Land and Underwater Gait Analysis Using Wearable IMU

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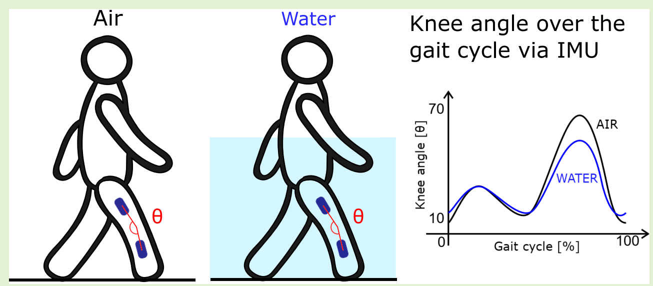
***Abstract*—Walking underwater reduces joint impacts, enhances stability and lowers the net body weight of the patient during rehabilitation. It is a recent rehabilitation method and few suitable methods exist to study underwater gait kinematics. We propose an underwater inertial measurement (IMU) system 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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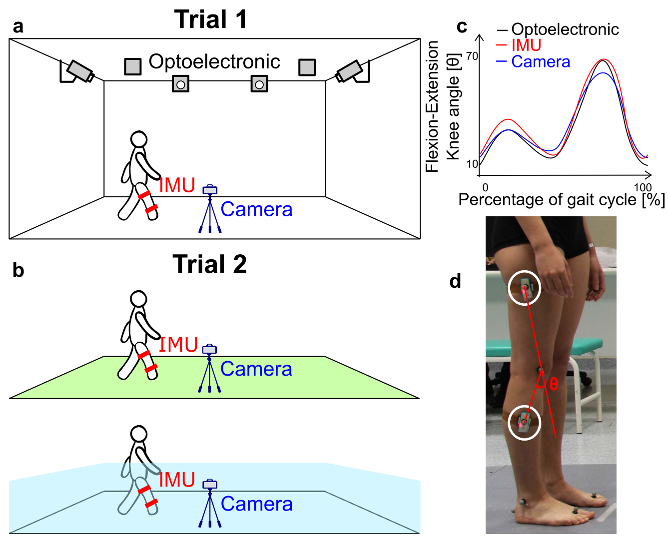

Fig. 1. a) Trial 1, comparison of the optoelectronic, motion-tracking and IMU systems. b) Trial 2, where the IMU and camera-based systems are employed on land and underwater. c) The knee angle over the gait for each of the three systems evaluated (IMU system in red, optoelectronic system in black and 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

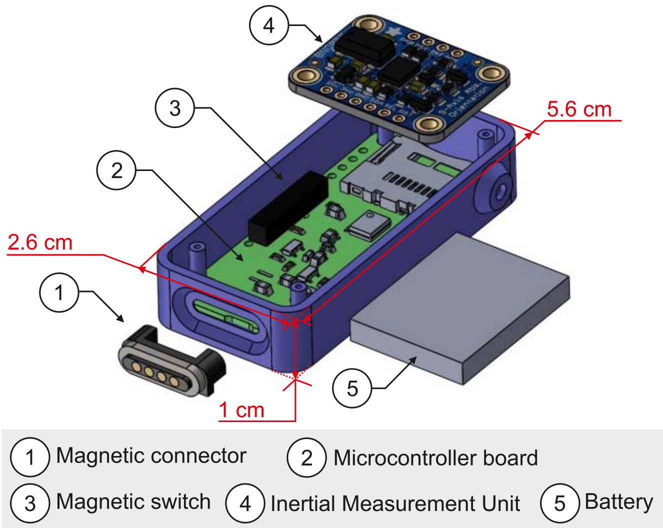

Fig. 2. Breakdown of the wearable IMU logger applied in this work to estimate the knee angle during the walking gait on land and underwater.

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 $63 \pm 5 \mu$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:

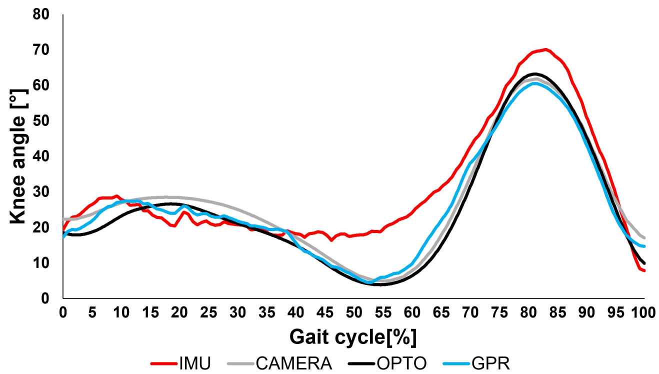

Fig. 3. Example of the knee angle during the gait as estimated by the IMU (red line) and compared with two gold standard references: motion-tracking (CAMERA, gray line) and optoelectronic (OPTO, black line). A Gaussian Process Regression (blue line) model was fitted based on the IMU knee angle as the 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

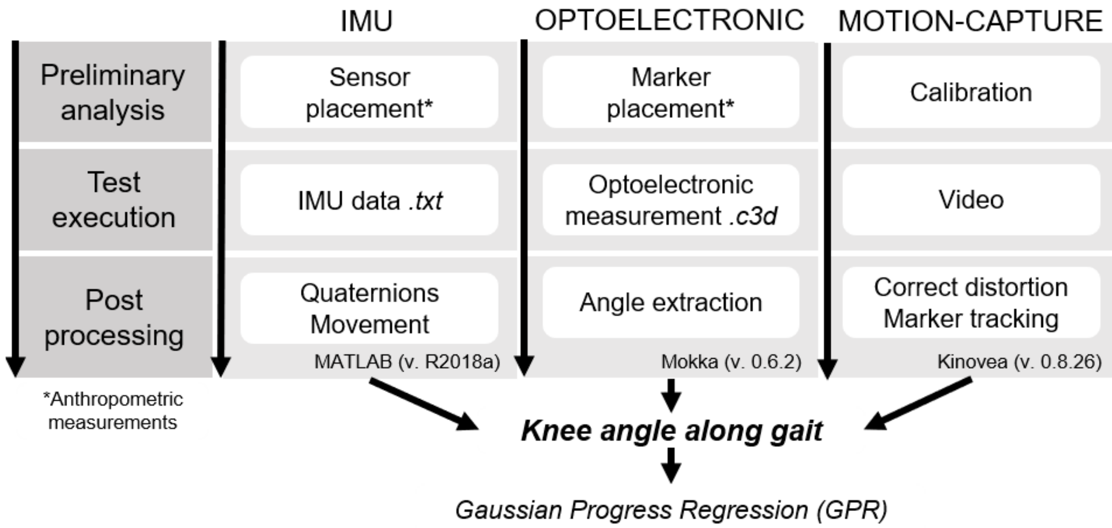

Fig. 4. Workflow of the methods used to evaluate the knee angle along a walking gait on land and underwater. The three main steps for all three sensor systems are preliminary analysis, test execution and post-processing. The IMU-based estimate of the knee angle was trained on optoelectronic and motion-capture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

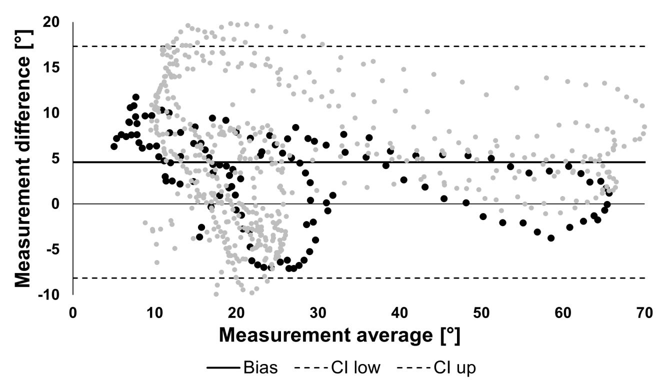

Fig. 5. Example of a Bland Altman plot exhibiting all 6 repetitions from Subject 1 (gray points). A single gait cycle is selected for emphasis (black points). For each time step i, the mean of the measurements (IMUi+OPTOi)/2 is shown on the horizontal axis, and the difference between measurements (IMUi-OPTOi)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

$(x_{1i} - x_{2i})$. 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.

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:

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

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.

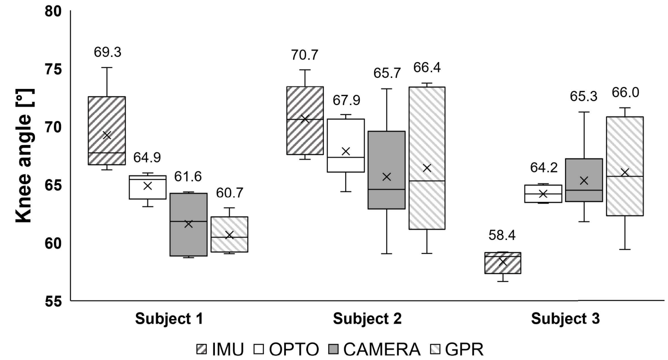

Fig. 6. Results of the knee maximum flexion angle for Trial 1, represented as box and whisker plots. The boxes represent the interquartile range (IQR) over the 25th to 75th percentiles, the centre line corresponds to the median, error bars extend from the IQR up to a factor of 1.5 from the IQR and the 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

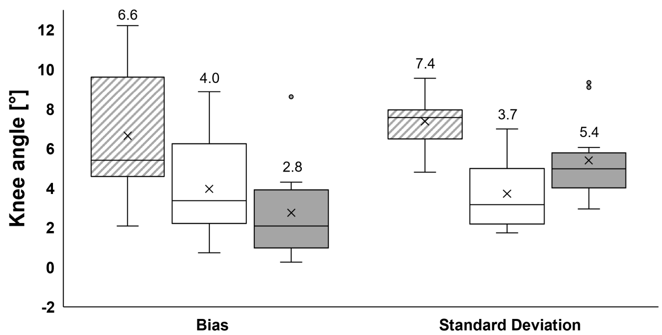

Fig. 7. Pairwise comparison of the Bland Altman coefficients for Trial 1. The optoelectronic system compared with the inertial system (IMU-OPTO), motion-capture vs. optoelectronic (CAMERA-OPTO) and GPR vs. optoelectronic (GPR-OPTO). The bias and standard deviation are represented as box and whisker plots. 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

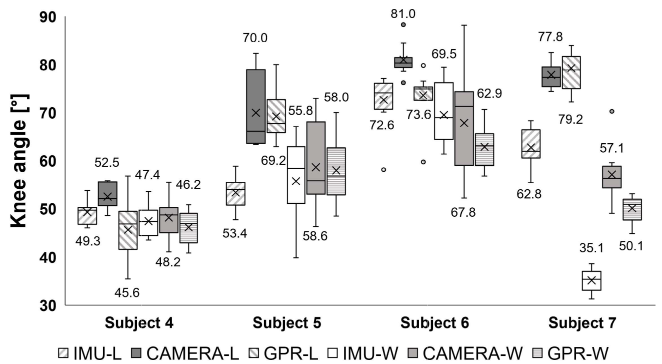

Fig. 8. Results of the knee maximum flexion angle for Trial 2, represented as box and whisker plots. The boxes represent the interquartile range (IQR) over the 25th to 75th percentiles, the centre line corresponds to the median, error bars extend from the IQR up to a factor of 1.5 from the IQR and the 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).

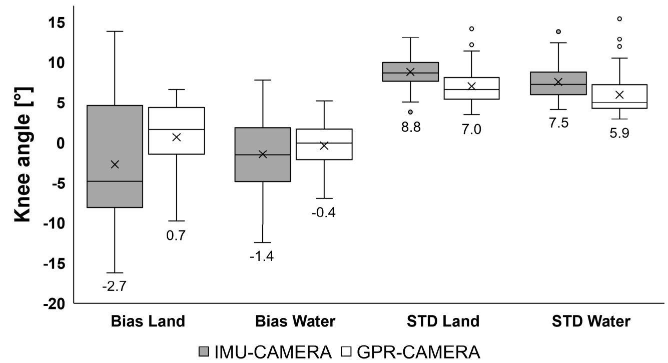

Fig. 9. Pairwise comparison of Bland Altman coefficients for Trial 2 as box and whisker plots. The difference between the inertial vs. motion-tracking (IMU-CAMERA) and between Gaussian Process Regression and motion-tracking (GPR-CAMERA) systems. The boxes of the bias and standard deviation (STD) represent 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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