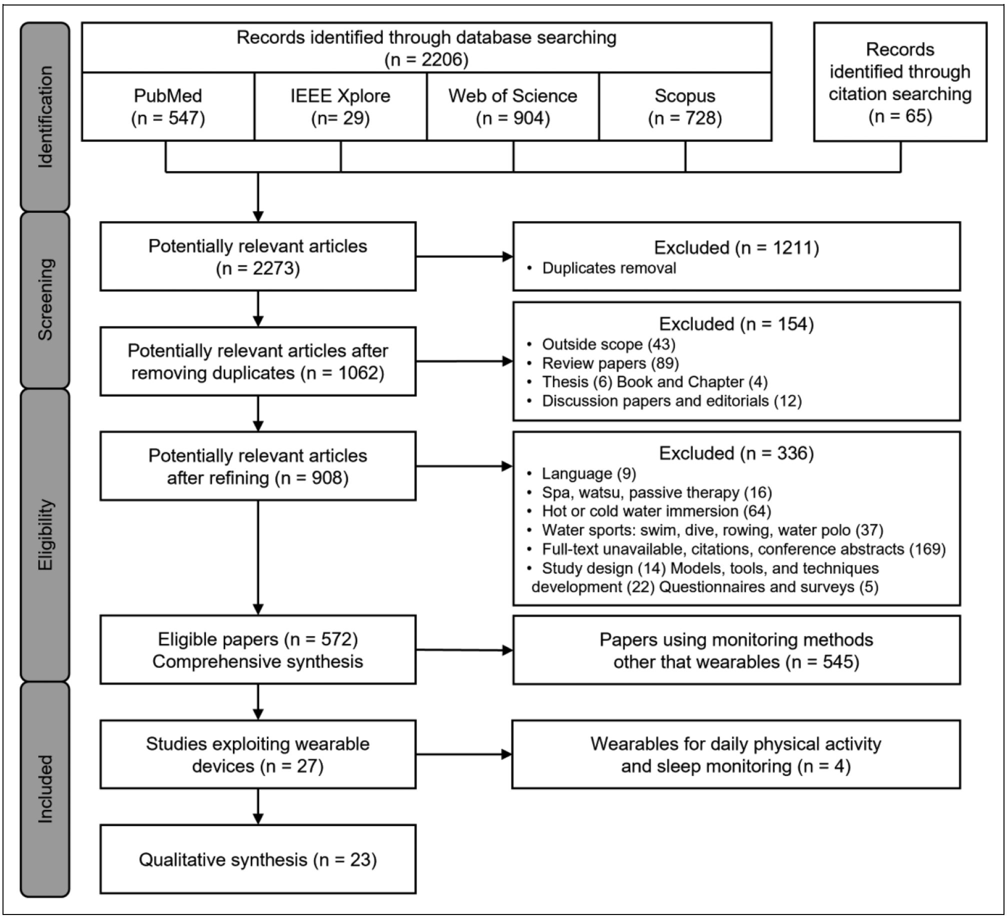

Figure 1. Flow diagram of the identification, screening, eligibility and inclusion steps of the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) systematic literature review process.

region.[47] Notably, only one article investigated the upper limbs.[44] The sensor data sampling rates ranged from 50 Hz to 500 Hz and the waterproofing methods featured in the studies relied mostly on external casings and plastic bags.

Taking into account the use of additional quantitative investigation tools, eight studies exploited wearable devices only.[34,37,38,41–43,48,52,53] Five articles included motion capture and optoelectronic system as support,[45,46,51] reference[32] or as gold standard to validate the inertial sensors.[44,49] Force plates were used by Marinho-Buzelli et al.[35,36,39,40] to estimate the centre of pressure parameters and sway, and by Pacini Panebianco et al.[46] and Chien et al.[50] to determine ground reaction forces. Lastly, Chien et al.,[31] accompanied the accelerometer data with electromyography for the investigation of muscular contraction and near-infrared spectroscopy to estimate the tissue saturation index.

Additional aquatic exercise monitoring methods included metabolic, cardiovascular and cardiorespiratory parameters were investigated using heart rate monitors[31–33,50] and gas analysers.[32,47] No studies were found to include functional or motion-related

Table 1. Review articles demographics. For each selected articles, the first author and publication year, participants investigated (Part), presence of control group (CG), sample size (Sample), gender distribution (M-F) and age are reported. The type of study and the environment investigated is listed in the final column (Measure).

Author	Year	Part	CG	Sample	M-F	Age	Study	Measure
Kaneda et al.[47]	2014	H		50	29-21	27–73	Observational	UW
Fantozzi et al.[48]	2015	H		11	6-5	27.0 ± 3.4	Observational	DL + UW
Cortesi et al.[52]	2016	ACL	H[48]	1 (CG 11)	NA	NA	Observational	DL + UW
Chien et al.[31]	2017	H		17	0-17	22.1 ± 0.7	Observational	DL + UW
Macdermid et al.[32]	2017	H		6	NA	29.8 ± 13.0	Observational	DL + UW
Macdermid et al.[33]	2017	H		8	NA	25 ± 12	Observational	UW
Mangia et al.[34]	2017	Elderly ACL	H	5 1 (CG 11)	3-2 1-0 (CG 6-5)	71.6 ± 2.2 39 (CG 27.0 ± 3.4)	Validation + Observational	DL + UW
Buzelli et al.[35]	2017	H		10	6-4	NA	Observational	DL + UW
Buzelli et al.[36]	2017	H		10	5-5	19–35	Observational	DL + UW
Severin et al.[37]	2017	H		25	14-11	22.1 ± 4.0	Observational	DL + UW
Severin et al.[38]	2017	AKP	H	20 (CG 20)	10-10 (CG 10-10)	22.8 ± 4.0 (CG 22.2 ± 2.9)	Observational	DL + UW
Buzelli et al.[39]	2019	iSCI		6	4-2	42–69	Observational	DL + UW
Buzelli et al.[40]	2019	iSCI		5	4-1	42–69	Observational	DL + UW
Severin et al.[41]	2019	Elderly		24	7-17	71.4 ± 5.4	Observational	DL + UW
Souza et al.[42]	2019	H		1	NA	NA	Validation	DL + UW
Fantozzi et al.[43]	2020	Elderly	H	9 (CG 11)	4-5 (CG 6-5)	73.5 ± 5.8 (CG 27.0 ± 3.4)	Observational	DL + UW
Gandoll et al.a[44]	2020	H		2	1-1	20	Validation	DL + UW
Kaneda et al.[45]	2020	H		10	6-4	30 ± 6	Observational	DL + UW
Pacini et al.[46]	2020	H		10	5-5	26.2 ± 3.3	Validation	DL + UW
Monoli et al.[49]	2021	H		7	4-3	NA	Validation	DL + UW
Chien et al.[50]	2022	H		12	0-12	23.6 ± 1.8	Validation	UW
Lee et al.[51]	2022	H		19	7-12	22.0 ± 1.9	Validation	UW
Fantozzi et al.[53]	2022	iSCI		10	9-1	65 ± 8	Observational	DL + UW

ACL: anterior cruciate ligament injury; AKP: anterior knee pain; CG: control group; DL: dry land; H: healthy; iSCI: incomplete spinal cord injury; NA: not available; UW: underwater. An empty cell indicates the absence of CG.

Table 2. Summary of articles included in the review. Organized by publication year, investigation purpose, the exercise protocol followed, the main outcomes and the methods exploited for the analysis of motion. Considering wearable devices, the type of sensor, number and positioning are listed.

Article, purpose	Protocol	Outcome measured	Monitoring methods	Conclusion
Kaneda et al.[47] – Develop model for Energy Expenditure water-walking	Gait UW (3times, 15m, various speed), [W: 1.1m depth, 30°C]	• Energy expenditure estimation (acceleration, velocity, O2 and CO2 exchange)	• A (1: head) • Gas analyser, dry gas meter	Energy expenditure estimation model showed good agreement to the classical measurement both acceleration and speed
Fantozzi et al.[48] – Compare land and water lower limb and thorax-pelvis joints kinematics	Gait DL and UW (3times, 10m, natural speed) [W: 1.2m depth, 28°C]	• Outwalk protocol (temporo-spatial param, joints kinematics) • Linear Mixed Model	• IMU (8: thorax, pelvis, laterally on thighs, shanks, feet)	IMU walking patterns of thorax-pelvis and lower limb joint angles in the sagittal and frontal planes consistent with motion-capture results
Cortesi et al.[52] – Method for land and water gait for joints kinematics analysis of an ACL injured	Gait DL and UW (3times, 10m, natural speed)	• Outwalk protocol (temporo-spatial param, joints kinematics)	• IMU (8: thorax, pelvis, laterally on thighs, shanks, feet)	Water gait can lead ACL patients to increase the knee flexion-extension ROM and improve overall gait patterns
Chien et al.[31] – Estimate impact of land and water knee extension	Three to five knee flexion-extension at various cadences, DL and UW [W: xiphoid depth, 33°C]	• HR, Blood flow, Total Saturation Index • RPE • Muscular activity • Knee extension kinematic	• A (1: below malleolus of the ankle) • HR monitor • Near-Infrared Spectroscopy • RPE Borg's scale • Surface EMG	Faster cadence of water knee extension increases training load (RPE), evoke more muscle contraction, harder cardiac stimulation, and more Total Saturation Index
Macdermid[32] – Compare land and water treadmill running	Treadmill running DL and UW (15min, fixed speed) [W: iliac spine depth, 21°C]	• Transfer function • Temporo-spatial param • Oscillation, shock attenuation, loading rate • Physiological data	• A (3: lateral right tibia, lower back, forehead) • Gas analyser • HR monitor • MC (reference)	Treadmill running in water is a valuable training mode: reduces lower-limb acceleration and shock attenuation, causes slower stride frequency, greater swing time, and increases physiological demand

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Table 2. (Continued)

Article, purpose	Protocol	Outcome measured	Monitoring methods	Conclusion
Macdermid et al.[33] – Evaluate effects of different depth water treadmill running	Treadmill running UW (2.61m/s, 3min) [W depths: mid-shin, mid-thigh, xiphoid, 23.5°C]	• Temporo-spatial param • Rate of impact loading Acceleration features (slope, peak at impact)	• A (1: lateral right tibia) • HR monitor	Progressive depth in UW treadmill running decreases risk of injury due to diminishing impact peak impact accelerations and loading rate at all depths
Mangia et al.[34] – Instrumental validation of IMUs in water, test in clinical and sport settings	Gait DL and UW (three times, 10m, natural speed) [W: 1.2m depth, 28°C]	• Outwalk protocol (temporo-spatial param, joints kinematics)	• IMU (8: thorax, pelvis, thighs, shanks, feet)	IMUs UW had an orientation estimation accuracy of about 6°, lower than gold standard but enough to provide useful information about gait and swimming
Buzelli et al.[35] – Influence of water on COP parameters and on trunk acceleration during quiet standing	Stand still; DL and UW (10 times, 5 eyes open and 5 eyes closed) [W: umbilicus depth, 34°C]	• COP param (time- and frequency-domain) • Trunk acceleration param (postural sway)	• IMU (2: lower and upper trunk) • FP	Aquatic environment may help improve balance control: increases postural instability (bigger COP parameters, larger upper trunk mediolateral acceleration) and changes postural control strategies
Buzelli et al.[36] – Investigate kinematics and kinetics of posture during water gait initiation	5–10s standing and gait initiation; DL and UW (10 times) [W: 1.1m depth, 35°C]	• COP trajectories • GRF components • Trunk acceleration param (postural sway)	• IMU (3: upper and lower trunk, shank) • FP	Water challenges postural control during gait initiation: increases length of COP trajectories, slower execution, larger anterior-posterior mean force and changes trunk acceleration pattern
Severin et al.[37] – Quantify differences between land and water S, SS and SLS	S, SS, SLS; DL and UW (10 times) [W: hip depth, 29.1°C]	• Joints kinematics (ROM, movement depth) • Peak velocities	• A + G (6: laterally on thighs and shanks, trunk, sacrum)	S, SS and SLS in water maintain the movement pattern: does not limit ROM, encourages vertical alignment of body segments, lowers speed, increases movement variability
Severin[38] – Assess kinematics and asymmetry during land and water S and SLS in AKP	S, SLS; DL and UW (10 times) [W: hip depth, 29.1°C]	• Joints kinematics • Asymmetry index score (shank, thigh, thorax)	• A + G (6: laterally on thighs and shanks, trunk, sacrum)	Water S and SLS for AKP increase ROM and asymmetry, suggesting the use of feedback to minimise any movement compensations

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Table 2. (Continued)

Article, purpose	Protocol	Outcome measured	Monitoring methods	Conclusion
Buzelli et al.[39] – Influence of water on quasi-static posture after iSCI	Stand still (10 times, 5 eyes open and 5 eyes closed, DL and UW) [W: umbilicus depth]	• COP parameters • % Body weight offloading • Trunk acceleration param (postural sway) • Perception questionnaire	• IMU (2: upper and lower trunk) • FP • Clinical examination, perception interviews	iSCI in water have larger medians of COP displacement, velocity and area, in both visual conditions. In water, increased trunk accelerations suggest a new postural strategy for balance
Buzelli et al.[40] – Influence of water on gait initiation in iSCI	5–10s standing and gait initiation DL and UW (10 times) [W: 1.1m depth, 34–35°C]	• COP parameters • Trunk acceleration param (postural sway) • Perception questionnaire	• IMU (2: upper and lower trunk) • FP • Clinical examination, perception interviews	Water influences the dynamic postural control during gait initiation prolonging the execution of gait initiation and facilitating longer step execution in iSCI
Severin et al.[41] – Impacts of water on ROM and peak velocities during S and SS	S and SS, DL and UW (10 times) [W: hip depth, 27.3°C]	• ROM trunk, hip, knee • Velocities • S depths	• IMU (6: trunk, sacrum, laterally on thighs, shanks)	Water immersion allow older aged adults greater squat depths and encourages less anterior trunk lean and more hip flexion than on land
Souza at al.[42] – Analyse walking inside and outside water	Gait DL and UW (8m, natural speed) [W: sternum depth]	• Temporo-spatial param	• A + G (4: inner side calf, medial malleoli)	The prototype presented good performance in gait evaluation in water
Fantozzi et al.[43] – Investigate land and water walking kinematics of elderly and young adults	Gait DL and UW (3 times, 10m, natural speed) [W: 1.2m depth, 28°C]	• Outwalk protocol (temporo-spatial param, joints kinematics) • Linear mixed models	• IMU (5: trunk, pelvis, laterally on thigh, shank, foot)	Healthy elderly had specific gait patterns in water, different from young adults influenced not only by speed and age, but also by the interaction between the two variables
Gandolla et al.[44] – Design a biofeedback for aquatic	Shoulder movements	• Measurement	• IMU (3: trunk, upper and lower arm)	Setup for underwater real-time human motion and biofeedback have been

(Continued)

Table 2. (Continued)

Article, purpose	Protocol	Outcome measured	Monitoring methods	Conclusion
movement analysis based on a multi-joints network of IMUs		uncertainty and algorithm validation • System usability	• Optoelectronic (land validation)	designed, produced, validated and tested demonstrating feasibility and usability with recorded good system usability evaluation
Kaneda et al.[45] – Compare land and water walking using IMU and video camera	Gait DL and UW (three times, three speeds, 10m) [W: 1.35m depth]	• Stance ratios and joints kinematics • Acceleration, angular velocity	• IMU (1: thigh midpoint front) • MC	During walking in water, acceleration and impact force, which burden the thighs or knees just before the heel contact, are reduced
Pacini et al.[46] – Water performance of 17 algorithms for land gait events estimation	Gait DL and UW (10m, five times, natural speed) [W: 1.2m depth, 28°C]	• Quality algorithms • Temporo-spatial param • GRF	• IMU (5: trunk, shanks, dorsal feet) • MC • FP	No proposed algorithm can be generally preferred over the others. Angular velocity-based algorithms with sensors on lower limbs result more reliable than acceleration-based, but not as accurate and repeatable
Monoli et sl.[49] – Test and validate developed underwater wearable IMUs	Gait DL (6 times) and UW (11 times, natural speed)	• Knee angle • Gaussian Process Regression enhancement	• IMU (2: laterally on thigh and shank) • MC • Optoelectronic (land validation)	The proposed IMU system is suitable for use on land and underwater to evaluate the knee angle during the gait
Chien et al.[50] – GRF measure and prediction in different accelerometer positions and jump intensities	UW countermovement jumps at different \% HR reserve [W: 1m depth, 31–33°C]	• Acceleration • GRF • GRF predicted via accelerometer data	• A (3: right ankle, lumbar, neck) • FP • HR monitor	The resultant acceleration measured at C7 was identified as the valid estimated GRF for body weight on land for jumping skeletal loading in water
Lee et al.[51] – Reliability of leg segment and joint	Gait UW (at least 14 steps) [W: 1.1m depth, 33°C]	• Joints kinematics and ROM (hip, knee)	• IMU (3 smartphones: frontal on trunk, thigh, and shank)	Smartphones provide reliable measurements of leg segments and

(Continued)

Table 2. (Continued)

Article, purpose	Protocol	Outcome measured	Monitoring methods	Conclusion
angles measurements with smartphones			• MC	joint angles during aquatic gait and are a relatively affordable option
Fantozzi et al.[53] – Compare gait initiation on iSCI subjects dry land and in water	Gait initiation DL and UW [W:1.2m depth, 30°C]	• Anticipatory Postural Adjustment time • First-step characteristics	• IMU (4: upper and lower trunk, left and right shanks)	In water is measured and increased first step duration and a decreased root mean squared acceleration for upper and lower trunk in the medio-lateral and anterior-posterior direction, respectively.

A: accelerometer; AKP: anterior knee pain; COP: center of pressure; DL: dry land test; EMG: electromyography; FP: force platform; G: gyroscope; GRP: ground reaction forces; HR: heart rate; IMU: Inertial Measurement Unit; iSCI: incomplete spinal cord injury; MC: motion capture; ROM: range of motion; RPE: rate of perceived exertion; S: squats; SS: split squats; SLS: single limb squats; UW: underwater; W: Water, characteristics of the pool.

tests, pain assessment or lifestyle and quality of life questionnaires. However, the rate of perceived exertion was evaluated by Chien et al.[31] using Borg's scale and Marinho-Buzelli et al.[39,40] performed a clinical examination on balance and perception via International Standards for Neurological Classification of Spinal Cord Injury, Berg's Balance Scale and Mini-BESTest and perception interviews.

The critical assessment of the selected articles is provided in Table A3, and summarizes the answers to the custom questionnaire (Table A2). The analysed studies were generally found to be of satisfactory value, since most of the inquiries were marked as present or partially answered. Nonetheless, it is worth noting that four questions received mostly negative answers. The articles did not specify the study design (question 1), with the exception of two case series,[39,40] a case study[52] and a cross-validation study.[47] Similarly, the study participants and inclusion/exclusion criteria were not clearly justified (question 9), apart from[38] which involved a gender-matched control group and[51] that conducted a power analysis to justify the number of subjects involved. Additionally, none of the studies included multiple measurements over a complete rehabilitation protocol (question 7), nor did any studies address the management of missing data (question 15).

Discussion

The synthesis of eligible articles addressed the first research question of this work, pointing out that the most frequent methods applied to perform aquatic motion analysis are dynamometers and force plates, followed by motion capture. Furthermore, it was possible to clearly differentiate between two major methodological categories: quantitative methods providing an objective evaluation of motion and qualitative or semi-quantitative methods to evaluate the quality of motion and the effects of water exercise across a scaled spectrum.

It is important to note that the current review did not distinguish between studies that evaluated motion underwater, on land or in both environments but considered all the methods exploited to assess motion in the context of aquatic exercise. The authors also wish to point out the limitations of this systematic review as the chosen keywords and inclusion criteria may have excluded some relevant studies. This review did not consider wearable sensors for swimming monitoring, choosing instead to focus on the investigation of water exercises. In contrast to Marinho et al.[21] which focused on defining the benefits of wearable technologies, this review identifies the research gaps and provides concrete suggestions to improve future aquatic exercise monitoring studies.

The second research question of this work focused on identifying major gaps in studies using wearable devices for monitoring of underwater exercises and making recommendations on how to improve aquatic motion analysis. Four major research gaps have been recognized. First, the absence of clinical protocols for underwater motion analysis studies. While the quality assessment indicates that the studies are of overall good quality, a lack of common methodologies renders the cross-comparison of study findings infeasible. Each article defined and used a distinctive protocol exploiting wearable devices, both in terms of number of sensors used and their placement on the body. Even when the task executed was similar, the study objectives, methods and outcomes varied greatly between studies. Future works may wish to define clear protocols for underwater wearables and allow for the quantitative comparison of water physical activities with increased confidence.

The second major research gap found is the substantial deficit of whole-body studies via wearable devices. This restriction is likely due to the technical difficulty of inertial sensor data analysis, especially in the water environment where standard methods do not exist. Focusing on a limited portion of the body, however, does not allow for the explicit consideration of the effects of drag and buoyancy as additional forces unique to the water environment.

The lack of longitudinal studies monitored via wearable devices was identified as the third main gap. All articles included in the qualitative synthesis had a maximum of 10 repetitions of the selected task, performed in one day and most of them included only healthy subjects. This may be due to the challenges associated with organizing repeated measures with wearable devices, resulting in limited insight into the influences of water on kinematic features as well as the effectiveness of long-term hydrotherapy.

The fourth gap identified a need for measurement and assessment methods specific to aquatic exercises, as studies remain heavily reliant on the use of land-based methods. When motion capture systems[32,44,45,49] or other sensing modalities[31,35,36,39,40,46,50] were used, they were nearly universally applied for cross-comparison or validation of a newly proposed method and data were infrequently related with wearable sensors data. Only a single study[46] combined multiple sensor data to improve motion assessment. Furthermore, only seven studies exploited additional methods for metabolism monitoring. A combined approach using multiple quantitative methods and the involvement of specific tests and questionnaires may improve the current interpretation of aquatic exercise and the effects of the water environment on kinematics.

The major finding of this review is that there is a substantial deficit of protocols and wearable monitoring methods for aquatic exercises. Specifically, we advocate for the establishment of common protocols for wearable sensor placement and whole-body monitoring during non-recreational aquatic exercise. Furthermore, we encourage longitudinal studies which include multiple sensing modalities to generate a more complete understanding of the effects of aquatic exercises on kinematic parameters.

Clinical messages

- There is a lack of clear protocols for the use of wearable devices in underwater motion analysis, hindering the cross-comparison of studies.
- Longitudinal studies monitored via wearable devices are necessary to estimate the effects of long-term aquatic exercises on kinematic parameters.
- Incorporating wearable sensing technology into long-term hydrotherapy programmes may improve monitoring processes and the cross-comparison of study outcomes.

Author's contribution

CM: Study design, data collection, analysis and interpretation and preparation of the manuscript.
JAT: Analysis and interpretation, preparation and revision of the manuscript.
LP: Study design and manuscript revision.
MG: Study design, interpretation of data and manuscript revision.

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ORCID iDs

Cecilia Monoli https://orcid.org/0000-0002-2033-0619
Manuela Galli https://orcid.org/0000-0003-2772-4837

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Appendix

Table A1. Summary of the literature source databases and corresponding keywords used in this systematic review. For each database, the number of articles included after screening is provided.

		PubMed[a]	IEEE Xplore	Web of Science[b]	**Scopus**[b]
Underwater OR water OR aquatic	(rehabilitation OR exercise OR kinematic OR therapy OR training OR hydrotherapy OR hydrokinesitherapy) AND (wearable OR sensor)	15	8	28	26
	treadmill OR walk OR gait	325[c]	5[c]	651	410
	wearable	10	4	10	12
	IMU OR accelerom* OR inertial	18	3	28	36
	EMG OR electromyog*	92	4	93	133
	motion capture OR camera	22	4	10[d]	8[d]
	force plat*	36	0	40	52
	dynamom*	24	0	33	40
	gonio*	5	1	11	11
	Total	547	29	904	728

[a]Additional filters: English AND Human.
[b]Additional filter: English.
[c]Additional keyword run: ((underwater) OR (aquatic) OR (water)) AND ((treadmill) OR (walk) OR (gait) OR (run)).
[d]Only motion capture: ((underwater) OR (aquatic) OR (water)) AND (motion capture).

Table A2. List of questions used in the quality assessment. Questions are based on the STROBE checklist, CASP appraisal tool and the McMaster Quality assessment instrument.

Topic	Q	Questions
		Characteristic of the articles
Study design	1	Is the study design described with commonly used terms?
Novelty	2	Are the novelty and significance of the articles described in the introduction?
		Introduction
Background	3	Are the scientific background and rationale for the investigation reported and properly referred?
Objectives	4	Are the objectives of the study clearly described?
	5	Are the research hypotheses or research questions stated?
		Method
Setting	6	Are the procedures, settings and locations described? (exercises protocol, environment characteristics)
	7	Is it considered a long-term protocol with repeated measurements over multiple weeks? Are measures taken pre/post intervention, or only one time?
Participants	8	Are the characteristics of the participants described? (age, gender, status, condition) Are the inclusion/exclusion criteria expressed?
	9	Is the size of the population justified? For matched studies, are matching criteria provided?
Instruments	10	Is the wearable method clearly described? (placement, number of sensors and physical and sensor characteristics)
	11	Is the wearable sensors-based protocol clearly described or referenced? (data extraction and data processing)
	12	Are any additional investigation methods applied? Is the comparison performed with a reference method? If yes, are they clearly described and referenced?
Variables	13	Are the main investigated features and outcomes clearly described?
Statistics	14	Are the statistical methods used described and justified?
	15	Is there a description of the missing data and their management?
		Results and Discussion
Results	16	Are the main findings clearly stated? Are the probability and confidence intervals stated? Is the accuracy of the measure estimated?
Limitations	17	Are the limitations of the study expressed, taking into account sources of potential bias or imprecision?
Interpretation	18	Are an overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidences provided?
Significance	19	Are the general validity of the study and significance of the study results for the scientific community and future studies mentioned?

Table A3. Methodological quality assessment results following the questions listed in Table A.2: (1–2) Characteristics of the article, (3–5) Introduction, (6–15) Method and (16–19) Results and Discussion. Possible answers: present (P), absent (A), partially present (PA) and not applicable (NA).

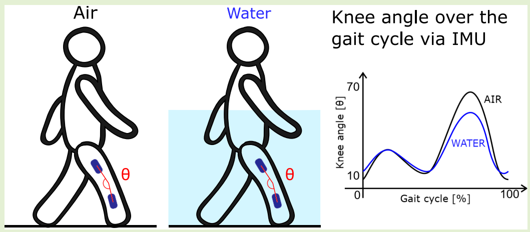
Article	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Kaneda et al.[47]	P	P	P	P	A	P	A	P	A	A	P	P	P	P	A	PA	P	P	P
Fantozzi et al.[48]	A	A	P	P	A	P	A	P	A	P	P	A	P	P	A	P	P	P	P
Cortesi et al.[52]	P	PA	P	P	A	PA	A	P	NA	P	P	A	P	A	A	P	A	P	A
Chien et al.[31]	A	P	P	P	A	P	A	P	A	PA	A	P	P	PA	A	P	P	P	P
Macdermid et al.[32]	A	P	P	P	P	P	A	P	A	P	P	P	P	P	A	P	A	P	A
Macdermid et al.[33]	A	PA	P	P	A	P	A	P	A	P	PA	P	P	PA	A	P	A	PA	A
Mangia et al.[34]	A	PA	P	P	A	P	A	P	A	P	P	A	P	P	A	P	A	P	P
Buzelli et al.[35]	A	PA	P	P	P	P	A	PA	A	P	P	P	P	P	A	P	P	P	P
Buzelli et al.[36]	A	P	P	P	P	P	A	P	A	P	P	P	P	PA	A	P	P	P	P
Severin et al.[37]	A	PA	P	P	P	P	A	P	A	P	P	A	P	P	A	P	P	P	PA
Severin et al.[38]	A	P	P	P	P	P	A	P	PA	P	P	A	P	P	A	P	A	P	P
Buzelli et al.[39]	P	A	P	PA	A	P	A	P	NA	P	P	P	P	PA	A	P	P	PA	P
Buzelli et al.[40]	P	A	P	PA	A	P	A	P	NA	P	P	P	P	PA	A	P	P	PA	P
Severin et al.[41]	A	PA	P	P	P	P	A	P	A	P	P	A	PA	P	A	P	P	P	PA
Souza et al.[42]	A	PA	P	P	A	P	A	A	A	P	P	A	P	A	A	PA	PA	PA	P
Fantozzi et al.[43]	A	A	P	P	P	P	A	P	A	P	P	A	P	A	A	P	PA	P	A
Gandolla et al.[44]	A	P	P	P	A	P	A	PA	A	P	P	P	PA	P	A	P	A	P	P
Kaneda et al.[45]	A	A	P	P	A	P	A	P	A	P	P	P	PA	P	A	P	P	P	P
Pacini et al.[46]	A	P	P	P	A	P	A	P	A	P	P	P	P	P	A	P	P	P	P
Monoli et al.[49]	A	P	P	P	P	PA	A	PA	A	P	P	P	P	P	A	P	P	P	P
Chien et al.[50]	A	P	P	P	A	P	A	P	A	P	P	P	P	P	A	P	P	P	P
Lee et al.[51]	A	P	P	P	A	P	A	P	P	P	PA	P	PA	PA	A	P	P	P	PA
Fantozzi et al.[53]	A	PA	P	P	P	PA	A	P	A	P	P	A	P	P	A	P	P	P	P

Appendix 2

Publication II
C. Monoli, J. F. Fuentez-Pérez, N. Cau, P. Capodaglio, M. Galli, and J. A. Tuhtan, "Land and underwater gait analysis using wearable imu," IEEE Sensors Journal, vol. 21, no. 9, pp. 11192–11202, 2021

Land and Underwater Gait Analysis Using Wearable IMU

Cecilia Monoli, Juan Francisco Fuentez-Pérez, Nicola Cau, Paolo Capodaglio, Manuela Galli, and Jeffrey A. Tuhtan, *Member, IEEE*



***Abstract*—Walking underwater reduces joint impacts, enhances stability and lowers the net body weight of the patient during rehabilitation. It is a recent rehabilitation method and few suitable methods exist to study underwater gait kinematics. We propose an underwater inertial measurement (IMU) system analogous to those used in land-based rehabilitation to investigate gait kinematics. The objective of this study was to test and validate the proposed system in two human trials by evaluating the knee angle during the gait. In the first trial, a three-way performance analysis was carried out between the IMU, optoelectronic and motion-capture systems in a traditional rehabilitation setting on land. In the second trial, the proposed underwater IMU is compared with camera-based motion-capture both inside and outside the water environment, using the same subjects in both phases of the trial. This allows for an evaluation of the walking gait in air and underwater as well as a cross-comparison of IMU-based knee angle estimates before and after Gaussian Process Regression. The major finding of this work is that the proposed underwater wearable IMU system provides reliable and repeatable measurements of the knee angle during the gait, both in air and underwater.**

***Index Terms*—Gait analysis, inertial measurement unit (IMU), kinematics, rehabilitation, underwater, optoelectronic tracking, motion-capture.**

I. Introduction

WATER provides a nearly ideal environment for physical rehabilitation. This is due to the additional forces acting on the submerged body, primarily caused by the dynamic pressure and drag. These hydrodynamic forces reduce the net body weight, lower joint loading and provide enhanced physical support and posture stabilization [1], [2]. Walking rehabilitation in water, shown in Figure 1, affects the muscular skeletal system [2], by reducing fatigue and pain, improving the physical recovery rate as well as joint range of motion. These effects are clinically evaluated using questionnaires which provide subjective, qualitative evidence validated by physiological and metabolic data [3], [4]. Despite the known benefits of water rehabilitation, the quantification of underwater kinematics remains a challenging task. The gold standard optoelectronic systems used for traditional walking gait rehabilitation analysis remain ill-suited for the underwater environment. Specifically, optoelectronic methods are negatively impacted by attenuation, refraction and reflection in water, especially in the lower infrared wavelengths in which most commercial systems operate.

The quantification of underwater rehabilitation activities currently rely on submerged force plates [5], [6] or camera-based motion-capture methods [7], [8]. A limited number of investigations have implemented underwater inertial measurement systems, showing promising results [9]–[14]. Force plates and camera-based methods are restricted to fixed investigation areas. Moreover, force plates do not allow for the investigation of whole body motion, but only those kinematic and dynamic parameters recorded via contact with the plate. Therefore, underwater wearable Inertial Measurement

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Cecilia Monoli is with the Centre for Biorobotics, Tallinn University of Technology, 12616 Tallinn, Estonia, and also with the Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, 20133 Milano, Italy (e-mail: cecilia.monoli@taltech.ee).

Juan Francisco Fuentez-Pérez is with the Department of Hydraulics and Hydrology, GEA-Ecohidráulica, University of Valladolid at La Yutera, 34004 Palencia, Spain (e-mail: jfuentes@iaf.uva.es).

Nicola Cau is with the IRCCS Fondazione Don Carlo Gnocchi, 20148 Milano, Italy (e-mail: ncau@dongnocchi.it).

Paolo Capodaglio is with the Istituto Auxologico Italiano, IRCCS, U.O. di Neurologia e Neuroriabilitazione, Ospedale S. Giuseppe, 28824 Piancavallo (Verbania), Italy, and also with the Dipartimento di Scienze Chirurgiche, Medicina Fisica e Riabilitazione, Universita' di Torino, 10124 Torino, Italy (e-mail: p.capodaglio@auxologico.it).

Manuela Galli is with the Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, 20133 Milano, Italy (e-mail: manuela.galli@polimi.it).

Jeffrey A. Tuhtan is with the Centre for Biorobotics, Tallinn University of Technology, 12616 Tallinn, Estonia (e-mail: jeffrey.tuhtan@taltech.ee).

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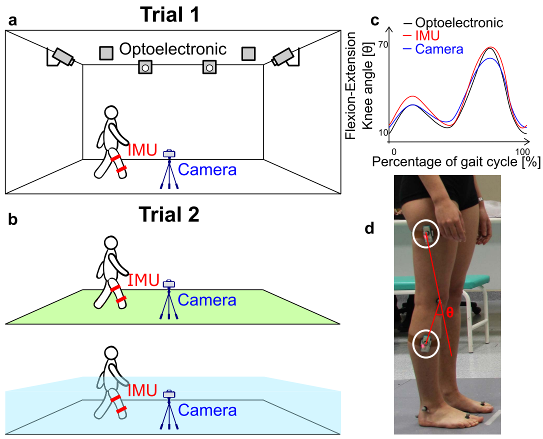

Fig. 1. a) Trial 1, comparison of the optoelectronic, motion-tracking and IMU systems. b) Trial 2, where the IMU and camera-based systems are employed on land and underwater. c) The knee angle over the gait for each of the three systems evaluated (IMU system in red, optoelectronic system in black and the camera-based system in blue). d) Wearable IMU sensors on a test subject (white circles), the measured knee angle θ is shown in red.

Units (IMU) provide a way to overcome these limitations. IMUs are widely used in the investigation of gait analysis on land, and are known to provide a suitable accuracy and reliability for clinical study use [15]–[20]. Our work builds on the small number of previous underwater studies [9], [10] which used the Outwalk protocol [21] for the investigation thorax-pelvis and lower limb kinematics using IMUs. This protocol is efficient for clinical studies and follows a simple calibration procedure.

The aim of this work is to develop and validate a method to monitor underwater human gait kinematics using wearable IMU sensors. In contrast with previous works, the devices exploited in this study have been specially developed for air and underwater body-mounted kinematic measurements. The sensors do not require an additional casing for clinical application, and both power and data storage are self-contained, eliminating the need for cables.

To the best of the authors' knowledge, this work is also the first to conduct a multi-method performance comparison for wearable IMUs, both in air and underwater. Specifically, the IMU measurements are compared with optoelectronic (air only) and motion-capture systems (air and water). Both of these systems represent the current gold standard for the kinematic analysis of the walking gait for rehabilitation exercises.

Our hypothesis is that the proposed wearable IMUs are able to evaluate underwater human gait kinematics as well as conventional land-based methods. If successful, these devices could provide a reliable methodology to monitor underwater rehabilitation, overcoming the technological gaps facing existing optoelectronic and motion-tracking methods.

The two major objectives of this study are: 1) Test and validate the knee angle measurement performance of the proposed underwater wearable IMU and assess its reliability and repeatability. 2) Evaluate the effect of the water

TABLE I

Summary of the Two Trials and Corresponding Measurement Systems: Inertial (IMU), Optoelectronic (OPTO) or Camera-Based Motion-Tracking (CAMERA), the Number of Individuals (Subjects) and Number of Repetitions (Rep) for Each Trial

Trials	Systems			Characteristics	
	IMU	OPTO	CAMERA	Subjects	Rep
Trial 1	x	x	x	3 (2F 1M)	6
Trial 2	x		x	4 (1F 3M)	11

environment on IMU gait analysis performance. To address these objectives, two trials were carried out. In the first trial, the performance of the IMU system is compared with both optoelectronic and motion-capture systems in a classical land-based rehabilitation environment. In the second trial, the inertial system is compared to the motion-capture system both on land and underwater to investigate how fluid-body interactions affect the measurement. As a final step, Gaussian Process Regression (GPR) was applied to improve the IMU knee angle estimation during the gait and compared with the optoelectronic and camera-based motion-capture system.

II. Method

In this study, the cross-comparison of methods is based on human gait kinematics, which represent a highly repeatable pattern of movement [22]. Walking does not require any specific skill and it is commonly used as a rehabilitation exercise [23], [24]. The knee angle during the gait cycle is used as the evaluation metric for cross-comparison in two different trials conducted in air and underwater, as illustrated in Figure 1. A summary of the two different trials is provided in Table I. This study also includes three simplifying assumptions. First, it is assumed that the gait pattern of each test subject is equally repeated. We therefore neglect the effects of fatigue and psychological state. When comparing gaits between different individuals, it is acknowledged that the general behaviour and pattern is maintained. However, each singular gait cycle is a unique event, and there will always remain some differences between any cycles [25]. Second, we presuppose that the commercial optoelectronic system used in this work represents the most accurate method to record human gait kinematics. Finally, in both experimental trials we consider the knee angle as predominantly planar, ignoring lateral variations of the body motion. This approximation is needed to cross-compare the motion-capture system with the IMU and optoelectronic methods.

A. Protocol

The same protocol was adopted for all experimental trials, as illustrated in Figure 1. The IMU sensors were placed on the right lower limb of the subjects. A two-pose static calibration similar to [26] was performed before beginning the gait evaluation. Each subject was asked to stand upright (pose one) and then lift their right leg, in hip flexion with the knee flexed to a comfortable angle (pose two) for at least 5 seconds. Afterwards, the subjects were asked to walk along a straight

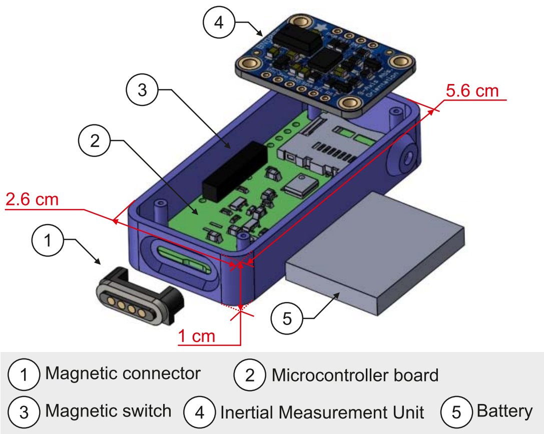

Fig. 2. Breakdown of the wearable IMU logger applied in this work to estimate the knee angle during the walking gait on land and underwater.

line while wearing the IMU and were simultaneously recorded by the optoelectronic and / or motion-capture system.

Trial 1: IMU, Optoelectronic and Motion-Capture (Figure 1 a) this experiment was conducted only on land at Clinical Lab for Gait Analysis and Posture of the Auxological Center of Piancavallo (Italian Auxological Institute, IRCCS, Piancavallo hospital, Italy) in order to provide a performance comparison between all three monitoring systems: optoelectronic (OPTO), camera-based (CAMERA) and IMU.

Trial 2: IMU and Motion-Capture (Figure 1 b) this study was conducted on land at the Tallinn University of Technology, (Tallinn, Estonia) and underwater in the indoor swimming pool at the Keila Health Center (Keila, Estonia). The IMU sensors and camera system used in this trial were identical in both environments, and the camera-based motion-tracking system was considered as the ground truth.

B. Motion Tracking Systems

1) Inertial Measurement Unit: The proposed IMU-based method uses two waterproof sensors which record the absolute orientation using an attitude and heading reference system (AHRS) where gravity is the vertical axis and the horizontal axes are defined as orthogonal to the Earth's local magnetic field. A schematic breakdown of the device is show in Figure 2 including the external dimensions and component locations, while the technical characteristics of the IMU provided in Table II. To evaluate the knee angle, sensors were taped on each subject's shank and outer thigh, located at the approximate height of the center of mass [25] as shown in Figure 1 d.

2) Optoelectronic Tracking: A commercial optoelectronic system was used in Trial 1, consisting of 6 infrared cameras (Vicon-460, Oxford Metrics Ltd) with a frame rate of 100 Hz. Before analysis, each subject was outfitted with passive plastic sphere markers covered by a reflective varnish. The sphere locations were chosen according to the anatomical reference points following the Davis protocol [27] determined from

TABLE II
TECHNICAL CHARACTERISTICS OF THE WEARABLE WATERPROOF IMU LOGGER USED IN THIS WORK

Processor	Cortex M0
IMU	BNO055
Sampling rate	100 Hz
Memory	16 GB
Battery	100 mAh
Data transmission	Serial
Outer dimensions	5.6x2.6x1.0 cm
Dry mass	22 g

anthropometric measurements of each test subject. The measurements used in this study included the subject's height, weight, tibial length and diameter of the knee [28]. During gait analysis, the infrared cameras identify and track the position of each marker, recording their coordinates in three dimensions. The coordinates and anthropometric measurements provide a three-dimensional reconstruction of motion within a volume of interest. Finally, a model of the subject's measured body segments is created which includes key kinematic parameters such as joint angles, velocities and accelerations. In this work, the optoelectronic measurements serve as the gold standard for the land-based kinematic evaluation. Previous investigation has shown that they have an accuracy of $63\pm5\mu$m and a precision of 15μm [29].

3) Motion-Tracking: Motion-tracking for both trials made use of two different cameras: ASUS ZenFone 3 (ZC520TL, 13 MP, autofocus, 30 fps) for Trial 1 and Sony Alpha A5000 (20MP, continuous autofocus, 25 fps) for Trial 2. In both trials, the camera was oriented to record imagery orthogonal to the gait direction at a fixed height of 0.8 m from the ground. The focal distance between camera and the subjects was 2.8 m for Trial 1, 2.9 m for the Trial 2 land-based experiments and 4.3 m for the underwater experiments. It is worth noting that the required focal distance for Trial 2 is noticeably larger in water due to the refractive index of water being some 33% higher in water than in air.

C. Data Processing

As the motion-tracking system is only able to investigate the planar knee angle, it was necessary to restrict our comparison to the planar angle for the optoelectronic and IMU assessment as well. A graphical depiction of the resulting knee angle for all three methods is shown in Figure 3, and the data processing workflow to obtain the knee angle for all three systems is provided in Figure 4.

The preliminary analysis of all systems included anthropometric measurements (length of the lower limb segments) in order to establish the location of the wearable sensors. We followed the Davis protocol [27] for the optoelectronic marker placement. The motion-capture system required an additional camera calibration using the *MATLAB camera calibration toolbox* [30]. For each test execution the subjects were asked to perform the static two-pose calibration, followed by the gait, and initiated by the leg carrying the sensors.

The raw datasets were then post-processed as follows to obtain the knee angle during the gait:

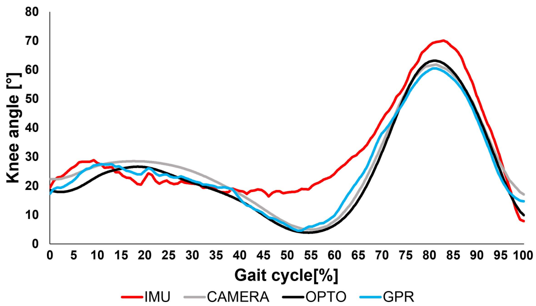

Fig. 3. Example of the knee angle during the gait as estimated by the IMU (red line) and compared with two gold standard references: motion-tracking (CAMERA, gray line) and optoelectronic (OPTO, black line). A Gaussian Process Regression (blue line) model was fitted based on the IMU knee angle as the predictor variable. The horizontal axis indicates the degree of completion of the gait cycle (%), and the vertical axis shows the knee angle (°).

- Each of the IMU sensors saved a comma delimited ASCII *.txt* file containing a n x 8 matrix, where the n row-wise entries were the timestamp (ms), accelerometer readings (x,y and z m/s^2) and absolute orientation (quaternions). The knee angle in each direction was calculated using a custom MATLAB script (version R2018a, Mathworks Inc., USA) using the following equation:

$$Knee_i(t) = tan^{-1}\left(\left\| V_i^1(t) \times V_i^2(t) \right\|, V_i^1(t) \cdot V_i^2(t)\right) \tag{1}$$

where $Knee_i(t)$ is the knee angle in the axis of interest i (x,y,z) at each time stamp, t. It is calculated using the *four-quadrant inverse tangent* (tan^{-1}) between the cross product and the dot product of the rotated vectors of the two sensors along the axis V_i^a; where i denotes the body frame axis of interest and a (1 or 2) is the index of the two sensors [31].
- The knee angle calculated from the commercial optoelectronic system was measured using the *Plug-in Gait body model* [32]. In this model the joint kinematics are obtained by combining marker positions with anthropometric measurements. The angles are expressed in the three anatomical planes, and the knee flexion angle is evaluated as the relative angle between the thigh and shank, keeping the pelvis as a mobile reference frame. Since the angle during the walking gait occurs mainly in one plane, the sagittal component of the knee has been used for this work. The optoelectronic system recorded a *.c3d* file, following the 3D Biomechanics Data Standard [33]. The knee angle was exported using Mokka software (3D Motion Kinematic & Kinetic analyzer, Version 0.6.2, Biomechanical ToolKit).
- The videos of each trial, collected by the camera-based system, were analysed using Kinovea (version 0.8.26) [34] to obtain the knee angle. For Trial 1, optoelectronic markers were tracked, while for Trial 2, circular black and yellow markers were used. After tracking the angle during the gait, a two-column *.txt* file was exported, with n row-wise timestamps (ms) in the first column and the corresponding knee angle (radiant) in the second column.

D. Gaussian Process Regression, GPR

In order to improve the IMU-based knee angle estimates (predictor variable), we applied Gaussian Process Regression (GPR) with 10-fold cross-validation using the optoelectronic and camera-based observations (target variable). This approach was chosen as it has been shown to be a robust, nonparametric method for both human and robotic gait analysis [35]. In this work, the Matern 5/2 kernel (covariance function) was chosen because it was found to exhibit the best performance (Root Mean Squared Error) when compared to the squared exponential, exponential, Matern 3/2 and rational quadratic kernels. The Matern 5/2 covariance function $k(x_i, x_j)$ for latent variables $f(x_i)$, $f(x_j)$ having a Euclidean distance between them, r is defined as:

$$k(x_i, x_j) = \sigma_f{}^2\left(1 + \frac{\sqrt{5}r}{\sigma_l} + \frac{5r^2}{3\sigma_l^2}\right)exp\left(-\frac{\sqrt{5}r}{\sigma_l}\right) \tag{2}$$

where $\sigma_f = 0.8568$ was the empirically-derived standard deviation of the IMU-derived knee angle during the gait, and $\sigma_l = 2.2084$ was the characteristic length scale. To provide a parsimonious model and avoid overfitting, data from all subjects from Trials 1 and 2, including both gold standard methods were concatenated into a single data set ('ensemble') of m = 20,514 knee angle estimates, on land and underwater, in order to develop a single GPR model.

Before performing GPR, the predictor and target data were normalized by subtracting the ensemble means and dividing by the ensemble standard deviations. The predictor variable (knee angle at each time step) was then converted to a time-shifted vector of length $n = 40$ lags. This length was chosen as it represented the mean (all subjects, all trials) of the knee angle autocorrelation zero crossing. The use of a time-shifted predictor vector of size $(m - n) \times n$ to improve regression performance was motivated by recent advances in data-driven modelling using Dynamic Mode Decomposition [36].

E. Data Analysis

To investigate the reliability of the proposed IMU system, MATLAB was used to synchronise and resample the data in order to have all the measurements at 100Hz.

Initially, the maximum flexion angle was evaluated by comparing the measurements made by each of the methods in the air or water environments. Subsequently, a statistical analysis was conducted using XLSTAT (version 2019.2, Alladinsoft, France), a statistical add-in software for Microsoft Excel. The statistical cross-comparison in this work was based on root mean squared error, correlation, Bland Altman plots and coefficient of variation. This juxtaposition was required to test our hypothesis that the proposed IMU system is able to measure the knee angle during the gait as effectively as the optoelectronic and motion-tracking methods.

1) Root Mean Squared Error: To determine the error between the measurements, the Root Mean Squared Error (RMSE) was

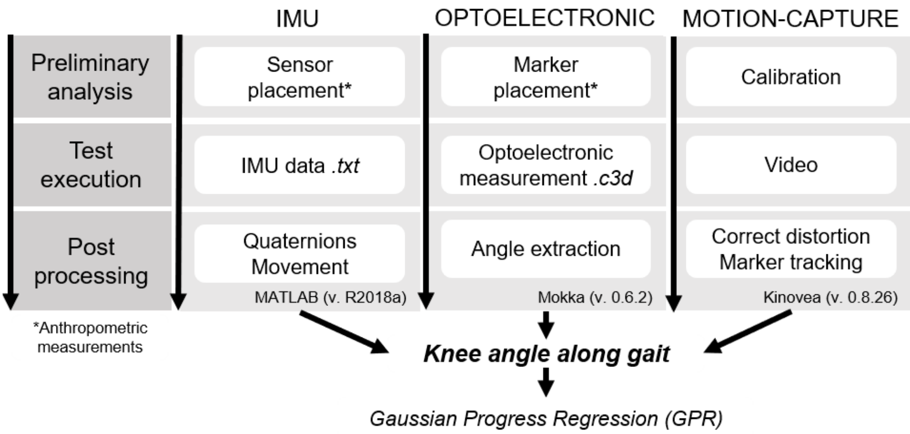

Fig. 4. Workflow of the methods used to evaluate the knee angle along a walking gait on land and underwater. The three main steps for all three sensor systems are preliminary analysis, test execution and post-processing. The IMU-based estimate of the knee angle was trained on optoelectronic and motion-capture knee angle calculations using Gaussian Process Regression in the final step.

evaluated using the following equation:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{3}$$

where $\hat{y}_i$ are the predicted values, y_i are the observed values and n is the sample size.

The RMSE values were used to assess the differences between pairs of measurement methods tested in this work.

2) Correlation: The statistical cross-comparison of knee angle during the gait between the proposed IMU, optoelectronic and motion-tracking methods were investigated using a one-way analysis of variance (ANOVA) using Pearson's product-moment correlation coefficient as the performance metric:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{4}$$

where n is the sample size, x_i and y_i are the sample points at time i, $\bar{x}$ and $\bar{y}$ are the sample means.

A correlation coefficient value, $r > 0.8$ is considered to be suitable for clinical trial use, and a $r < 0.5$ is considered to be too poor for practical use in rehabilitation studies. For all trials, comparisons were made using a significance level of $\alpha = .05$.

3) Bland Altman Plot: As shown in Figure 5, Bland Altman plots are a graphical method used to evaluate the agreement between measurements made with two different systems. It provides an efficient and quantitative evaluation of a new method compared with a gold standard when investigating the same phenomena [37]. Specifically, Bland Altman plots are a type of dispersion diagram where the abscissa and ordinate illustrate the synthesis of the measurements. Considering the investigation methods 1 and 2, and i indicating the time step; the arithmetic average of the measurements $((x_{1i}+x_{2i})/2)$ is reported on the horizontal axis, while on the vertical axis is shown the measurement difference between methods $(x_{1i} - x_{2i})$. In addition, the graph commonly displays the bias as the average of the differences ($\bar{b} = (\sum_{i=1}^{n} d_i)/n$) as well as the 95% confidence interval (evaluated as $bias \pm 1.96\sigma$), σ being the standard deviation of the differences between methods. A significant, systematic error occurs when a nonzero bias is found outside of the confidence interval.

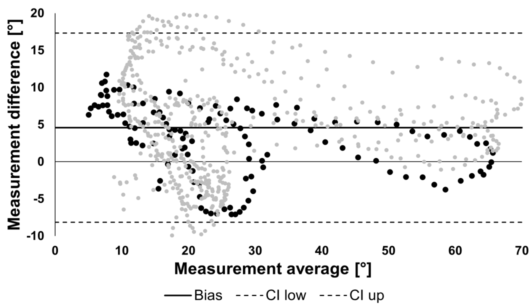

Fig. 5. Example of a Bland Altman plot exhibiting all 6 repetitions from Subject 1 (gray points). A single gait cycle is selected for emphasis (black points). For each time step *i*, the mean of the measurements (IMUi+OPTOi)/2 is shown on the horizontal axis, and the difference between measurements (IMUi-OPTOi) on the vertical axis. The black line is the bias, and the dashed lines indicate the confidence interval (taken as the bias $\pm 1.96\sigma$).

4) Coefficient of Variation: The Coefficient of Variation (CV), was calculated in this work based on the phase average of gaits for each test subject [25]. The coefficient represents the inter- and intra-subject variability of the knee angle over the observed walking gait for repeated trials.

To calculate the CV, a stride period was defined as the time from an initial contact of right foot to the end of the gait cycle. The stride period was then divided into equal intervals (e.g. 2%, 5%), and the mean value of multiple strides (ensemble) was calculated at each interval, as well as its standard deviation. The coefficient of variation was evaluated based on the ensemble of repeated gait cycles for each test subject, applying the following equation:

$$CV = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\sigma_i^2}}{\frac{1}{N}\sum_{i=1}^{N}|X_i|} \tag{5}$$

where N is the number of intervals over the stride, $|X_i|$ is the mean value of the knee angle at the i-th interval and σ_i is the standard deviation of X.

Although the general motion pattern is maintained during the gait, each gait cycle is specific and different for every subject. Indeed, it has been shown that in some cases it is even possible recognise a person by their gait pattern. According to previous investigations, the knee angle during gait for healthy adults lead to similar results for male and female, with relatively small changes between the two. In general, the variability of a single individual's gait can be approximated to have a CV of about 8%; with an expected inter-subject variability of up to 23% [25].

F. Limitations

Three main limitations of this study have been identified. First, it should be stated that the knee angle during the gait is assumed to be two-dimensional. We believe that this is an appropriate simplification based on the findings of research which compared planar to fully three-dimensional measurements [38], [39]. Future studies should consider the internal rotation of the knee and its effect on the longitudinal axes over the gait. Second, the number of test subjects involved and the repetitions made are not sufficient for a clinical trial, but are adequate to cross-compare the three methods evaluated in this work. Finally, it is important to point out that due to logistic constraints, tests were conducted in Estonia and in Italy and it was not possible to investigate the same test subjects with all three methods.

III. Results and Discussion

A. Trial 1

In the first trial, a cross-comparison of the proposed IMU system was made with both the optoelectronic and motion-tracking systems on land. The cross-comparison involved repetitions of the walking gait by three test subjects. One trial from Subject 1 was faulty, leaving 5 repetitions. The other two test subjects were observed over 6 repetitions, for a total of 17 experiments for cross-comparison. An example visualization of the results obtained from a single randomly selected gait cycle of the first trial is shown in Figure 3. The differences between the IMU-based knee angle estimate before (red) and after applying the Gaussian Process Regression (blue) are clearly seen.

1) Maximum Flexion Angle: The maximum knee flexion for each measurement system used and investigated subjects in Trial 1 is shown in Figure 6. A one-way ANOVA test with 95% confidence, $p < 0.05$ indicated no significant difference when comparing the different methods (p=.7). This supports our hypothesis that the IMU-based method can be used in air and underwater studies of the knee angle during gait in air and underwater, although the small number of limits the interpretation of this finding to non-clinical settings.

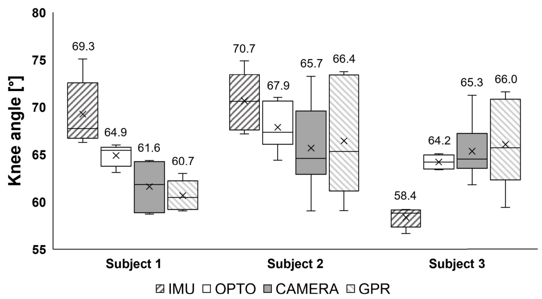

Fig. 6. Results of the knee maximum flexion angle for Trial 1, represented as box and whisker plots. The boxes represent the interquartile range (IQR) over the 25th to 75th percentiles, the centre line corresponds to the median, error bars extend from the IQR up to a factor of 1.5 from the IQR and the cross symbol indicates the mean, which is shown as a numeric value near each boxplot. The results are shown for each subject and measurement method (IMU, OPTO, CAMERA) and after applying the IMU-based Gaussian Process Regression (GPR) model.

2) Root Mean Squared Error: Table III provides a summary of RMSE for Trial 1, expressed as the mean and standard deviations. A slightly larger RMSE is observed between the inertial and optoelectronic methods (IMU-OPTO), with an average deviation of 10.1 degrees. Smaller average errors were obtained for the other comparison, at 6.1 and 7.9 degrees for the IMU-CAMERA and OPTO-CAMERA, respectively. When comparing the IMU-based knee angles and the optoelectronic system, the GPR model reduced the RMSE from 10.1 to 6.3, and from 8.1 to 5.9 when comparing the IMU and camera-based motion tracking systems. This indicates that the GPR model is able to systematically reduce the RMSE of the IMU-based knee angle during the gait when compared to both gold standard systems.

3) Correlation: The Pearson product moment cross-correlation (r) was calculated with equation 1 between each evaluation method exploited in Trial 1 and the results are summarized as mean and standard deviation in Table III. IMU-OPTO is the cross-correlation between the optoelectronic system and IMU; IMU-CAMERA considers the IMU and motion-tracking system. Similar to the RMSE, the Gaussian Process Regression improved the system performance by increasing the correlation coefficient values when compared to the gold standard optoelectronic (IMU-OPTO vs. GPR-OPTO) from r = 0.9 to 0.95 and camera-based systems (IMU-CAMERA vs. GPR-CAMERA) from r = 0.9 to 0.94. We also compared the gold standard systems, and the OPTO-CAMERA pairing (r = 0.98) represents an expected upper limit of the cross-correlation performance for these experiments. In this work, we followed standard practice by assigning a threshold value for successful performance as having a cross-correlation r = 0.80. All coefficients were found to exceed the threshold, varying from 0.82 to 0.99. One-way ANOVA tests (95% confidence) found significant differences (p <.001) between the correlation coefficients of the four groups. It is worth noting that the values of the cross-correlation remain similar when comparing the IMU with the optoelectronic and motion-tracking systems, where

TABLE III
ROOT MEAN SQUARED ERROR (RMSE) AND CORRELATION COEFFICIENT (r) FOR TRIAL 1. COEFFICIENTS ARE EXPRESSED AS MEAN ± THE STANDARD DEVIATION, CALCULATED BETWEEN THE PAIRS OF KNEE ANGLE EVALUATION METHODS: IMU-OPTO, IMU-CAMERA, GPR-OPTO, GPR-CAMERA, OPTO-CAMERA

Trial 1	IMU-OPTO	IMU-CAMERA	GPR-OPTO	GPR-CAMERA	OPTO-CAMERA
RMSE [°]	10.1 ± 2.7	8.1 ± 2.1	6.3 ± 2.2	5.9 ± 2.0	5.7 ± 2.5
r [unitless]	0.90 ± 0.03	0.90 ± 0.03	0.95 ± 0.05	0.94 ± 0.05	0.98 ± 0.02

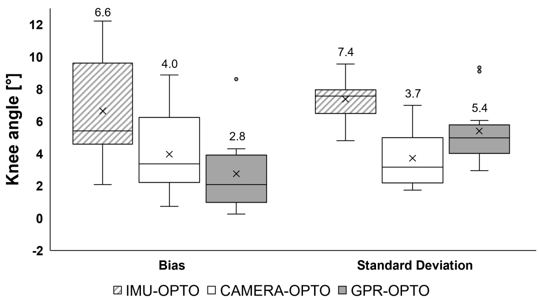

Fig. 7. Pairwise comparison of the Bland Altman coefficients for Trial 1. The optoelectronic system compared with the inertial system (IMU-OPTO), motion-capture vs. optoelectronic (CAMERA-OPTO) and GPR vs. optoelectronic (GPR-OPTO). The bias and standard deviation are represented as box and whisker plots. The boxes represent the interquartile range (IQR) over the 25th to 75th percentiles, the centre line corresponds to the median, error bars extend from the IQR up to a factor of 1.5 from the IQR and the cross symbol indicates the mean, shown as a numeric value near each boxplot.

the same value of mean (r = 0.9) and standard deviation (STD = 0.03) were obtained.

4) Bland-Altman Plot: The Bland Altman plot is a graphical assessment of the measurement reliability of the proposed IMU-based system as compared with the gold standard methods. For Trial 1, the Bland Altman plot was evaluated for each subject and repetition with the optoelectronic system as reference. An example is shown in Figure 5, where the Bland Altman plot of the 6 repetitions of Subject 1 are superimposed (grey) and the results from a single trial are highlighted for visual comparison (black). The graph displays the measurement averages along the horizontal axis, and the measurement differences on the vertical axis; it is completed by the bias (black line) and the confidence interval is defined by the dashed lines. An overview of the coefficients obtained during the Bland Altman investigation is provided in Figure 7, shown as boxplots of the bias (mean value of the differences), and as the standard deviation of the differences obtained after comparing the different measurement methods. The evaluation was made by comparing the optoelectronic system with both the inertial (IMU-OPTO), the Gaussian Regression (GPR-OPTO) and the camera-based method (CAMERA vs OPTO). In this way, a full performance comparison has been made using the most current technologies.

The small number of subjects evaluated in this study do not provide evidence at a clinical level of significance. However, the results are sufficient to assess the performance of the proposed IMU system. The bias, which represents the mean value of the differences, was always found to be greater than zero. This indicates that on average, the IMU systematically overestimates the knee angle along the gait. The standard deviation remained consistent among all test subjects and measurement technologies, as is visible from the boxplot height dispersion. An acceptable similarity was observed between the upper and lower part of the table for all coefficients, which indicates the similarity between the IMU and camera-based methods. The GPR results show that the regression model reduced the bias (2.8 vs. 6.6) and standard deviation (5.4 vs. 7.4) when compared with the IMU-based knee angle estimates.

TABLE IV
COEFFICIENTS OF VARIATION (CV) FROM TRIAL 1 FOR THE INERTIAL (IMU), OPTOELECTRONIC (OPTO), CAMERA-BASED MOTION-TRACKING SYSTEM (CAMERA) AND GAUSSIAN PROCESS REGRESSION (GPR) APPROACHES

Subject	IMU	OPTO	CAMERA	GPR
1	11.6	14.0	14.6	13.1
2	20.0	28.4	22.4	23.6
3	6.5	10.5	12.5	12.7

5) Intra-Subject Variability: The coefficients of variation calculated following equation 5, are shown in Table IV. Values are provided for the IMU, optoelectronic (OPTO), camera-based motion-tracking (CAMERA) system and Gaussian Process Regression (GPR). The intra-subject variability, expressed as the coefficient of variation indicates that all three methods have similar trends, but tend to be highly subject-specific. The values obtained are larger than the 8% suggested in the literature [25], which may be partially due to the small number of repetitions (6) utilized in this study.

B. Trial 2

In the second trial, the same subjects were evaluated on land and underwater. The IMU performance was compared with the motion-tracking system, and the estimation of the knee angle improved after applying Gaussian Process Regression. The same statistical methods applied in the first trial have been used to cross-compare the methods. A total of 11 repetitions were recorded from each subject, producing 40 available gaits for land and 40 for underwater. During the water trial, a repetition for Subject 4 and one for Subject 7 were excluded due to a camera malfunction during experimentation.

1) Maximum Flexion Angle: Figure 8 shows the results of maximum knee flexion angle for Trial 2 for Land and Water trials with inertial (IMU), motion-capture (CAMERA) and Gaussian Process Regression (GPR). Large differences are noticeable between subjects, which were identified using one-way ANOVA tests (95% confidence). Considering the

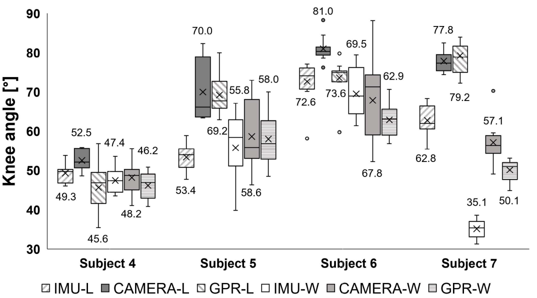

Fig. 8. Results of the knee maximum flexion angle for Trial 2, represented as box and whisker plots. The boxes represent the interquartile range (IQR) over the 25th to 75th percentiles, the centre line corresponds to the median, error bars extend from the IQR up to a factor of 1.5 from the IQR and the cross symbol indicates the mean, which is shown as a numeric value near each boxplot. For each subject, the group of four boxes correspond to the three measurement methods (IMU, OPTO and CAMERA) and the IMU-based Gaussian Process Regression (GPR), on Land (L) and underwater (W).

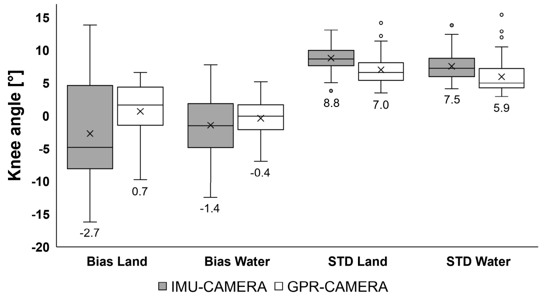

Fig. 9. Pairwise comparison of Bland Altman coefficients for Trial 2 as box and whisker plots. The difference between the inertial vs. motion-tracking (IMU-CAMERA) and between Gaussian Process Regression and motion-tracking (GPR-CAMERA) systems. The boxes of the bias and standard deviation (STD) represent the interquartile range (IQR) over the 25th to 75th percentiles, the centre line corresponds to the median, error bars extend from the IQR up to a factor of 1.5 from the IQR and the cross symbol indicates the mean, which is shown as a numeric value near each boxplot.

three methods (IMU, Camera and GPR), the *p-value* was consistently smaller than ($p < 0.05$), indicating statistically significant differences between measurements taken on land and underwater.

2) Root Mean Squared Error: Values of RMSE evaluated between the inertial system and IMU-CAMERA are displayed in Table V as the mean and standard deviation. The error was found to be slightly higher in air and for IMU-based estimates (RMSE = 11.8 for IMU-CAMERA and 8.3 for GPR-CAMERA) than underwater (RMSE = 8.8 for IMU-CAMERA and 6.6 for GPR-CAMERA), and slightly lower for GPR-based estimates. Similarly to the first trial, RMSE between GPR and the motion-capture system is smaller than the one between the IMU and the gold standard; both in water and on land.

3) Correlation: Values of the cross-correlations comparing the land and underwater trials are reported in Table V as mean and standard deviation. Here, the motion capture system was kept as the reference and compared with the inertial method (IMU-CAMERA) and the Gaussian Process Regression (GPR-CAMERA) results in both environments. Considering a threshold cross-correlation value of $r = 0.80$, land trials had an $r \geq 0.8$ for 83% of the gaits, whereas underwater trials had an $r \geq 0.80$ for 93% of gaits compared. One-way ANOVA tests were also conducted, and did not detect a significant difference between subjects and methods applied for the cross-correlation. The averages and standard deviations are similar on land and in water for both comparisons; slightly bigger when comparing GPR and Camera.

4) Bland Altman Plot: Bias and Standard Deviation coefficients from of Bland Altman plot for Trial 2 are showed in Figure 9 as boxplot. Motion Capture system measurements are compared with inertial method (IMU-CAMERA) and Gaussian Regression results (GPR-CAMERA), both on Land and in Water. From the figure, it is observable that the Bias is distributed around zero in both environments and has a smaller variance when evaluated between GPR and motion capture. This indicates that there is a low probability of a systematic error, although a larger number of test subjects is needed to thoroughly investigate this claim. Comparable values of standard deviation have been obtained, slightly smaller for the GPR-CAMERA comparison.

5) Coefficient of Variation: Table VI provides the coefficient of variation for Trial 2. For each subject on land and underwater, the *CV* was calculated using equation 5 for the IMU, the camera-based motion-tracking system (CAMERA) and the Gaussian Process Regression (GPR). Considering the intra-subject variability of *CV* for Trial 2, the values were higher than those suggested by Winter [25]. The uniqueness of the stance portion of the Subject 4 land knee angle during the gait cycle resulted in a systematic underestimation of the GPR knee angle during the gait for this subject and resulted in a high CV of 73.8. Nevertheless, the *CV* for the motion-tracking system on land remained similar to those obtained in Trial 1, as shown in Table IV. This provides evidence reinforcing our claim that the proposed IMU-based system is reliable on land as compared with the two gold standard methods, especially after applying the GPR model to the IMU-based knee angle estimates.

Trial 2 was conducted to investigate the potential influence of the fluid-body interaction. From Figure 8 it can be observed that the maximum knee angle is generally reduced in water. In Table V, it can be seen that the values of the correlation coefficient remain stable across all methods, on land and underwater. We suggest that the presence of water does not interfere with the IMU measurement, rather that the observed systematic differences are largely caused by augmentations in the underwater gait body kinematics. The additional forces augmenting the gait are primarily the drag and buoyancy, and further investigation is required to decompose their individual contributions during a gait cycle.

The outcomes of this investigation suggest that the proposed device is suitable for the study of underwater rehabilitation based on walking gait kinematics. The novelty and contributions of this paper are five-fold:

TABLE V

ROOT MEAN SQUARED ERROR (RMSE) AND CORRELATION COEFFICIENT (r) FOR TRIAL 1. COEFFICIENTS ARE EXPRESSED AS MEAN ± THE STANDARD DEVIATION, CALCULATED FOR EACH ENVIRONMENT (LAND AND UNDERWATER) BETWEEN THE KNEE ANGLE EVALUATION METHODS IMU-CAMERA AND GPR-CAMERA

Trial 2	Land		Water	
	IMU-CAMERA	GPR-CAMERA	IMU-CAMERA	GPR-CAMERA
RMSE [°]	11.8 ± 3.0	8.3 ± 2.1	8.8 ± 2.6	6.6 ± 2.6
r [unitless]	0.85 ± 0.10	0.91 ± 0.07	0.88 ± 0.06	0.91 ± 0.08

TABLE VI

COEFFICIENTS OF VARIATION (CV) FROM TRIAL 2 CALCULATED FOR THE INERTIAL (IMU), CAMERA-BASED MOTION-TRACKING (CAMERA) AND GAUSSIAN PROCESS REGRESSION (GPR) KNEE ANGLE EVALUATION METHODS, ON LAND AND UNDERWATER

Subject	IMU		CAMERA		GPR	
	Land	Water	Land	Water	Land	Water
4	18.5	20.1	28.1	23.8	73.8	18.6
5	20.6	24.9	16.1	21.3	15.3	23.0
6	18.4	14.5	15.1	16.7	15.6	12.8
7	17.4	16.3	12.2	18.3	14.7	24.8

- It is the first work to cross-compare the measurement of knee gait angles during a walking gait using wearable IMUs, optoelectronic and motion-capture systems both on land and underwater.
- A Gaussian Process Regression model of the knee angle significantly improved the IMU performance by reducing the RMSE and Bland-Altman biases and standard deviations, on land and underwater, when compared to the optoelectronic and camera-based motion-capture systems.
- Instead of using commercial IMUs with a separate waterproof case, we propose a new cableless, self-contained wearable system suitable for both air and underwater environments.
- 93% of the underwater experiments using IMU and motion-tracking remained above the cross-correlation threshold required for clinical use, r>0.8.
- Land-based experiments of the knee angle comparing the IMU to optoelectronic and motion-capture systems resulted in a cross-correlation r>0.8 for 94% of the experiments.

IV. CONCLUSION AND FUTURE WORK

Previous studies have indicated that IMU-based systems can be used to measure human underwater kinematics [9]–[11], [14]. Our work shows that the proposed method to assess the knee angle during the gait is substantially in agreement with previous land-based performance comparisons between IMU and motion-tracking systems [12], [13]. In contrast to previous investigations, the current study included a land-based IMU performance evaluation using both optoelectronic and camera-based motion-capture systems. Additional analysis of the IMU-based knee angle estimates after applying Gaussian Progress Regression substantially improved the overall performance of the proposed system, both on land and underwater.

The results of our study confirm the hypothesis that the proposed wearable IMU system is able to reliably measure the knee angle along gait both on land and underwater. This was shown through the results of two different trials. In Trial 1, the proposed IMU system was tested and validated through a performance comparison with gold standard optoelectronic and motion-tracking systems on land. Trial 2 was conducted on land and underwater using the motion-tracking system as the reference, and the differences between the air and underwater environments were investigated.

Considering Trial 1, the cross-correlations and coefficients of variation indicated strong similarities between the camera-based and IMU systems, and no statistically significant differences were found between the two systems. In Trial 2, it was observed that the IMU measurements of the knee angle during the gait in the underwater environment were more consistent than those recorded on land. The coefficients of variation from Trial 2 show that the proposed IMU system remain similar to those obtained using motion-tracking. We therefore conclude that the proposed IMU system is indeed suitable for use on land and underwater to evaluate the knee angle during the gait. In contrast to the literature, the inertial sensors developed in this work did not require the use of cables [14] nor did they require and additional external waterproof casing [9], [14]. The investigation conducted differs also from previous studies by conducting a performance comparison between three methods in air and underwater. The current findings imply the suitability of the developed sensors for underwater rehabilitation. To the best of the author's knowledge, this is the first survey that uses non-commercially available, wireless and cableless inertial sensors for air and underwater gait analysis. The physical characteristics of the bespoke sensors minimize potential movement restrictions, allowing for the continuous monitoring of sports and rehabilitation-specific movements. The study proves an investigation method suitable for monitoring endurance activities performed in and outside water as triathlon.

Although the generally positive results of this work, we would like to point out some limitations and challenges. First, it is important to state that the small number of subjects and repetitions considered did not allow to make a conclusive assessment of the proposed system's performance in clinical settings. It should be noted that in this work, we did not take into account soft tissue disturbance as potential source of error, or solicit feedback from the test subjects regarding their physical comfort during testing. However, the findings in this study are sufficient to warrant the future application of the proposed IMU system for future human testing in clinical trials.

Moreover, in this investigation we purposefully neglected the full range of body movement and focused only on the knee angle during the gait. In addition, we found that there were practical limitations while using Kinovea for motion-tracking, as it required considerable manual readjustment of the markers between frames. Correspondingly, this resulted in a larger measurement uncertainty for the motion-capture based knee angle measurements, which is inline with findings of another land-based study comparing the two methods [34].

Despite of these limitations, we are encouraged by the key findings. Future applications of the proposed sensors will include more complex human underwater kinematics including swimming, diving and exiting and entering the water environment to and from land. Our long-term objective is to develop a rugged and wearable IMU system with simple and affordable hardware which can be quickly and easily implemented, allowing for more advanced kinematic investigations indoors and outdoors, on land and underwater.

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Cecilia Monoli received the B.Sc. degree in biomedical engineering and the M.Sc. degree in biomedical engineering, specialization in biomechanics and biomaterials from the Polytechnic University of Milan, Italy, in 2016 and 2019, respectively. She is currently pursuing the Ph.D. degree with the Tallinn University of Technology, Estonia. Her research interests include underwater biomechanical motion analysis and mixed perception.

Juan Francisco Fuentez-Pérez received the Ph.D. degree in conservation and sustainable use of forest systems from the University of Valladolid, Spain, in 2017, and the Ph.D. degree in information and communication technology from the Tallinn University of Technology, Estonia, in 2019, within the framework of the European Academy for Marine and Underwater Robotics (ROBOCADEMY EU Project). He is currently a Postdoctoral Fellow with the GEA-Ecohidráulica, University of Valladolid and the Itagra.ct. He has been collaborating in several national and European research projects, focused on the design, simulation, and evaluation of fishways, and involved in artificial lateral line technology and its applications for the evaluation of aquatic ecosystems and its use in underwater robotics. His current research interests include underwater and flow sensing, sensor networks, environmental monitoring, fluid mechanics, ecohydraulics, and fishways.

Nicola Cau received the M.S. degree in bioengineering from the Polytechnic University of Milan in 2005 and the Ph.D. degree in industrial engineering from the University of Cagliari in 2010. He was a Research Fellow with the Department of Electronics, Information and Bioengineering, Politecnico di Milano. He worked with "Luigi Divieti" Posture and Movement Analysis Laboratory for six years. He is currently the Head of the Technology Transfer Office, IRCCS Don Carlo Gnocchi Foundation and attending as a Master in "Management of Research, Innovation and Technology" with the Polytechnic University of Milan. He carried out research activities in the rehabilitation field with the Italian Auxological Institute of Piancavallo on issues related to the rehabilitation of subjects with metabolic and eating disorders. His main activity is focused on Technology Transfer field, particularly on life sciences.

Paolo Capodaglio received the M.D. degree from the University of Pavia, Italy, in 1988. In 1991, he obtained his specialization in Physical Medicine and Rehabilitation (PMR) from the University of Pavia. He is currently the Director of the Department of PMR (80 inpatients) and the Laboratory for Research in Biomechanics and Rehabilitation, Istituto Auxologico Italiano IRCCS, Verbania-Piancavallo, Italy. He has published more than 200 articles on peer-reviewed journals and seven books. He devoted most of his research to the functional evaluation in ageing and pathological conditions (spinal cord injuries, musculoskeletal disorders, and in the last ten years, obesity and metabolic conditions). He serves as reviewer for several indexed articles.

Manuela Galli received the M.S. degree in mechanical engineering and the Ph.D. degree in applied mechanics (biomechanics) from Politecnico di Milano, Milan, Italy. She is currently an Associate Professor with the Department of Electronics, Information and Bioengineering (DEIB), Politecnico di Milano. She is responsible for the "Luigi Divieti" Posture and Movement Analysis Laboratory, DEIB, Politecnico di Milano. She has authored several scientific works in the field of the movement analysis for clinical applications.

Jeffrey A. Tuhtan (Member, IEEE) received the B.Sc. degree in civil engineering from California Polytechnic State University, San Luis Obispo, CA, USA, in 2004, and the M.Sc. degree in water resources engineering and management and the Dr.Eng. degree from the University of Stuttgart, Germany, in 2007 and 2011, respectively. He is currently with the Centre for Biorobotics, Tallinn University of Technology, where he leads the Environmental Sensing and Intelligence Group. His current research interests include environmental intelligence and bio-inspired underwater sensing.

Appendix 3

Publication III
C. Monoli, M. Galli, and J. A. Tuhtan, “Improving the reliability of underwater gait analysis using wearable pressure and inertial sensors,” PLOS ONE, vol. 19, pp. 1–15, 03 2024

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RESEARCH ARTICLE

Improving the reliability of underwater gait analysis using wearable pressure and inertial sensors

Cecilia Monoli[1,2]*, **Manuela Galli**[2], **Jeffrey A. Tuhtan**[1]

1 Department of Computer Systems, Tallinn University of Technology, Tallinn, Estonia, **2** Department of Electronics, Information and Bioengineering, Politecnico di Milano, Milano, Italy

* cecilia.monoli@taltech.ee

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Abstract

This work addresses the lack of reliable wearable methods to assess walking gaits in underwater environments by evaluating the lateral hydrodynamic pressure exerted on lower limbs. Sixteen healthy adults were outfitted with waterproof wearable inertial and pressure sensors. Gait analysis was conducted on land in a motion analysis laboratory using an optoelectronic system as reference, and subsequently underwater in a rehabilitation swimming pool. Differences between the normalized land and underwater gaits were evaluated using temporal gait parameters, knee joint angles and the total water pressure on the lower limbs. The proposed method was validated against the optoelectronic system on land; gait events were identified with low bias (0.01s) using Bland-Altman plots for the stride time, and an acceptable error was observed when estimating the knee angle (10.96° RMSE, Bland-Altman bias -2.94°). The kinematic differences between the land and underwater environments were quantified, where it was observed that the temporal parameters increased by more than a factor of two underwater ($p<0.001$). The subdivision of swing and stance phases remained consistent between land and water trials. A higher variability of the knee angle was observed in water (CV = 60.75%) as compared to land (CV = 31.02%). The intra-subject variability of the hydrodynamic pressure on the foot ($CV_z^{foot} = 39.65\%$) was found to be substantially lower than that of the knee angle ($CV_z = 67.69\%$). The major finding of this work is that the hydrodynamic pressure on the lower limbs may offer a new and more reliable parameter for underwater motion analysis as it provided a reduced intra-subject variability as compared to conventional gait parameters applied in land-based studies.

Introduction

Physical activity in water can reduce the risk of injury during rehabilitation exercises due to the lessening of joint loading caused by buoyancy and the increased resistance to motion caused by drag [1]. Water rehabilitation can also aid in the management of chronic conditions [2], promote injury recovery, enhance exercise performance [3], and has shown to positively contribute to the psychological well-being of participants [4].

The authors' recent systematic review highlighted the scarcity of quantitative underwater motion analysis methods [5]. The methods and protocols used in underwater studies are commonly taken from land-based methods [6], but may be unsuitable for aquatic environments [7]. Optoelectronic systems remain the gold standard for land-based motion analysis, but rely on cable-connected infrared cameras and passive light-reflective markers [8]. Accordingly, optoelectronic systems are not well-suited for both outdoor and underwater applications [9]. Previous underwater studies have made use of external cameras to monitoring motion in a underwater treadmill tank [10], and a similar system has been developed which utilized blue LEDs and cameras for aquatic motion analysis [11]. Waterproof action cameras have also been used for kinematic analysis [9], where the analysis was restrained to planar investigations with a limited field of view [12].

Wearable inertial measurement units (IMUs) can be implemented as an alternative to optoelectronic and camera-based motion analysis systems for land-based and underwater motion analysis [13]. Unlike optoelectronic and camera-based methods, IMUs do not have limitations on the field of acquisition and can capture physical activities in natural and highly unstructured settings [14]. Previous studies have performed underwater motion analysis using IMUs to assess the walking gait [15–18], gait initiation [19, 20] as well as double and single limb squat exercises [21]. Although the physical activities considered in these works was often similar, the protocols adopted differed substantially between studies. This variability indicates an overall lack of structured clinical procedures and methodologies for underwater motion analysis. These shortcomings hinder the cross-comparison of findings and effective quantitative kinematic analysis, limiting the understanding of underwater characteristics of motion [5].

This paper illustrates that IMUs outfitted with pressure sensors, (PIMU) can provide a new and reliable method for motion analysis of the walking gait in water. The choice of walking in this study stemmed from its predictable patterns and extensive application in rehabilitation [22]. Gait analysis is an established method for assessing locomotion, diagnosis and the general well-being of test subjects [23–25]. The objectives of this work are three-fold: (i) to compare PIMU performance against an optoelectronic system as a land-based reference, (ii) to quantify the kinematic differences between land and underwater gaits, and (iii) to evaluate the reliability of the lateral hydrodynamic pressure on the lower limbs as a new motion analysis parameter for underwater gaits. To achieve the first two objectives, temporal gait parameters and knee angle kinematics were analyzed on land and underwater. Finally, the hydrodynamic pressure time series during a gait cycle at the thigh, shank and foot were compared with that of the knee angle.

Materials and methods

Participants

Sixteen adults were enrolled in this study: 9 Females: 24.8±1.1 years, 1.66±0.06 m height, 59.2 ±6.7 kg mass and 7 Males: 25.4±2.9 years, 1.78±0.05 m height, 73.6±11.6 kg mass. All subjects were healthy with no functional impairments, neurological or orthopedic conditions and were free of musculoskeletal injury or pain at the time of data collection. Additionally, the volunteers had no previous experience with water rehabilitation exercises. The experimental tests on land and underwater were conducted in compliance with the World Medical Association Declaration of Helsinki and were approved by the Ethics Committee of Politecnico di Milano (Decision 22/2021 on June 14th, 2021. Milan, Italy). The recruitment of volunteers started on September 1st, 2021 and was completed on December 20th, 2021. Written informed consent of the participants was collected.

Inertial and pressure wearables

This study implemented Pressure and Inertial Measurement Units (PIMU) sensors designed at the Tallinn University of Technology (Tallinn, Estonia) [26] for underwater kinematics. The wearable loggers are ideally suited for human motion analysis because they are small and lightweight (6.9 g dry mass), minimizing potential discomfort and interference with the subjects' movement. The PIMU sensors log data at 100 Hz and include a tri-axial IMU (BMX160, Bosch Sensortec, Germany) which incorporates a linear accelerometer, gyroscope and magnetometer as well as a pressure sensor (MS5837–2BA, TE Connectivity, Switzerland). The devices are wirelessly activated using a magnetic switch after placement on the test subjects. The data are stored as comma-separated values (CSV) to an onboard memory module with 2 GB storage, and are retrieved through a USB connection by downloading the CSV file after each activity. Table 1 summarizes the technical characteristics of the loggers, and Fig 1 provides the dimensions and placement of the main components.

Experimental protocol

All subjects participated in two distinct trials: first, a land-based trial and afterwards the underwater trial. In both trials, subjects were asked to walk ten times in a straight line, at their preferred self-selected speed, with their arms folded across their chest. Three PIMUs were positioned laterally on the right leg, as shown in the right panel of Fig 1. The sensors were fixed with self-adhesive medical tape at the approximate center of mass of thigh, shank and foot [27], following a modified version of the Outwalk protocol [28].

The land trial fully addressed the first objective, which was to validate the PIMU motion analysis data through comparison with the optoelectronic system. In addition, the land trial provided data needed for the second objective, to evaluate differences between land and underwater gaits. The trial was conducted in the Posture and Movement Analysis Laboratory "Luigi Divieti" of Politecnico di Milano (Milan, Italy). The walking gait was recorded simultaneously with the three PIMU placed on the right lower limb and an 8-camera optoelectronic system BTS-SmartDX 400 (BTS Bioengineering S.p.a., Italy) sampling at 100Hz. The optoelectronic markers were placed on the test subjects following the Davis protocol [29]. To synchronize the optoelectronic system and the sensors, a two-pose static calibration after [30] was performed before each trial. Subjects were asked to stand upright (pose one) and then lift their right leg, in hip flexion with the knee flexed to a comfortable angle (pose two) for at least 2 seconds. After the completion of the calibration poses, the volunteers initiated walking, beginning with their right leg.

The underwater trial was conducted to fulfill the second and third objectives, namely to investigate the differences between land and underwater gaits and evaluate the hydrodynamic

Table 1. Technical characteristics of the wearable, waterproof Pressure and Inertial Measurement Unit (PIMU).

Dimensions	35x13x13.5 mm (length x height x width)
Mass in air	6.9 ± 0.3 g
Microcontroller	32-bit ARM Cortex-M0+ SAM D21G
Absolute orientation sensor	BMX160 (Bosch)
Pressure sensor	MS5837–02BA (TE Connectivity)
Battery	Lithium-Polymer(+4v with USB charging) 3.7V 40mAh
Data Storage	SD card, 2 GB
Data logging rate	100 Hz
Waterproofing	Epoxy resin

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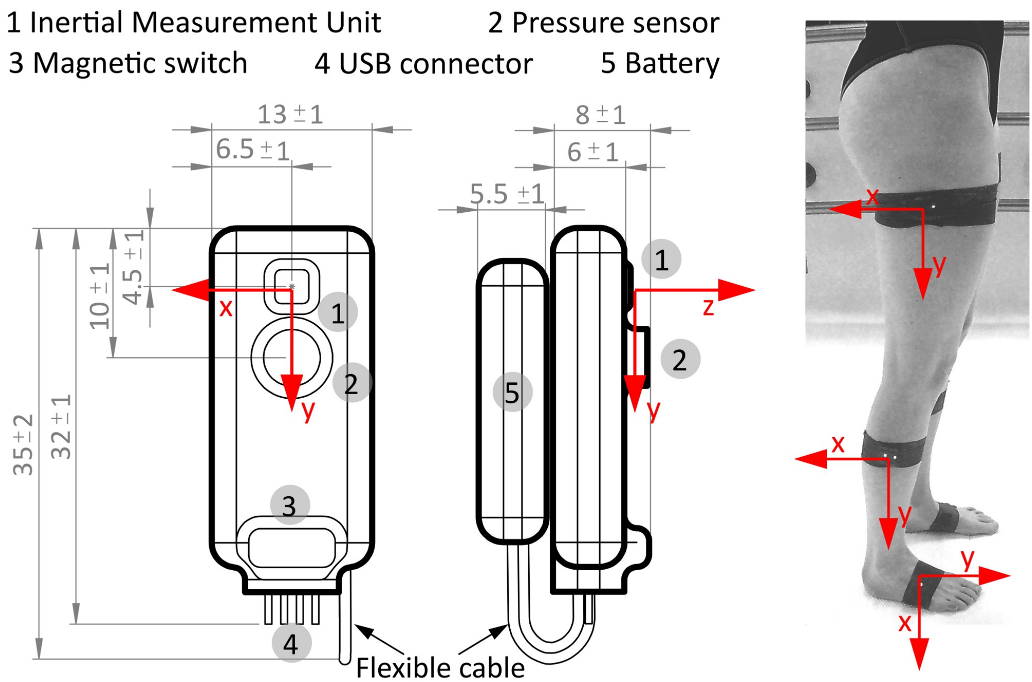

Fig 1. Technical drawing and placement of PIMU sensors for land and underwater walking gait motion analysis. (Left) Dimensions (mm) and locations of the main components. (Right) Placement and axial orientations of three PIMU on a test subject. The measurement axes of each sensor are highlighted in red.

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pressure as a potentially new parameter for underwater motion analysis. The modified Outwalk protocol used in the land-based trials was repeated in water, with the three PIMUs placed on each subject's right lower limb. The underwater trials were conducted at the rehabilitative swimming pool of the Enjoy Sport Center (Cernusco sul Naviglio, Milan, Italy). The pool has a fixed depth of 1.20m, is 3m long, and the water temperature remained at 31˚C throughout the trials. Following the protocol of the land-based trial, the PIMU calibration poses and gait initiation with the right leg were performed in water to ensure consistency between trials.

Data processing and analysis

The second right-leg stride temporal gait parameters and knee angular kinematics were assessed for land and water trials and the hydrodynamic pressure was considered for the water trial. All parameters were normalized over the gait cycle to enable cross-comparison between repetitions and subjects. A total of 160 samples per parameter were evaluated: 16 subjects with 10 repetitions.

The standard gait classification was applied, defining a gait cycle as the motor tasks between two subsequent ipsilateral heel strikes [24]. The toe-off is the moment of final contact, occurring between two heel strikes and is the other main gait event. The identification of these three gait events, two heel strikes and the toe-off occurring in between, enabled to estimate the temporal parameters of interest. The first is the stride time, which is the duration of a complete gait cycle. The second is the stance time, which is the fraction of the gait cycle when the foot is on the ground and the third is the swing time, corresponding to the remaining fraction of the gait when the foot is lifted from the ground and moves forward. The equations used to evaluate the temporal parameters are reported in the supporting information S1 Appendix. The stance and swing fractions were expressed also as a percentage of the normalized gait cycle for the comparison between land and water trials. The knee joint kinematic in the sagittal plane was investigated normalizing the flexion-extension angle over the gait cycle. In addition to the angular kinematics, the maximal flexion and maximal extension were identified and the Range Of Motion (ROM) was estimated as the difference between them.

The optoelectronic data was processed using the BTS Smart Clinic software (BTS Bioengineering S.p.a., Italy) by manually identifying the gait events. Data collected with the PIMU sensors was post-processed in MATLAB (version R2022b, Mathworks Inc., USA). A bespoke algorithm was developed by the authors to automatically detect gait events based on the acceleration magnitude of the foot mounted sensor. The PIMU knee angle was estimated from the gyroscope and accelerometer data after applying the Madgwick filter to calculate the relative angle between the thigh and shank mounted IMUs, following Song et al. [31]. The hydrodynamic pressure was processed by subtracting the median value for each dataset to account for the different heights of the subjects, and was subsequently normalized in time over the gait cycle. Hydrodynamic pressure parameters similar to the knee angle were estimated: maximal and minimal pressure as well as the Range Of Pressure (ROP) which was calculated as their difference.

Addressing the first objective of this investigation, the PIMU-based method was validated by comparing its performance with the optoelectronic system. For temporal and joint parameters the root mean squared error (RMSE), Spearman correlation coefficient (ρ) and Bland-Altman plots were evaluated to assess measurement errors, biases and reliability. Differences between the land and water trials were assessed comparing descriptive statistics of the temporal parameters and joint kinematics, to address the second objective. The Brunner-Munzel test using a 95% confidence interval was performed [32, 33] for pair-wise comparison of the PIMU gait parameters on land and underwater and between the PIMU and optoelectric systems on land. This non-parametric test method was chosen as it is a generalised and more robust version of the Mann-Whitney U test which does not require the assumption of equal variances between sample populations [34]. The test groups were generated based on the ensemble gait data from all participants for each system (PIMU vs. optoeletronic) and environment (land or underwater).

Lastly, the third objective evaluated the lateral hydrodynamic pressure parameter as a novel underwater motion analysis parameters estimating its coefficient of variation (CV). The CV was based on the phase average of multiple gaits following Winter et al. [27], and quantifies the variability of a parameter considering multiple subjects conducting the same physical activity. To compare the CVs of the knee angle and the hydrodynamic pressure, the *z-scored Coefficient of Variation* (CV_z) was calculated. This was done for each time-stamp over a gait cycle, where the z-scored values were obtained by subtracting the time stamp mean and dividing by the time stamp standard deviation. The equations and descriptions of statistical methods applied for the validation of the devices and the cross-comparison of land and water gait parameters are provided in the supporting information, S2 Appendix.

Results

The temporal gait parameters, knee angle and lateral hydrodynamic pressure were calculated on a total of 159 samples, as one subject had only 9 acceptable trials. Data were tested for

Table 2. Temporal gait and knee joint parameters estimated from the optoelectronic land trials and PIMU system for land and water trials. The summary statistics for comparison include the median, first (Q1), third (Q3) quartiles and interquartile ranges (IQR) of the distributions, as well as the knee joint coefficients of variation (CV and CV_z).

		Optoelectronic		PIMU Land		PIMU Water	
		Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
Temporal gait parameters	Stride time [s]	1.12 (1.04, 1.21)	0.17	1.11 (1.04, 1.21)	0.17	3.02 (2.61, 3.33)	0.72
	Stance time [s]	0.70 (0.64, 0.77)	0.13	0.66 (0.62, 0.71)	0.09	1.73 (1.54, 2.04)	0.50
	Swing time [s]	0.41 (0.40, 0.45)	0.05	0.46 (0.41, 0.51)	0.10	1.23 (1.05, 1.43)	0.38
	Stance phase [%]	62.50 (61.57, 63.62)	2.05	58.59 (56.59, 60.72)	4.13	58.18 (56.08, 61.30)	5.22
	Swing phase [%]	37.50 (36.38, 38.43)	2.05	41.41 (39.28, 43.41)	4.13	41.82 (38.70, 43.92)	5.22
Knee joint parameters	ROM [˚]	62.70 (58.53, 67.33)	8.80	60.79 (57.41, 65.56)	8.15	60.19 (50.00, 72.01)	22.01
	Max flexion [˚]	66.44 (61.32, 69.01)	7.69	63.93 (59.46, 69.39)	9.93	65.71 (54.97, 78.02)	23.05
	Max extension [˚]	1.76 (-2.16, 5.40)	7.56	2.34 (0.45, 5.22)	4.77	6.37 (0.99, 11.85)	10.86
	CV [%]	27.84		31.02		60.57	
	CV_z [%]	20.97		31.20		67.69	

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normality using a Kolmogorov-Smirnov test, and were found to be non-normally distributed for the majority of trials. Accordingly, median and interquartile ranges (IQR) were used as summary statistics for further comparison. Table 2 summarizes for the optoelectronic system (land only) and for the PIMU land and water trials the results for the temporal and knee angle parameters, as well as the CV and CV_z of the knee angle.

Validation of the technology

The proposed PIMU technology was confronted against the optoelectronic system during the land trial to assess its reliability. It was found that the median and IQR of stride time estimations were consistent between optoelectronic and PIMU measurements (Table 2). Differently, the PIMU underestimated the stance time when compared to the optoelectronic system (median difference of 4%), and therefore overestimated the swing time by the same percentage. The validation parameters used to compare the optoelectronic and PIMU data for land-based trials are reported in Table 3. Considering temporal gait parameters, the results show a modest RMSE difference ranging from 0.03 to 0.06s, and acceptable values of the Spearman correlation coefficient with the lowest value of 0.80 for the swing time, 0.84 for the stance time and a maximum of 0.95 for the stride time. The Bland-Altman measurement biases (averages of the differences) for stride and stance times are minimal, suggesting a slight underestimation of the parameter by the IMU method. In the supporting information S1 Fig. are provided additional Bland-Altman plots of the gait temporal parameters. The Brunner-Munzel test was applied to evaluate differences between the temporal gait parameters obtained from the

Table 3. Validation parameters used to compare the optoelectronic and the PIMU system for land-based trials. Root Mean Squared Error (RMSE), Spearman correlation coefficient (ρ), Bland-Altman plot coefficients: mean of the differences (bias), the standard deviation of the differences (σ), lower and upper boundaries of the confidence interval (CI = bias ± 1.96σ).

	RMSE	ρ	Bland-Altman plot coefficients			
			bias	σ	CI low	CI up
Stride time [s]	0.03	0.95	0.01	0.03	-0.06	0.07
Stance time [s]	0.06	0.84	0.05	0.04	-0.03	0.12
Swing time [s]	0.05	0.80	-0.04	0.04	-0.11	0.03
Knee angle [˚]	10.96	0.74	-2.94	10.56	-23.64	17.76
Knee ROM [˚]	3.81	0.81	1.40	3.55	-5.56	8.36

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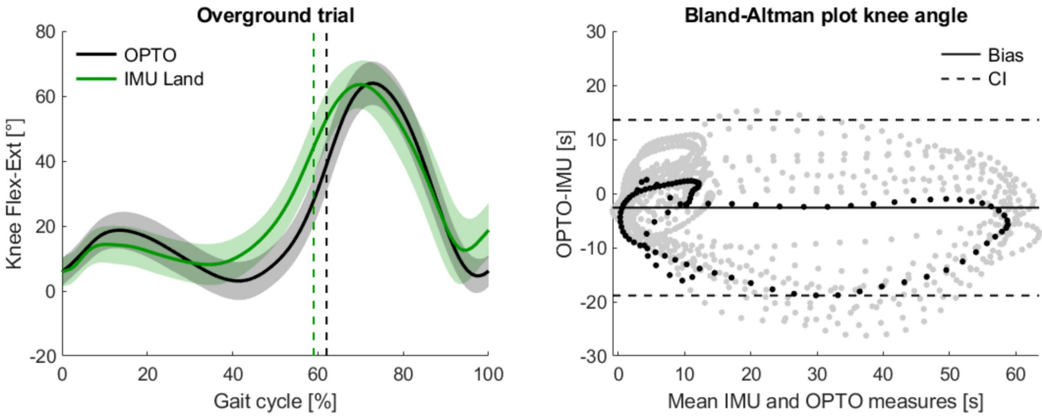

Fig 2. Comparison of optoelectronic and PIMU systems estimation of the knee angle for land-based trials. (Left) Mean and standard deviation of the knee joint flexion-extension angle, normalized over the gait cycle. Dashed vertical lines identify the toe-off. (Right) Bland-Altman plot of a single test subject with 10 repetitions (gray dots). A single gait cycle is highlighted (black points), and the bias (solid black line) and upper and lower 95% confidence interval boundaries (dashed gray lines) indicate that there were few substantial deviations between optoelectronic and PIMU knee angle estimates.

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optoelectronic and the PIMU methods. Stride times did not differ significantly between methods ($p = 0.60$) whereas both the stance and swing times were found to be significantly different ($p<0.001$).

Regarding the knee joint parameters (Table 2) it was observed that the PIMU underestimated the ROM by 1.91˚ and the maximal flexion by 2.51˚, expressed as the differences between medians. The CV comparison also revealed that PIMU knee joint variability on land was slightly higher, at 31.02%, compared to the 27.84% of the optoelectronic system. The CV values for both systems on land are in good agreement with the reference inter-subject CV for slow cadence of 26%, as defined by Winter and colleagues [35]. The knee joint validation parameters in Table 3 report a RMSE of 10.96˚ when comparing PIMU and optoelectronic measurements over the normalized gait. The Bland-Altman bias of less than 3˚ and a RMSE of the ROM of 3.81˚ indicate a small measurement bias of the PIMU and confirm the overall reliability of the proposed PIMU system to assess knee joint parameters during a walking gait. The knee flexion-extension angle results for the all land-based trials comparing the optoelectronic and PIMU systems are provided in the left panel of Fig 2. A Bland-Altman plot for the knee angle estimation of a single test subject is shown in the right panel of Fig 2. In general, the ROM estimated by the IMU sensors was found to be marginally lower (1.40˚) when compared to the optoelectronic system on land. The PIMU knee flexion angle also exhibited a reduced peak value during the stance phase (0 to 20% of the stride) and was found to have a higher residual flexion angle at the termination of the gait cycle being around 18˚, while about 6˚ for the optolectronic system. Statistical differences between optoelectronic and PIMU observations were evaluated using the Brunner-Munzel test, where it was found that knee ROM ($p = 0.02$) and maximal extension ($p = 0.02$) were significantly different and the maximal flexion was not ($p = 0.67$).

Gait differences on land and underwater

The kinematic differences between the walking gait on land and in water from healthy test subjects were investigated comparing temporal and knee joint estimations of the two trials

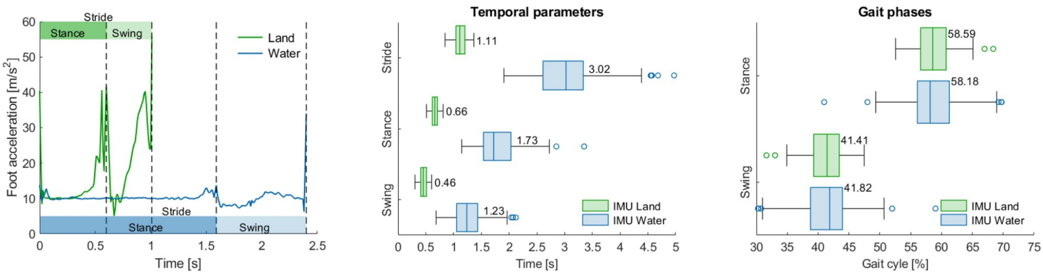

Fig 3. Comparison of the temporal gait parameters between land and underwater trials. (Left) Foot-mounted accelerometer magnitude time series during a single gait cycle on land and in water. The stride time of the underwater gait is nearly 2.5x longer in duration than that of the stride time on land. (Center) Boxplots of the temporal gait parameters. (Right) Boxplots of the gait phases. Boxes represent the interquartile range (IQR) over the 25th to 75th percentiles, the centerline corresponds to the median value of the distribution, error bars extend by a factor of 1.5 from the IQR and outliers are marked as circles.

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estimated with the PIMUs. Temporal gait events (heel strike and toe-off) were identified using peaks in the acceleration magnitude obtained from the foot-mounted PIMU for all trials, an example is shown in the leftmost panel of Fig 3. Boxplots of the estimated temporal gait parameters and gait phases are provided in the center and right panels of Fig 3, respectively. All the parameters reported increased variability during the water trial (Table 2). Compared to the parameters of the land-based trials, the underwater stride duration increased by a factor of 172%, while it was observed that the stance time increased by 162% and the swing phase by 167%. Despite the substantial increase in the temporal gait parameters observed in water, the subdivision into stance and swing phases remained similar to the overground assessments, respectively about 58% and 42% of the gait cycle (rightmost panel of Fig 3).

The differences between land and underwater knee flexion-extension angles were modest, as shown in the left panel of Fig 4. Overall, the underwater gait reported increased variability, as indicated by the IQR of the knee angle parameters and a near doubling of the CV values when compared with land-based trials (Table 2). Interestingly, the knee angle in water did not exhibit an initial peak during the stance phase, where subjects showed an average 18° knee angle at 0% of the gait cycle. In addition, while it was found that the median values of maximal flexion and extension were higher in water of respectively 1.78° and 4.03°, a similar ROM was observed between the two environments. The underwater and overground gait and joint parameters were found to have significant differences ($p<0.001$) based on the Brunner-Munzel test, with the exception of the knee range of motion ($p = 0.46$) and knee maximal flexion ($p = 0.47$).

Lateral hydrodynamic pressure

During the underwater trial, the hydrodynamic pressure was recorded and normalized over the gait cycle. The mean pressure over the gait and standard deviation envelopes are shown in the right panel of Fig 4 for the thigh, shank and foot PIMU locations. Characteristic behaviours can be observed for each of the three sensor mounting locations. During the majority of the stance phase, up to about 40% of the gait cycle, the three signals remained close to their initial pressure values. The pressure on the shank begins to decrease at 40% of the gait cycle, indicating that the leg is lifting towards the water surface, whereas the thigh and foot pressures remained nearly stationary until 50% of the gait. This portion of the gait cycle corresponds to

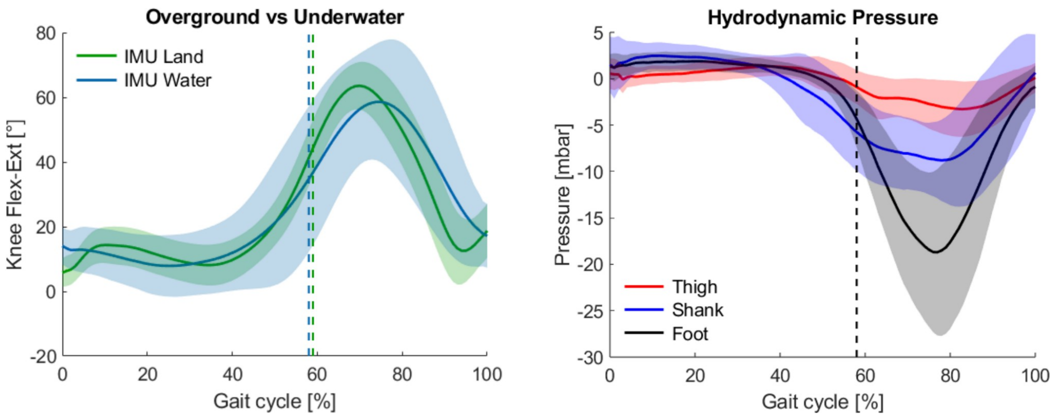

Fig 4. Normalized knee flexion-extension angles and hydrodynamic pressure over the gait cycle. (Left) Mean and standard deviation envelope (shaded regions) of the knee joint angle calculated from land (green) and water (blue) trials with PIMUs. (Right) Hydrodynamic pressure envelopes (shaded regions) obtained from the underwater trials from the PIMU mounted on the thigh (red), shank (blue) and foot (black). Dashed vertical lines in both panels indicate the toe-off.

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the heel-off, where the foot begins to leave the ground and prepare for the swing phase. After the 50% of the gait, the thigh and foot pressure were observed to decrease, across the pre-swing and initial swing phases (50 to 80% of the gait). Finally, for the last portion of the gait cycle (80% to 100%), during the mid and terminal swing phases, the leg prepares for the following heel contact and the hydrodynamic pressure continues to increase and until it reaches its initial value as the leg returns back to the floor. The hydrodynamic pressure fluctuation amplitude was observed to be proportional to the amount of movement: smaller for the thigh, intermediate for the shank and larger for the foot. Moreover, the thigh and shank average pressure showed two distinct curves at about the 60% and 80% of the gait, corresponding to the initial swing and mid-swing phases.

To quantify the behaviour of the hydrodynamic pressure during underwater gait, parameters analogous to the ones estimated for the knee angle have been approximated and are reported in Table 4. Among the three locations, the pressure measured on the thigh showed the smallest ROP both in terms of median (7.68mbar) and IQR (5.60mbar), as well as the biggest CV (138.35%). Conversely, the foot location reported the biggest ROP (19.97mbar with an IQR of 11.78mbar) and the smallest CV (80.06%). Finally, the shank location displayed

Table 4. Hydrodynamic pressure statistics of underwater gaits. Sensors were placed on the thigh, shank and foot and observations were summarized as the median, first (Q1), third (Q3) quartiles and interquartile ranges (IQR) of the Range of Pressure (ROP), maximal and minimal pressure, as well as the coefficient of variation (CV and CV_z).

	Thigh		Shank		Foot	
	Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR	Median (Q1, Q3)	IQR
ROP [mbar]	7.68 (4.20, 9.84)	5.64	13.98 (11.04, 19.52)	8.48	19.97 (16.69, 28.69)	12.00
Max pressure [mbar]	2.50 (1.66, 3.30)	1.64	3.13 (2.31, 4.10)	1.79	2.43 (1.79, 3.27)	1.48
Min pressure [mbar]	-4.54 (-7.07, -2.51)	4.56	-11.35 (-15.79, -7.80)	7.99	-17.64 (-26.79, -14.12)	12.67
CV [%]	138.34		98.99		80.06	
CV_z [%]	126.88		70.15		39.65	

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intermediate values for both ROP (13.98 with an IQR of 8.34) and CV (98.99%). The normalization of the CV (CV_z in Table 4) confirms that the hydrodynamic pressure on the foot (CV_z = 39.65%) is more reproducible between subjects and repetitions.

Discussion

Previous studies [13, 16] have demonstrated the potential of IMU-based systems for underwater quantitative motion analysis. However, a recent systematic review by the authors [5] revealed a lack of suitable wearable IMU-based technologies and parameters for monitoring physical activity in water. To address these gaps, this work developed novel wearable devices that combine IMU and pressure sensors suitable for both overground and underwater gait analysis. Hydrodynamic pressure was proposed as a unique parameter that reflects the interaction between the body and the fluid during motion. The devices were tested on 16 healthy adults who performed gait analysis in both overground and underwater conditions. A total of 159 trials were collected and analyzed per condition for temporal and joint gait parameters.

Validation of the technology

The proposed PIMU sensors were validated by comparing their performance with an optoelectronic system in a motion analysis laboratory. The temporal gait parameters measured by the PIMU sensors had a low RMSE (up to 5% of the gait cycle for stance time) and a high Spearman coefficient (above 0.8), which are consistent with similar studies [36]. The Bland-Altman bias was also small, especially for stride time [37]. The knee joint estimation by the PIMU sensors reported had a relatively high RMSE with respect to the optoelectronic assessments for both the whole curves and ROM, but a low Bland Altman bias (around -3˚), which is aligned with [38]. The Brunner-Munzel test reported statistically significant differences between optoelectronic and PIMU gait parameters, with the exception of the stride time and maximal flexion angles, which were found to be highly comparable. Moreover, the algorithm used in this study to estimate the knee flexion-extension [31] improved the RMSE and CV of the knee joint estimation compared to the previous algorithm used by the authors in a similar investigation [18], and achieved a similar CV as the optoelectronic system (31.02% vs 27.84%), as shown in Table 2.

These results indicate that the PIMU sensors have good accuracy and reliability for motion analysis in water, and can measure both temporal and joint parameters with a reasonable trade-off between precision and ease of application.

Differences between the two environments

When applied to the water environment, PIMUs registered temporal and kinematic parameters in good agreement with previous IMU-based investigations [15–17]. The results of this study indicate the gait cycle duration more than doubled in water, while the proportion of stance and swing phases was constant in the two environments, comparably to previous researches [39]. However, a larger variability, indicated by the interquartile range, has been observed in the temporal parameters (Table 2). A similar trend was found for the knee joint angle assessment, where values of ROM were comparable to previous studies with IQR doubled in water for all the joint parameters [40]. Additionally, the CV of the knee joint in water more than doubled when compared to the land-based trials. Therefore, we conclude that underwater gait kinematics are likely to be inherently less repeatable than those on land. Potentially caused by the kinematic differences observed between underwater and overground kinematics (Fig 3), was further confirmed by the Brunner-Munzel test results of the gait parameters, which indicated statistically significant differences between walking gaits on land

and underwater. For example, the knee flexion curve at heel strike and during the load acceptance phase was absent in water [39]. This could be related to the slower walking speed in water, which has been shown to reduce the flexion angle during initial stance [10]. Moreover, the maximal flexion angle during the swing phase in water was smaller than on land. This finding is consistent with some studies [10, 15], but not with others [39]. Previous works have pointed out that such discrepancies may be partially explained by different experimental conditions, such as water depth and participants' age [15]. To account for the effect of participants' height on the indexes estimated, we also calculated the CV for the knee angle after z-score normalization and found that this also is more than doubled in water.

These kinematic differences reflect the properties and resistance of the fluid medium. Water density imposes higher resistance to movement, which can lead to slower, less controlled and less repeatable motions and different motor strategies [15]. These factors limit the cross-comparison of results between subjects and studies on land and underwater.

Lateral hydrodynamic pressure

The higher density of water provides substantially more resistance to the movement than air resulting in various advantages in terms of rehabilitation and wellness. In this study, a characterization of the hydrodynamic pressure occurring on the lower limb during gait in water was performed. It is the first investigation attempting to describe the interaction between water and the body in motion exploiting the unique characteristics of water rather on relying only on inertial measurements. Three PIMU sensors were attached laterally on the thigh, shank and foot. The pressure data were processed as the knee angle data: data have been z-scored normalized to account for different heights and the ROP, as well as other parameters have been estimated (Table 4). It was found that the pressure on the thigh and shank was smaller, whereas the pressure on the foot was higher and more consistent, reporting a CV_z of 39.65%. Since the hydrodynamic pressure depends on the depth and to allow for a comparison with the knee angle variability, the coefficient of variation of both pressure and joint angle was estimated on z-scored data. The CV_z of the foot pressure was therefore compared with the CV_z of the knee angle on land (31.20%) and in water (67.69%). These results suggest that the foot hydrodynamic pressure may provide a less variable parameter to evaluate the walking gait underwater than the knee angle.

Limitations of the study

The hydrodynamic pressure on the lower limbs has been proposed as a novel parameter for underwater gait analysis allowing a reasonable reconstruction of the gait phases. Nevertheless, the conducted study has severe limitations in the subjects and protocol considered.

Despite gathering reference data on a segment of the population, valuable for future investigations, this research involved only healthy adults. This does not allow for a comprehensive understanding of the importance of aquatic physical therapy and of the overall effects of the water on the body systems. The protocol also involved as physical activity of interest simple locomotion because of its relevance [6] and its well-known characteristics and established parameters [24]. However, other exercises commonly used in aquatic physical therapy [5] might help characterizing better the fluid-body interaction through the assessment of hydrodynamic pressure. Furthermore, this investigation exploited three pressure and inertial sensors positioned laterally to the leg, but it remains to be established if there are more suitable locations for the assessment of the hydrodynamic pressure. Future studies should therefore investigate different sensor positions and alternative tasks, as well as consider different populations, to improve our fundamental knowledge of water's effects on lower limb kinematics. The use of

IMUs resulted in the investigation of solely the flexion-extension angle limiting the analysis of the knee joint kinematics to the sagittal plane and to its superficial angle. This, limited the study of underwater locomotion and might be especially restricting when considering pathological subjects, for which the analysis of all the anatomical planes is fundamental [41]. The interpretation of the results is somewhat dependent on the particular choice of statistical method used to test for significant differences between the sample populations. While being robust and effective, the Brunner-Munzel test as applied in this work cannot account for inter-group repeated measures. Accordingly, the authors cannot evaluate the differences between individuals using the same method and in the same environment. This assumption was tested in a previous work and determined to be acceptable when relying on ensemble statistics for activity recognition [42].

Additionally, IMUs which include magnetometers and rate gyroscopes are susceptible to ferromagnetic disturbances and gyroscopic drift that limited the synchronization ability of the three PIMUs, resulting in time-consuming data post-processing which affected the final estimation of kinematics parameters. Future improvements in the application of more advanced calibration algorithms [43, 44] and through the combination of IMU-based and computer vision assessments [18] are recommended to improve the efficiency and quality of PIMU-based gait analyses.

Conclusions

This work investigated how wearable devices outfitted with IMU and pressure sensors can be used to improve the investigation of underwater motion analysis. In contrast to previous studies that relied on methods and parameters designed for land-based assessments [5], this work proposes a parameter tailored to the underwater environment. The devices have been initially validated through a performance comparison against the gold standard optoelectronic system focusing on temporal and knee joint parameters during gait. The results indicate acceptable accuracy and reliability. By applying the sensors to the aquatic environment, kinematic differences between overground and underwater gait and knee joint parameters have been observed pointing out that underwater locomotion is subjected to higher variability and uncertainty. For example, the stride time on land reported an IQR of 0.17s, while underwater of 0.72s, being respectively about 15% and 24% of the gait cycle. Similar conclusion can be reached considering the knee angle coefficient of variation that, after normalization (CV_z), was 67.69% in water, a result far from the standard CV defined by Winter [35] of 26%. The variability of standard gait parameters in water lead us to the consideration of a new and alternative parameter: the hydrodynamic pressure exerted on the lower limbs during the gait cycle. The hydrodyanamic pressure was investigated for three lower limb locations, namely thigh, shank and foot, and was compared to the more commonly used knee flexion-extension angle. The normalized coefficient of variation on the foot was the lowest, 39.65%, suggesting that hydrodynamic pressure can provide a new parameter to complement traditional gait analysis. We propose the pressure as a measure of the interaction between the body in motion and the underwater environment to promote a comprehensive understanding of how the presence of the water changes the way we move in it.

Supporting information

S1 Appendix. Computation of temporal gait parameters.
(TEX)

S2 Appendix. Statistical indexes estimated throughout the investigation.
(TEX)

S1 Fig. Bland-Altman plots of the temporal parameters for the IMU validation.
(ZIP)

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Author Contributions

Conceptualization: Cecilia Monoli, Manuela Galli, Jeffrey A. Tuhtan.

Data curation: Cecilia Monoli.

Formal analysis: Cecilia Monoli, Jeffrey A. Tuhtan.

Funding acquisition: Manuela Galli, Jeffrey A. Tuhtan.

Investigation: Cecilia Monoli.

Methodology: Cecilia Monoli, Jeffrey A. Tuhtan.

Resources: Manuela Galli, Jeffrey A. Tuhtan.

Supervision: Manuela Galli, Jeffrey A. Tuhtan.

Validation: Cecilia Monoli.

Visualization: Cecilia Monoli.

Writing – original draft: Cecilia Monoli, Jeffrey A. Tuhtan.

Writing – review & editing: Cecilia Monoli, Manuela Galli, Jeffrey A. Tuhtan.

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Curriculum Vitae

Name	**Cecilia Monoli**
Date and place of birth	20 December 1993, Busto Arsizio, Italy
Nationality	Italian
E-mail	cecilia.monoli@taltech.ee
ORCID	0000-0002-2033-0619
LinkedIn	ceciliamonoli20
ETIS	https://www.etis.ee/CV/Cecilia_Monoli/eng

Education

2019–...	Tallinn University of Technology, School of Information Technologies PhD, Computer and Systems Engineering
2019–...	Politecnico di Milano, Department of Electronic, Information and Bioengineering PhD, Biomedical Engineering
2017– 2018	*Erasmus+* at Tallinn University of Technology
2016–2019	Politecnico di Milano, Department of Electronic, Information and Bioengineering MSc, Biomedical Engineering

Thesis: Validation of underwater IMU sensors for rehabilitation in pool environment: investigation of the knee kinematics through gait analysis.

2012–2016	Politecnico di Milano, Department of Electronic, Information and Bioengineering BSc, Biomedical Engineering

Thesis: Amyotrophic Lateral Sclerosis: analysis of the respiratory kinematic via optoelectronic plethysmography.

Language competence

Italian	Native
English	Fluent
Spanish	Basic

Elulookirjeldus

Nimi	**Cecilia Monoli**
Sünniaeg ja -koht	20 Detsember 1993, Busto Arsizio, Itaalia
Kodakondsus	Itaalia
E-post	cecilia.monoli@taltech.ee
ORCID	0000-0002-2033-0619
LinkedIn	ceciliamonoli20
ETIS	https://www.etis.ee/CV/Cecilia_Monoli/est

Haridus

2019–. . . Tallinna Tehnikaülikool, Infotehnoloogia Teaduskond
PhD, Arvuti- ja süsteemitehnika
2019–. . . Politecnico di Milano, Elektroonika-, Info- ja Biotehnika Osakond
PhD, Biomeditsiinitehnika
2017– 2018 *Erasmus+* Tallinna Tehnikaülikoolis
2016–2019 Politecnico di Milano, Elektroonika-, Info- ja Biotehnika Osakond
MSc, Biomeditsiinitehnika
Magistritöö: Veealuste IMU andurite valideerimine taastusravil veekeskkonnas: põlveliigese kinemaatika kõnnianalüüsi abil.
2012–2016 Politecnico di Milano, Elektroonika-, Info- ja Biotehnika Osakond
BSc, Biomeditsiinitehnika
Bakalaureusetöö: Lateralne amüotroofiline skleroos: hingamiskineemaatika analüüs optoelektroonilise pletüsmograafia abil.

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