An Accurate Wearable Foot Clearance Estimation System: towards a real time measurement system

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***Abstract*— This work presents an accurate, robust, wearable measurement system for foot clearance estimation along with algorithms to provide a real-time estimate of foot height and orientation. Different configurations of infrared distance meter sensors were used, both alone and in combination with an inertial measurement unit. In order to accurately estimate the foot clearance when in presence of daylight and when the foot orientation changes dynamically during walking, several algorithms were designed based on physics of sensors and tuned using the acquired data against a reference system. These algorithms, specific to the number of sensors, include the estimators of the foot orientation and estimators of the foot clearance. These estimators are tested on normal walking (RMS error ≤ 8.4mm) and walking with exaggerated step heights and inversion-eversion rotations. A Bayesian fusion of estimators was also implemented to better cope with the extreme and abnormal walking kinematics while maintaining a high performance for normal walking. All estimators were trained on uniformly distributed bootstrapped sub-samples of data and tested on several normal and abnormal walking data. The results proved the robustness of the proposed system against variations in the gait kinematics (|mean| ± standard deviation of error for heel and toe clearance was equal to or smaller than 3.1±9.3 mm when using a Bayesian fusion of three different estimators) and environment lighting (with an introduced error of 1 to 4% of actual distance).**

***Index Terms*—Foot clearance, infrared range meter, inertial measurement unit, Bayesian fusion.**

I. Introduction

GAIT analysis has been attracting more attention in the clinical domain as it reveals reliable information about the evolution of different diseases and neurological conditions affecting the sensorimotor function. For instance, gait analysis has been used to assess musculoskeletal complications, disease due to aging, cardiopathies, and neurological conditions such as stroke, Parkinson's disease, and multiple sclerosis [1]–[7]. Gait analysis can reflect the quality of life of patients and the effect of treatment and rehabilitation programs [5], [7]–[10].

Recent advances in wearable technologies have enabled field gait analysis, outside of laboratory measurement, to evaluate the subject's function at the workplace, and during activities of daily life [9]. This can better represent the sensorimotor function of individuals, provide a more comprehensive assessment of treatment or rehabilitation programs in place, and could provide predictors of risk factors such as the risk of fall in elder adults [11].

Among individuals above 65 year-old, one out of three falls each year. Falls are the leading cause of fatal and nonfatal injuries [12]. The secondary fear of falling and the self-imposed restrictions of a person in mobility and function can lead to loss of personal autonomy and adversely affect the quality of life of subjects [13]. Falls are costly for the health care system, with the medical costs of falls in the US approximating $34 billion in 2013 [12].

Although several gait descriptors, e.g. stride length and velocities and temporal parameters, were used to identify the fall-related factors, the swing phase parameters were less investigated. For instance, tripping, caused by insufficiency of or fluctuations in foot clearance, i.e. the height of foot/shoe sole above the ground during the swing phase, accounts for about the 50% of falls in the older population [14], [15]. The pattern of foot clearance and/or some extracted features such as the minimum toe clearance have been considered recently as important factors related to the risk of fall [16], [17].

Wearable sensors were used to measure the foot clearance parameters [18], [19]. Different estimation techniques were implemented to obtain foot clearance [18] where the best-chosen algorithms resulted in the relative error of 40.6±22.5mm (15.1±8.4% of the actual value) for the maximum heel clearance. The obtained results were better for minimum toe clearance and the maximum toe clearance at the terminal swing with relative errors smaller than 7±10%. While much worse results were obtained for the estimation of the maximum toe clearance just after toe-off with a relative error of 54.5±38.6%. In [19] regression models were built on the post-processed parameters obtained from the measurement of foot-worn inertial measurement sensor to estimate the minimum ground clearance (minimum foot height). They reported a mean error of 17.77mm and R^2 of 0.83.

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However, accurate foot clearance estimation with wearable sensors such as inertial measurement units remained a challenge. This is due to the limited achievable accuracy of position estimation through the integration of acceleration [18], [19]. Not only the orientation estimation errors undermine any accurate estimate of the vertical acceleration but also the double integration of acceleration noise result in a great drift in position estimate. This latter error can be reduced only after the gait cycle has been completed using the fact that during foot flat the foot height should be zero [18]. Data fusion algorithms were applied also benefiting from magnetic sensors to improve the orientation estimates [20]–[22]; however, due to non-uniform distribution of ferromagnetic materials in modern buildings the magnetic measurement of a sensor attached to the foot is much more prone to the distortions than the sensors on the upper body. The few centimeter errors obtained by IMU-based systems can hardly satisfy the needs of a reliable monitoring system since the foot vertical range of motion is small in healthy subjects, e.g. the expected local maximum toe clearance after the toe off was reported below 8cm and the second maximum toe clearance prior to the heel strike is also less than 15cm [18], and can be much lower in pathologic gaits [22] and in the elderly population, e.g. for adults above 70 y/o the two maximum toe clearances were reported around 6cm and 13cm respectively [23]. These older adults and patients with neurological disorders have a higher risk of fall. Therefore, there is a need for the addition of new sensors capable of providing a much more accurate estimation of foot clearance.

The drift cancellation technique used in [18] also impeded the use of such techniques for accurate estimation of foot height and clearance parameters in real time. Real-time foot clearance estimation can play an important role in the control of neural prostheses [24] and assistive devices to prevent fall in at-risk populations. The lower limb kinematics, in particular, the foot clearance, needs to be measured in order to close the feedback loop of such a control system. The kinematics measurements in [24] were obtained using the stereophotogrammetry motion capture system. However to translate the neural prostheses to the people's daily lives there is a need for an accurate wearable system that can provide robust and real-time estimates of foot clearance.

This study was thus aimed at designing a wearable system along with estimation algorithms for accurate foot clearance estimation. The proposed system can measure the heel and toe clearances more accurately than previously used wearable systems in normal and abnormal walking conditions, while the estimation algorithms exclusively use the instantaneous measurement of sensors in a real time manner.

II. Method and Materials

Different configurations of infrared (IR) distance sensors, GP2YOA41SKOF (SHARP®, Japan), were used to measure foot clearance in the range of 4 to 30 cm. These IR sensors function based on the reception angle of the reflected IR beam to the IR detectors. The further the distance, the smaller the angle will be. When the sensor is parallel to the ground it can measure the sensor height, though when tilted can only provide an estimate of the distance to the ground in the sensor perpendicular plane. This distance estimation must be corrected with an estimation of the sensor orientation using additional IR sensors or an inertial measurement unit (IMU). In total we considered three configurations comprising one to three IR sensors and a configuration of single IR sensor and IMU. Our prototype can be seen in Fig. 1.

A Butterworth low pass filter with 16Hz cutoff frequency was implemented for the IR sensors to minimize the noise effect. A data acquisition system (National Instruments, USA) was used to read the sensor measurements at 1 kHz.

When the IR sensor points towards the ground, the emitter and receiver point towards the ground, an exponential model can be used to translate each IR sensor raw measurement to a distance estimate as follows:

$$\hat{d}_i = a e^{b S_i} + c \tag{1}$$

where S_i and $\hat{d}_i$ are the i[th] sensor raw measurement and estimated distance respectively. a, b, and c are parameters that can be estimated using nonlinear least square. In this work, a robust version of Levenberg-Marquardt Method was used with a Tukey's biweight function [25] to obtain those parameters.

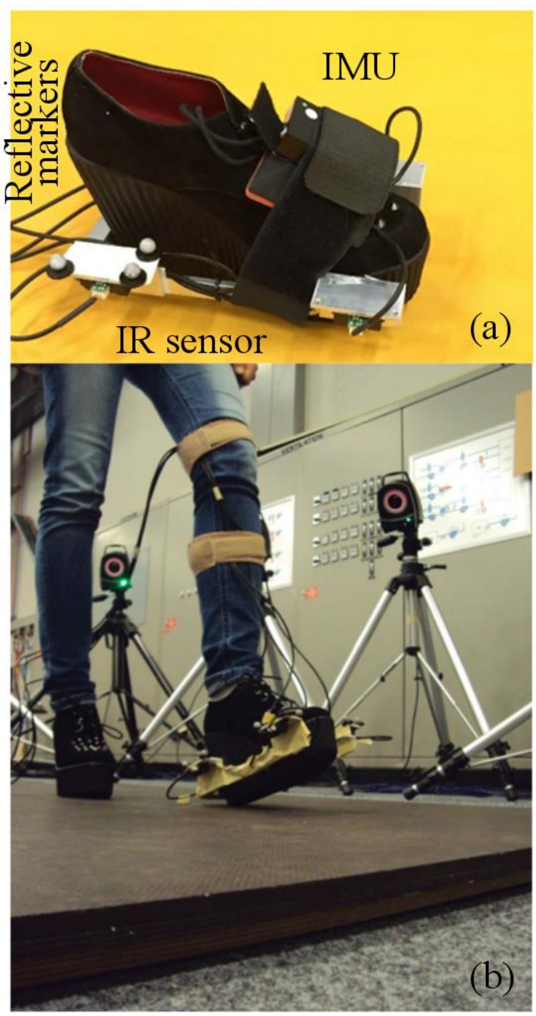

Fig. 1. (a)The shoe prototype composed of IR sensors and IMU attached with a strap. Reflective markers are used with motion capture camera for validation. (b) Motion capture (Vicon UK) during a typical walking trial.

A. Foot orientation estimation

Using each pair of IR sensors fixed on the shoe (Fig. 2), we can compute the corresponding foot angle (sensors' orientation). For instance, the foot angle extracted from Sensor 1 and 2 (Fig. 2) can be computed from their corresponding distances (1) as follows:

$$\beta = \tan^{-1}\frac{d_2 - d_1}{l_{12}} \tag{2}$$

where l_{12} is the distance between Sensor 1 and 2, and d_1 and d_2 are distances to the ground where the Sensor 1 and 2 are pointing respectively.

Among the three ankle rotations, namely inversion-eversion, dorsi- plantar-flexion and pronation-supination, only the first two affect the sensors measurement and their heights. Therefore, estimation of inversion angle (α) and dorsiflexion angle (β) are reformulated as follows:

$$\hat{\alpha} = \tan^{-1}\frac{\hat{d}_1 - \hat{d}_3}{l_{13}} \tag{3}$$

$$\hat{\beta} = \tan^{-1}\frac{\hat{d}_2 - \hat{d}_1}{l_{12}} \tag{4}$$

where Sensor 3 is assumed to be on the same anatomical frontal plane with Sensor 1, and on the opposite side of the foot with l_{13} distance from Sensor 1.

B. Foot clearance estimation

The height of each sensor (h_i) can be calculated using the estimated foot angles, accordingly.

$$\hat{h}_i = \hat{d}_i \times \cos\hat{\alpha}\cos\hat{\beta} \tag{5}$$

As mentioned earlier four different sensor configurations were investigated:

- 1-IR sensor (S1): the angles α and β cannot be estimated, they were thus set at zero for estimation of foot clearance.
- 2-IR sensor (S1-S2): angle α was set at zero while β was estimated using (4).
- 3-IR sensor: (3) and (4) were used to convert the sensors measurements into the estimation of those angles to be used in the estimation of foot clearance.
- IR-IMU: the foot orientation was estimated with IMU (using strapdown integration of angular velocities [26]), and the sensor distance was estimated with one IR sensor. The orientation from IMU was reset when the IR sensor measured zero distance. The height of the sensor was obtained by incorporating both sensors' information.

Using the estimated sensor height, foot orientation and known geometry of the shoe, the heel clearance and toe clearance can be estimated using trigonometric equations as follows:

$$\hat{h}_{heel} = \begin{cases} \hat{h}_i - l_{iheel}\sin\hat{\beta}\,, & \lambda\hat{\alpha} \le 0 \\ \hat{h}_i - l_{iheel}\sin\hat{\beta} - \lambda l_{heel\ width}\sin\hat{\alpha}\,, & \lambda\hat{\alpha} > 0 \end{cases} \tag{6}$$

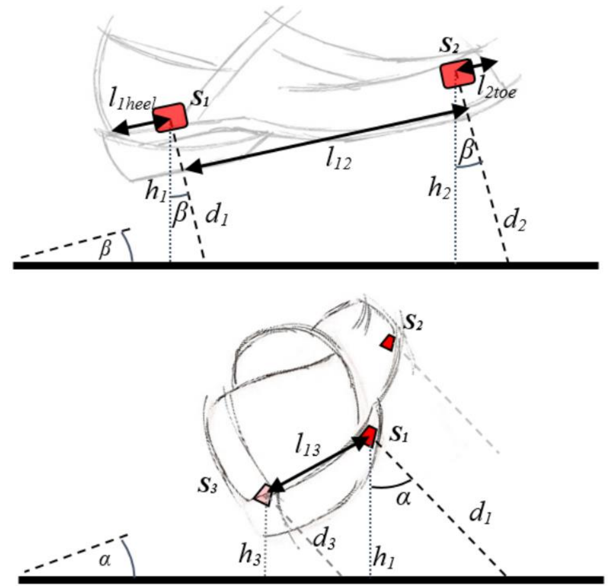

Fig. 2. Sensor configuration, IR sensors (S1, S2 and S3) and IMU. Top: a lateral view; bottom: a posterior view. It also shows how the measurable distance by the IR sensors relates to the actual height and foot orientation.

$$\hat{h}_{toe} = \begin{cases} \hat{h}_i + l_{itoe}\sin\hat{\beta}\,, & \lambda\hat{\alpha} \le 0 \\ \hat{h}_i + l_{itoe}\sin\hat{\beta} - \lambda l_{toe\ width}\sin\hat{\alpha}\,, & \lambda\hat{\alpha} > 0 \end{cases} \tag{7}$$

where $\hat{h}_i$ is the estimated height of i^{th} sensor on the medial side of the shoe, l_{iheel} and l_{itoe} are the distance of the sensor to the same side heel and shoe toe respectively, and $l_{heel\ width}$ and $l_{toe\ width}$ are the widths of shoe heel and shoe toe box. λ is 1 if the sensors are placed on the medial side of the shoe and -1 for the sensors affixed on the lateral side of the shoe.

Two types of data driven models were used in this study for estimating foot clearance. The first was based on the distance estimators solely trained on normal walking which included three different speeds. The second model was based on a Bayesian fusion of three estimators separately trained on normal walking ($\hat{d}^N$) and walking with exaggerated foot inversions ($\hat{d}^{Inv}$) and eversions ($\hat{d}^{Eve}$).

In the second model, a Normal distribution for α angles of normal walking (Φ_N) was first estimated over the training data (μ_N and σ_N were computed). Then, separate distributions were fitted to the extreme α values (Φ_{Eve} and Φ_{Inv}) by temporarily excluding the training samples of exaggerated walking which fell into normal walking α range. On the other hand, the means and standard deviations of Φ_{Eve} and Φ_{Inv} were computed over the samples of these distributions with no intersection with samples of Φ_N.

$$\Phi_j = (\sigma_j\sqrt{2\pi})^{-1} e^{-\frac{(\hat{\alpha}-\mu_j)^2}{2\sigma_j{}^2}} \tag{8}$$

where $j \in \{N, Eve, Inv\}$, μ_j and σ_j are mean value and standard deviation of j^{th} distribution. $\Phi_j(\alpha)$ is the likelihood of the inversion angle given the j^{th} walking class from $\{N, Eve, Inv\}$. The probability of each of the gait classes given this angle, $P(j|\alpha)$, can be obtained using the Bayes rule. By assuming the equal prior probability of normal walking, and exaggerated inversion, and eversion, the conditional probability of each walking class was expressed in (9). $\widetilde{\Phi}_j$s were used as weights for each estimator in the Bayesian fusion as follows:

$$P(j|\hat{\alpha}) = \widetilde{\Phi}_j(\hat{\alpha}) = \frac{\Phi_j(\hat{\alpha})}{\sum_{k\in\{N,Inv,Eve\}}\Phi_k(\hat{\alpha})} \quad (9)$$

$$\hat{d}^{Fusion} = \widetilde{\Phi}_N \times \hat{d}^N + \widetilde{\Phi}_{Inv} \times \hat{d}^{Inv} + \widetilde{\Phi}_{Eve} \times \hat{d}^{Eve} \quad (10)$$

The applied fusion technique works based on the inversion angle estimate ($\hat{\alpha}$), which is only available in the 3-IR and IR-IMU configurations, therefore, the estimator fusion was only implemented for these two sensor configurations.

C. Experiments setup

First, single sensor measurements in different fixed distances from the ground in two different lighting conditions, completely dark (under a box) and normal room lighting with sunlight, were performed.

A stereophotogrammetry motion capture system, including 11 Cameras (7 Mx3+ and 4 T10s, Vicon) and a set of 12 markers, was then used as the reference kinematic system, and the gait episodes were recorded with two video cameras, providing the frontal and lateral views. The measurements of IR sensors, IMU and Vicon cameras were virtually synchronized and used to train the distance estimators (Eq. 1).

The collected data include repeated normal gait, walking with exaggerated step height, and also exaggerated inversions and eversions in three different self-chosen speeds, namely normal, slow and fast. Three trials of several gait cycles were recorded for each type of walking in each speed, result in nine trials for each type of walking. For all the trials the gait cycles were extracted and the rest of data were eliminated.

D. Data analysis and system validation

Three different analyses were performed, namely training and testing on the normal walking, training on normal walking and testing on the exaggerated conditions, and training and testing on normal walking, and the gait with exaggerated inversion and eversion in the case of Bayesian fusion of the estimators. They are detailed as follows:

First, the data for normal walking in different speeds were exclusively considered. A leave-one-out cross-validation was used to evaluate the estimators trained on the normal walking data. Since during each gait cycle the majority of samples belong to the stance phase in which the sensors measure very low distances, the data are biased in favor of lower foot heights. For estimator training, each time over eight out of nine trials, a random subsampling was thus implemented to generate 10 training sets with uniform histogram over the sensor measurements range. Therefore 10 different estimators were trained for each of the trials. Each training set consisted of 16 gait cycles. Every 10 trained estimators were then tested on the left out trial. The expected performance of the system comes from testing performance of the 90 resultant estimators (tuned for each of 10 subsamples of each 8 combinations out of 9 trials), which provides a robust and reliable evaluation of the system. The expected value and standard deviation of the expected error (μ_e), standard deviation of error (SD_e), root mean square error (RMS_e) and coefficient of determination (R^2) were computed for testing the 10 estimators on each testing dataset (at each fold of the cross-validation). Then, the statistical analysis of the nine testing trials in leave-one-out cross validation was performed. Wilcoxon rank sum test was used to explore any significant differences between the coefficients of determination of the estimated heights when using different sensor configurations, namely 1-IR, 2-IR, 3-IR, and IR-IMU.

Second, in order to evaluate the robustness of estimators against possible gait abnormalities, the estimators trained on the normal walking were tested similarly on walking with exaggerated foot height, inversion and eversion each performed in the slow, normal and fast gait.

Furthermore, during the Bayesian fusion of three estimators, each was exclusively trained on one of either the normal, exaggerated-inversion or exaggerated-eversion walking data. Then the resultant fused estimator was tested on each normal and abnormal walking data.

III. Results

A. Foot clearance estimation

Typical height (heel clearance) and angle (foot dorsiflexion angle) estimates during normal walking are shown in Fig. 3.

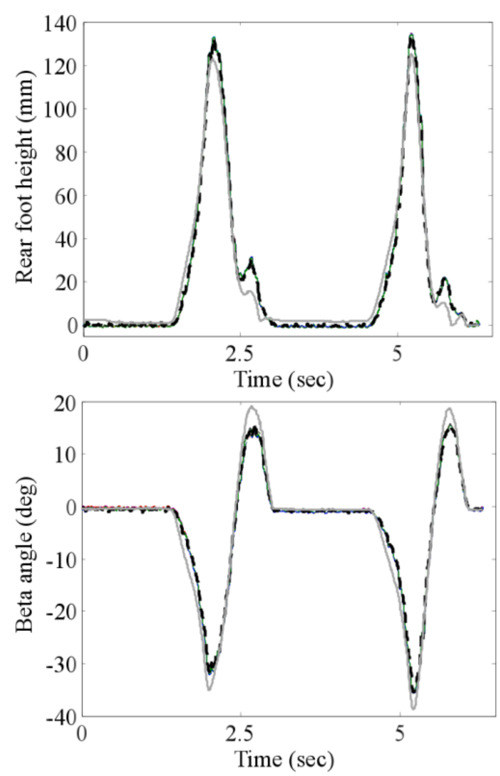

Fig. 3. A typical estimate of foot clearance (top), and orientation (bottom) with 2-IR sensor configuration. Reference values, obtained using motion capture system, plotted in solid gray while the black dashed lines are the estimated values.

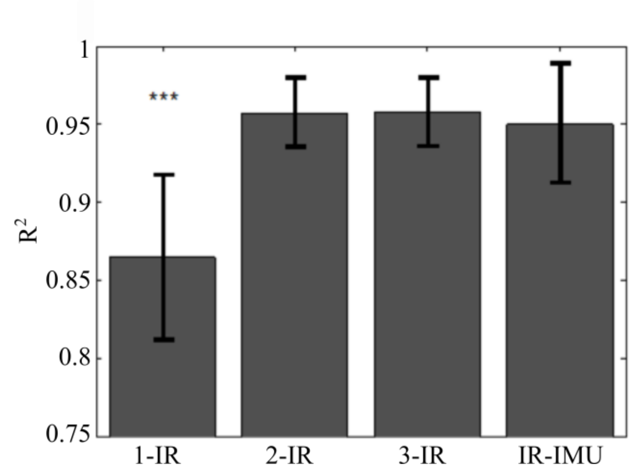

Fig. 4. The coefficient of determination (R^2) of estimating the heel clearance obtained during normal walking (leave one out cross validation).

1) Cross-validation of different configurations on walking data

Table I describes the testing performance during normal walking for heel and toe clearance estimation. While all the estimators are slightly biased, 2-IR configuration showed the smallest offset. The largest bias appeared in the 1-IR configuration which was still smaller than 7mm. The precision (standard deviation of error) in the estimation of foot clearance are in similar range for all estimators except 1-IR which showed an inferior performance. The highest precision for the estimation of heel clearance obtained by 2-IR and 3-IR configurations, while IR-IMU showed to have slightly higher precision in the estimation of toe clearance. Wilcoxon rank sum test on the coefficient of determination (Fig. 4) between the reference and estimated heights during normal walking showed a significant difference between 1-IR and the rest of configurations, but no significant difference across 2-IR, 3-IR and IR-IMU configurations. Toe and heel clearance estimations during normal walking showed similar accuracy and precision.

2) Cross-validation on different extreme conditions (exaggerated step height, and inversion/eversions)

Testing the estimators, trained on normal walking, during abnormal walking trials showed performance deteriorations (Table II-IV) particularly in the case of extreme inversion (R^2 dropped by 13 to 20%) and eversions (R^2 dropped by 8-16%). The RMS error of clearance estimation increased by 2 to 4.5 fold for extreme inversion gait cycles, while the RMS error of extreme eversion cycles has no remarkable change. The RMS error in steps with exaggerated height was also increased by 2 to 3 fold; however, this latter error increase was also due to an expansion of the vertical range of motion by 70%. The R^2 values remained high in case of exaggerated step heights.

The expected error escalated for 1-IR and 2-IR configurations, especially for heel clearance in exaggerated step height and exaggerated eversion, and for toe clearance in exaggerated inversion. However, expected errors of 3-IR and IR-IMU configurations almost always remained robust to extreme cases except in extreme inversion case.

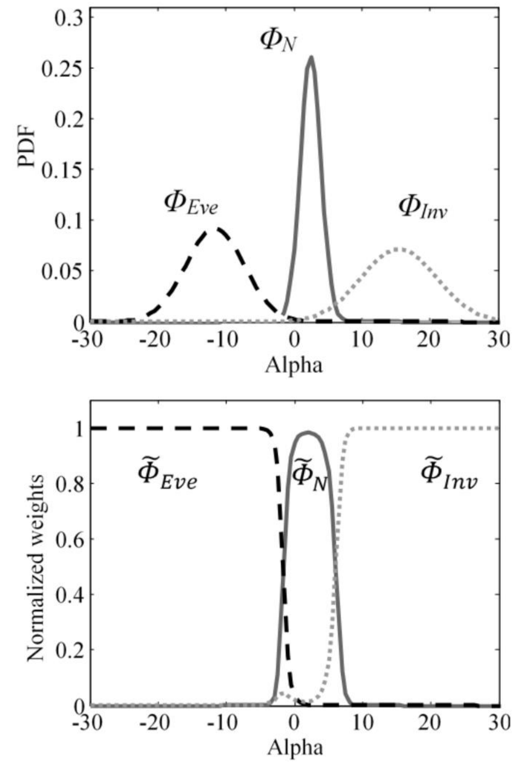

Fig. 5. Top: probability density function over inversion-eversion angle, bottom: normalized weights used in the Bayesian fusion.

In exaggerated step height and inversion trials, the standard deviation of errors increased dramatically for heel height for almost all configurations while the increases were less pronounced in toe clearance estimations.

A Bayesian fusion algorithm was implemented to benefit from specialized estimators to different conditions, namely normal walking, exaggerated inversion, and eversion. Fig. 5 shows the estimated likelihood functions of the inversion angle (α), Φ_N , Φ_{Eve} , Φ_{Inv}, and the conditional probability of each estimator, i.e. the normalized weights applied in the fusion. The heel clearance estimation results are depicted in Table V with the fusion applied to 3-IR and IR-IMU configurations. Comparing this table with Tables I, III, and IV, displays that standard deviation of the estimation error improved drastically when tested on walking with exaggerated inversion, with more than 58% and 81% reduction for IR-IMU and 3-IR configurations respectively. Estimation bias decreased in Bayesian fusion with both sensor configurations in normal walking and exaggerated inversion, but slightly increased in the case of exaggerated eversion. The R^2 value of the fused estimators increased for both exaggerated cases, yet maintained and slightly decreased for IR-IMU and 3-IR configurations when tested on normal walking.

B. Environmental lighting effect

Comparing the room lighting with the dark condition, we observed a 4% difference in the estimated distances for the short range, i.e. 4 to 7cm. Between 7-15cm, the difference was 1% and beyond 15cm, the difference reached almost 8%. The lighting effect can thus be considered negligible for the foot clearance estimation applications.

IV. Discussion

Separate distance estimators were trained for each sensor configuration using normal walking trials. Foot clearance RMS error of the best estimators in normal walking was 3.5% and 4.3% of the range for heel clearance and toe clearance respectively. Testing the obtained estimators in extreme step height condition resulted in an increase in absolute errors, mainly due to an increase of range of motion. While the relative RMS error to the vertical range of motion slightly increased to 5.6% for heel clearance, it decreased to 2% for toe clearance estimation. However, there was a similarity between the patterns of RMS errors across different configurations obtained on normal walking test data and walking with exaggerated step height (Tables I and II). One possible reason is the similarity of the range of dorsiflexion and inversion angles in both gait data. These results along with high R^2 in this extreme case, suggest that the trained estimators in normal walking can be successfully used in such conditions. This is however not the case for the extreme

TABLE I
PERFORMANCE OF DIFFERENT CONFIGURATIONS: TRAINING AND TESTING SETS WERE OBTAINED FROM THE NORMAL GAIT DATA

Estimators	Heel clearance: [0 213.7] mm				Toe clearance: [0 147.8]mm			
	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2
1-IR	-6.1 ± 0.2	13.2 ± 0.1	14.5 ± 0.1	0.87 ± 0.05	4.4 ± 0.6	7.6 ± 0.3	8.8 ± 0.3	0.83 ± 0.11
2-IR	0.8 ± 0.2	7.5 ± 0.0	7.6 ± 0.0	0.96 ± 0.01	0.2 ± 0.6	6.3 ± 0.1	6.3 ± 0.3	0.91 ± 0.01
3-IR	1.3 ± 0.2	7.6 ± 0.0	7.6 ± 0.0	0.96 ± 0.01	0.4 ± 0.6	6.3 ± 0.1	6.3 ± 0.3	0.91 ± 0.01
IR-IMU	1.9 ± 0.2	8.2 ± 0.0	8.4 ± 0.0	0.95 ± 0.03	0.9 ± 0.6	6.1 ± 0.1	6.3 ± 0.3	0.92 ± 0.01

$\alpha \in [-5.1\ 7.5]°$, $\beta \in [-50.8\ 28.7]°$

TABLE II
PERFORMANCE OF DIFFERENT CONFIGURATIONS: TRAINING OVER NORMAL AND TESTING OVER EXAGGERATED-HEIGHT GAITS

Estimators	Heel clearance: [0 367.9] mm				Toe clearance: [0 241.3] mm			
	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2
1-IR	-16.5 ± 0.2	28.3 ± 0.2	32.7 ± 0.2	0.90 ± 0.02	-1.1 ± 0.8	13.8 ± 0.1	13.8 ± 0.3	0.95 ± 0.00
2-IR	-5.1 ± 0.2	20.6 ± 0.1	21.2 ± 0.1	0.95 ± 0.00	-0.1 ± 0.8	16.5 ± 0.3	16.5 ± 0.4	0.94 ± 0.00
3-IR	-1.8 ± 0.2	20.4 ± 0.1	20.5 ± 0.1	0.95 ± 0.00	3.1 ± 0.8	16.2 ± 0.3	16.5 ± 0.4	0.94 ± 0.00
IR-IMU	-1.5 ± 0.1	24.9 ± 0.0	24.9 ± 0.0	0.92 ± 0.00	4.6 ± 0.7	13.8 ± 0.3	14.5 ± 0.3	0.95 ± 0.00

$\alpha \in [-10.9\ 7.6]°$, $\beta \in [-44.0\ 30.0]°$

TABLE III
PERFORMANCE OF DIFFERENT CONFIGURATIONS: TRAINING OVER NORMAL AND TESTING OVER EXAGGERATED-INVERSION GAITS

Estimators	Rearfoot (sensor) height: [0 161.9] mm				Forefoot (sensor) height : [0 284.3] mm			
	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2
1-IR	-0.4 ± 0.2	34.8 ± 0.1	34.8 ± 0.1	0.76 ± 0.00	16.9 ± 0.8	7.3 ± 0.6	18.4 ± 0.6	0.93 ± 0.01
2-IR	2.7 ± 0.2	34.4 ± 0.1	34.5 ± 0.1	0.74 ± 0.00	14.8 ± 0.8	3.7 ± 0.4	15.3 ± 0.4	0.95 ± 0.00
3-IR	-11.4 ± 0.2	31.6 ± 0.1	33.5 ± 0.1	0.77 ± 0.00	0.5 ± 0.7	10.2 ± 0.2	10.2 ± 0.3	0.97 ± 0.00
IR-IMU	-7.6 ± 0.2	22.5 ± 0.1	23.7 ± 0.1	0.83 ± 0.00	5.3 ± 0.7	14.2 ± 0.4	15.2 ± 0.4	0.94 ± 0.01

$\alpha \in [-2.1\ 37.0]°$, $\beta \in [-40.1\ 45.9]°$

TABLE IV
PERFORMANCE OF DIFFERENT CONFIGURATIONS: TRAINING OVER NORMAL AND TESTING OVER EXAGGERATED-EVERSION GAITS

Estimators	Rearfoot clearance: [0 123.9] mm				Forefoot clearance: [0 160.3] mm			
	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2
1-IR	-12.0 ± 0.2	12.5 ± 0.1	17.3 ± 0.1	0.73 ± 0.00	-8.2 ± 0.7	10.5 ± 0.1	13.3 ± 0.4	0.89 ± 0.01
2-IR	-9.2 ± 0.2	10.0 ± 0.1	13.6 ± 0.1	0.83 ± 0.00	-10.3 ± 0.7	7.9 ± 0.1	13.0 ± 0.3	0.95 ± 0.01
3-IR	0.3 ± 0.2	9.0 ± 0.1	9.0 ± 0.1	0.84 ± 0.00	-0.7 ± 0.7	6.4 ± 0.1	6.4 ± 0.3	0.96 ± 0.01
IR-IMU	0.9 ± 0.2	8.4 ± 0.0	8.4 ± 0.0	0.87 ± 0.00	-0.1 ± 0.7	6.2 ± 0.1	6.2 ± 0.3	0.96 ± 0.01

$\alpha \in [-21.4\ 5.9]°$, $\beta \in [-38.3\ 35.5]°$

TABLE V
PERFORMANCE OF FUSED ESTIMATORS FOR HEEL CLEARANCE

Estimators	IR-IMU				3-IR			
	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2	μ_e (mm)	SD_e (mm)	RMS_e (mm)	R^2
Normal	0.4 ± 0.1	8.2 ± 0.0	8.2 ± 0.0	0.95 ± 0.00	-0.6 ± 0.6	8.5 ± 0.3	8.5 ± 0.3	0.83 ± 0.11
Ext-Inv	3.1 ± 0.2	9.3 ± 0.1	9.8 ± 0.2	0.91 ± 0.00	0.7 ± 0.6	6.0 ± 0.1	6.1 ± 0.3	0.91 ± 0.01
Ext-Eve	1.4 ± 0.2	7.5 ± 0.1	7.6 ± 0.1	0.88 ± 0.00	0.8 ± 0.6	6.6 ± 0.1	6.7 ± 0.3	0.91 ± 0.01

inversions and eversions. For instance, in the former case, the heel clearance RMS error reached 14.6% of the vertical range of motion. The patterns of RMS errors across different sensor configuration differed from the normal walking and exaggerated step height conditions. This can be attributed to the difference between the ranges of inversion angle. The R^2 values of heel clearance estimation in both extreme inversion and eversion cases dropped. This is also the reason a Bayesian fusion was used to cope with walking with possible deviated inversion-eversion cycles.

Heel clearance error (expected mean error ± expected standard deviation) when using the best-performed estimators during normal walking was 0.8±7.5mm and during the worst case abnormal walking was smaller than 0.8±6.6mm (obtained based on Bayesian fusion) which appeared to be one order of magnitude less than errors of previously proposed systems [18], [19]. Toe clearance estimation errors were 0.9±6.1mm and 4.6±13.8mm for normal and worst-case abnormal walking respectively, thus showing superior performance to [18], [19].

When the estimators, trained on normal walking, were tested on the exaggerated inversion, IR-IMU presented slightly better estimation of the heel clearance while the best results for the toe clearance was achieved by 3-IR configuration. IR-IMU configuration obtained the best performance when being tested on exaggerated eversion. This can be explained by the fact that any increase of inversion and eversion range would result in an increase of scattering of IR signals emitted to the ground since fewer beams travel back to the sensor receiver; the distance estimation thus becomes less reliable which also affects the estimation of foot orientation and the ultimate clearance estimates. In contrast, the foot orientation estimation in IR-IMU was done mainly by IMU's data which are not disrupted by experiencing a higher range of rotation.

The estimated distance showed slight bias in all cases. This can be investigated using the applied exponential model relating distance and the raw measurements of the IR sensor. Assuming that sensor measurements follow a normal distribution, $S_i \sim N(\mu, \sigma^2|\mathrm{d_i})$, the estimated distance will have a lognormal distribution, which theoretically results in a biased estimate as showed in the following equations.

$$E\,(ae^{b\times S_i}+c) = ae^{b\mu+b^2\sigma^2/4}+c \qquad (11)$$

$$bias = E\big(\hat{d}_i\big) - d_i = E\,(a\times e^{b\times S_i}+c) - a\times e^{b\times E(S_i)} - c \qquad (12)$$

$$bias = ae^{b\mu}(e^{b^2\sigma^2/4}-1) \qquad (13)$$

where E is the expectation operator, and (11) is the expected value of the estimated distance. The bias is defined as the difference between the expected distance estimate and the actual distance (12), i.e. the distance calculated based on the expected value of the sensor's measurements. Since b and σ in (13) are nonzero, the bias is always nonzero.

The emitted IR wavelength is 870±70nm which is beyond near-infrared wavelengths; therefore the color of the surface would not have any effect on the measurements. Surfaces with three different colors (white, orange and brown) were tested and no difference in measurements was observed. Sunlight and indoor illumination have infrared components, which could have an effect on distance estimation via the IR sensors. A set of static measurements were thus performed in two different lighting conditions, i.e. dark and normal room lighting, showed 1% to 4% difference in short distances, and up to 8% in the distances larger than 15cm. These results confirm the robustness of this system against some of the environmental factors.

One of the main limitations of IR distance meter sensors is their dependency on the flatness of the ground. Any carpet or rough surface would aggravate the results due to the scattering of the IR beam. Although this study only explored flat surfaces such as white and colored papers, in the case of extremely rough surfaces the IMU in the IR-IMU configuration can be used for estimation of foot clearance. However, the accuracy of IMU-based estimation of foot clearance is much lower than the configurations including the IR sensors when used over flat grounds.

A comparison between the different configurations showed that if the target population has no extended range of inversion-eversion, then the minimal IR sensor configuration would provide sufficiently good results, i.e. better than previously designed wearable systems. However, if the population of interest has a different range of inversion-eversion due to a pathology or lack of joint stiffness the configuration with 3 IR sensors or the combination of IR sensor and IMU can be used.

The weak performance of minimal IR sensor configuration in high ranges of foot rotations originates from the inability of this configuration in the estimation of orientation. Even when using multiple IR sensors to estimate the orientation, errors remained high for walking with extreme inversion angles. The trained distance and orientation estimators on normal walking data were not reliable for such extreme conditions. The Bayesian fusion of three separately trained estimators on the normal walking and extreme inversion and eversion cases demonstrated on average superior performance when tested on the data collected from normal walking and extreme cases.

While both 3-IR and IR-IMU configurations showed the superior performance when compared to the other tested configurations, the IR-IMU also benefitted from the ability to estimate other spatiotemporal parameters of gait such as cadence, speed, and step length [21]. This configuration can be used as a multipurpose system for a robust and thorough gait analysis. The already developed wireless data transfer in IMUs will be used to transfer both IMU and IR sensor data for real-time analysis. The size of this prototype can be reduced and an adjustable sensor fixation can be developed in order to adapt the system to every size shoes. An algorithm can be developed for the IR-IMU configuration to switch the foot clearance estimation to the IMUs if insufficient IR signal is received by the sensors receptors, which might happen in the case of walking on rough surfaces such as carpet. The scattering on the general rough surfaces can be quantified in a separate study and be used for the mentioned algorithm. A future application of the proposed device would be to provide real time foot clearance feedback to close a neural prosthesis control loop for spinal cord injury patients. In that neural prosthesis, electrical stimulation will be given in specific sequences to the spinal cord column with an accurate timing corresponding to the foot clearance in gait cycles.

V. Conclusion

A wearable system for foot clearance parameter estimation was developed along with different data-driven estimators. Four sensor configurations including one to three IR sensors and a combination of one IR and one IMU were used to estimate the heel and toe clearances. In order to estimate the sensor's height the foot orientation was estimated using separately designed estimators based on the physics of the sensors while their parameters were tuned using a nonlinear least square technique. This system was evaluated in normal walking, and walking conditions with exaggerated step height, inversion and eversion rotations. To improve the estimation performance in the exaggerated inversion and eversion separate estimators were trained and then fused together with the normal walking estimators.

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