Heel and Toe Clearance Estimation for Gait Analysis Using Wireless Inertial Sensors

Benoit Mariani*, Stephane Rochat, Christophe J. Büla, and Kamiar Aminian, *Member, IEEE*

***Abstract*—Tripping is considered a major cause of fall in older people. Therefore, foot clearance (i.e., height of the foot above ground during swing phase) could be a key factor to better understand the complex relationship between gait and falls. This paper presents a new method to estimate clearance using a foot-worn and wireless inertial sensor system. The method relies on the computation of foot orientation and trajectory from sensors signal data fusion, combined with the temporal detection of toe-off and heel-strike events. Based on a kinematic model that automatically estimates sensor position relative to the foot, heel and toe trajectories are estimated. 2-D and 3-D models are presented with different solving approaches, and validated against an optical motion capture system on 12 healthy adults performing short walking trials at self-selected, slow, and fast speed. Parameters corresponding to local minimum and maximum of heel and toe clearance were extracted and showed accuracy $\pm$ precision of 4.1 $\pm$ 2.3 cm for maximal heel clearance and 1.3 $\pm$ 0.9 cm for minimal toe clearance compared to the reference. The system is lightweight, wireless, easy to wear and to use, and provide a new and useful tool for routine clinical assessment of gait outside a dedicated laboratory.**

***Index Terms*—Foot clearance, inertial sensors, spatiotemporal parameters, walking assessment, wearable device.**

I. Introduction

AMONG community-dwelling people older than 65 years, one third falls each year. Falls have many adverse consequences in older people, including major injuries, functional decline, activity restriction, and reduced quality of life. Foot clearance, defined as the foot's height during the swing phase, seems an important gait parameter related to the risk of falling. Contrary to other gait parameters, there is an unambiguous mechanism that links impaired foot clearance to falls. During walking, insufficiency or fluctuations in foot clearance could lead directly to tripping, a major cause of fall in older people. In previous studies investigating circumstances of falls in community-dwelling older people, tripping was the most frequent condition causing falls [1], [2]. In these studies, tripping accounted for up to 50% of all falls.

Surprisingly, despite this intuitive relationship, only few studies investigated so far the characteristics of foot clearance pattern, and only in a small selected population. Therefore, several major gaps remain in our knowledge about the clinical significance of foot clearance in older persons. Some studies have evaluated specific features of foot clearance during level walking, mostly minimum toe clearance (MinTC), also referred as minimal foot clearance which can be defined as the minimal vertical distance between the shoe sole and the ground during the swing phase [3], [4]. A recent systematic review on the association between falls history and MinTC concluded that a greater MinTC variability was observed in older fallers compared to older nonfallers [5]. A recent study showed an increased MinTC variability in ten older people reporting a fall in previous year compared with older people without fall history [6]. Theoretical models based on MinTC variability to predict the risk of falling have also been proposed recently [4], [6].

These promising preliminary clinical results have several limitations, mostly due to technical issues. First, foot clearance was evaluated only in very small samples of young and elderly subjects due to the complexity of the measurement protocol in a gait laboratory, using camera-based motion capture systems and treadmills. Systems using these technologies provided information for a limited number of gait cycles and could be used only in a closed environment. In addition, analyses then had to assume that observed performance corresponds to the usual performance, even though walking requires several steps to reach a steady state [7], and aspects such as the variability of gait requires extended periods of time to be assessed [8]. Finally, results can be strongly influenced by the placement of reflective markers on the foot by the operator.

In the past years, technical progresses made possible the development of wearable sensors featuring combinations of accelerometers, gyroscopes, and force sensors fixed to lower limbs to measure gait characteristics [9]–[13]. Due to very low energy consumption, these sensors can be battery powered and thus have a potential application for extended ambulatory monitoring. They allow mobile as well as outdoor motion capture and can provide information over extended periods of time. In addition, since there is no localization marker, the signals can be continuously recorded without any trajectory loss due to a marker occlusion. Lately, a new generation of miniature wireless sensors fixed directly on the foot was developed and was able to estimate sagittal [11] and global 3-D foot kinematics [14]. Those methods relied on periodical corrections of sensors drift

Manuscript received February 15, 2012; revised July 20, 2012; accepted August 27, 2012. Date of publication August 31, 2012; date of current version October 16, 2012. This work was supported in part by the Swiss National Funds under Grant 320030_138525. *Asterisk indicates corresponding author.*

*B. Mariani is with the Laboratory of Movement Analysis and Measurements, Ecole Polytechnique Fédérale de Lausanne, 1015 Lausanne, Switzerland (e-mail: benoit.mariani@epfl.ch).

S. Rochat and C. J. Büla are with the Service of Geriatric Medicine and Geriatric Rehabilitation, University of Lausanne Medical Center, 1066 Epalinges, Switzerland (e-mail: Stephane.Rochat@chuv.ch; Christophe.Bula@chuv.ch).

K. Aminian is with the Laboratory of Movement Analysis and Measurements, Ecole Polytechnique Fédérale de Lausanne, 1015 Lausanne, Switzerland (e-mail: kamiar.aminian@epfl.ch).

Digital Object Identifier 10.1109/TBME.2012.2216263

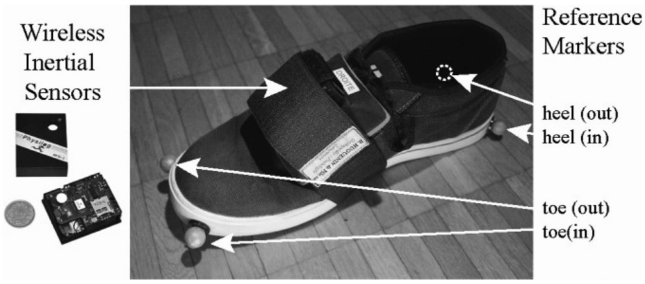

Fig. 1. Physilog wireless unit with embedded inertial sensor attached on foot. Internal (in) and external (out) markers fixed on heel and toe for reference optical motion capture.

based on biomechanical assumptions such as zero velocity at foot-flat of stance.

So far, only few attempts have been made to apply this inertial sensors technology to estimate a limited set of foot-clearance parameters, such as minimal toe clearance [15], [16] or maximal foot clearance [14].

This study aims at addressing those technical limitations in order to investigate various aspects of foot clearance in clinical studies. The paper presents a method based on a portable and wireless foot-worn inertial sensor system, and dedicated biomechanical model to estimate both heel and toe clearance patterns during gait in real-world conditions. To this end, two independent models relying on 2-D and 3-D movement hypothesis, and three solving approaches are presented, compared, and validated against a gold standard system composed of optical motion capture. Several parameters are then introduced to characterize the foot clearance and their changes according to different walking speeds are analyzed and discussed.

II. Method

A. Inertia-Based Measurement System

A standalone Physilog unit integrating a microcontroller, memory, a three-axis accelerometer (MMA7341LT, Freescale, range ±3 g), a three-axis gyroscopes (ADXRS, Analog Device, range ±600 °/s), and a battery (3.7 V, 595 mAh) was designed. The Physilog module is small (50 mm × 40 mm × 16 mm) and low power (71 mA in recording, 51 mA in standby mode), lightweight (36 g), and was conveniently fixed in a few seconds on the upper part of the foot of the subjects using an elastic strap (see Fig. 1) with shape memory foam beneath the system to guarantee a stable position together with easy manipulation. The kinematics data (3-D acceleration and 3-D angular velocity) were low-pass filtered at 17 Hz [13], [14], sampled on 16 bits at a frequency f_s of 200 Hz, converted to physical units (g or °/s), and recorded on micro SD cards before transferring to the PC. Signals from two modules were synchronized wirelessly. Preliminary, by assuming that during walking, the pitch angular velocity was maximal in the sagittal plane, each sensor was aligned with the principal axis of the measured angular velocity. In addition, in the absence of foot movement (e.g., standing posture), the vertical gravity axis was determined from the accelerometer. Subsequently, the sensor inclination was corrected so that the pitch angle θ_Y was null at rest. The components of angular velocity (pitch: Ω_p, yaw: Ω_y, and roll: Ω_r) and acceleration (forward: a_f, vertical: a_v, and lateral: a_l), expressed as functions of discrete time, were aligned accordingly. This way, the measurement was not influenced by the sensor location on the foot.

B. Foot Kinematics Estimation

The foot kinematics was estimated from sensor data fusion using methods inspired from previous work in 2-D [11] and in 3-D [14]. Principal steps and equations are presented in this paragraph. At first, for each cycle n, the temporal events expressed in the space of natural numbers N^+ were detected on Ω_p, namely foot-flat (tff_n), heel-strike (ths_n), and toe-off (tto_n). Foot-flat was detected as the minimum of absolute value of Ω_p, whereas heel-strike (respectively toe-off) was detected as the negative peak of Ω_p, before (respectively after) foot-flat. Each gait cycle n was defined by the time interval between two consecutive foot-flats $[tff_n : tff_{n+1}]$.

In 2-D, for each cycle n, the pitch angle or inclination in the sagittal plane θ_Y expressed as a function of time t was obtained from integration of Ω_p

$$\theta_Y(t) = \sum_{i=tff_n}^{t} \Omega_p(i)/f_s. \quad (1)$$

Estimated pitch angle $(\hat{\theta}_Y)$ was then obtained from linear dedrifting of θ_Y, assuming a flat orientation of the foot at *tff*

$$\hat{\theta}_Y(t) = \theta_Y(t) - \left(\frac{t - tff_n}{tff_{n+1} - tff_n} * \theta_Y(tff_{n+1})\right). \quad (2)$$

Accelerations were then aligned in fixed frame and the gravity component was canceled on the vertical axis Z

$$a_Z(t) = -\sin(\hat{\theta}_Y(t)) * a_f(t) + \cos(\hat{\theta}_Y(t)) * a_v(t) - 1. \quad (3)$$

By considering the gravity g, the vertical velocity and the vertical trajectory in fixed frame, expressed as functions of time t, were estimated by successive integration. Linear dedrifting was performed based on the assumption of zero velocity update and locomotion on flat ground

$$v_Z(t) = g * \sum_{i=tff_n}^{t} a_z(i)/f_s$$

$$\hat{v}_Z(t) = v_Z(t) - \left(\frac{t - tff_n}{tff_{n+1} - tff_n} * v_z(tff_{n+1})\right) \quad (4)$$

$$Z^{2D}(t) = \sum_{i=tff_n}^{t} \hat{v}_z(i)/f_s$$

$$\hat{Z}^{2D}(t) = Z^{2D}(t) - \left(\frac{t - tff_n}{tff_{n+1} - tff_n} * Z^{2D}(tff_{n+1})\right). \quad (5)$$

In 3-D, the orientation of the sensors was represented by a 3-D rotation matrix $(M(t))$, expressed as a function of time, relative to the fixed frame (*XYZ*) [14], and was updated at each time frame by a quaternion-based time integration of the angular velocity between two consecutive foot-flats $[tff_n : tff_{n+1}]$.

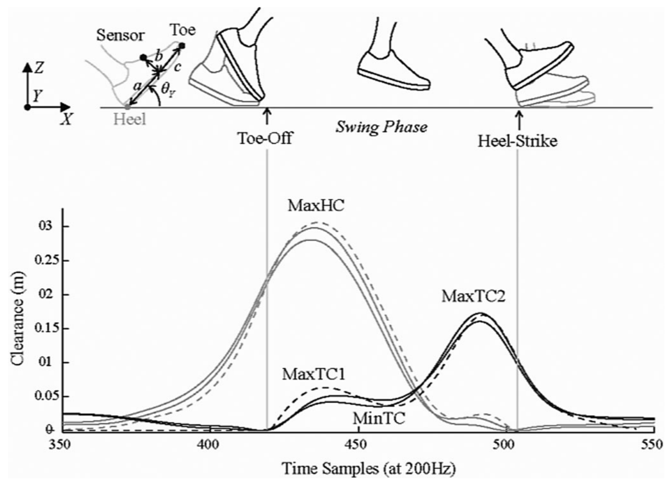

Fig. 2. Sensor location relative to heel and toe $\{a, b, c\}$. Schematic of foot kinematics, temporal events, and clearance parameters during one gait cycle. Heel (light gray) and toe (dark gray) clearance are dashed for 3-D model (Z^{3D}), and plain lines for internal and external reference markers (Z^{REF}).

$M(t)$ was then used to express the accelerations in *XYZ* from (a_f, a_v, a_l). A double time integration using a p-chip interpolation function was performed to find the 3-D position of the foot sensor, and its projection on Z-axis $\hat{Z}^{\mathrm{3D}}$ [14].

C. Heel and Toe Trajectory Estimation

From previous paragraph, the sensor trajectory has been estimated in 2-D and 3-D. Considering the sensor location relative to the heel and the toe (coordinates $\{a, b, c\}$ in Fig. 2), the vertical trajectory of sensor, heel, and toe, expressed as a function of time t, can be computed as follows in 2-D space

$$\begin{aligned} Z^{\mathrm{2D}}_{\mathrm{Sensor}}(t) &= \hat{Z}^{\mathrm{2D}}(t) + b \\ Z^{\mathrm{2D}}_{\mathrm{Heel}}(t) &= Z^{\mathrm{2D}}_{\mathrm{Sensor}}(t) - b * \cos(\hat{\theta}_Y(t)) - a * \sin(\hat{\theta}_Y(t)) \\ Z^{\mathrm{2D}}_{\mathrm{Toe}}(t) &= Z^{\mathrm{2D}}_{\mathrm{Sensor}}(t) - b * \cos(\hat{\theta}_Y(t)) + c * \sin(\hat{\theta}_Y(t)) \end{aligned} \tag{6}$$

and in 3-D space

$$\begin{aligned} Z^{\mathrm{3D}}_{\mathrm{Sensor}}(t) &= \hat{Z}^{\mathrm{3D}}(t) + b \\ U(t) &= M(t)|_X = M(t)^T * (1, 0, 0) \\ W(t) &= M(t)|_Z = M(t)^T * (0, 0, 1) \\ Z^{\mathrm{3D}}_{\mathrm{Heel}}(t) &= Z^{\mathrm{3D}}_{\mathrm{Sensor}}(t) - b * W(t) - a * U(t) \\ Z^{\mathrm{3D}}_{\mathrm{Toe}}(t) &= Z^{\mathrm{3D}}_{\mathrm{Sensor}}(t) - b * W(t) + c * U(t). \end{aligned} \tag{7}$$

Nevertheless, in (6) and (7), the values of a, b, and c are unknown. They could have been manually measured after the sensor placement on the foot, but it would be practically cumbersome and could lead to imprecision. Thus, an automatic method independent of sensor placement was proposed to estimate those unknown variables at cycle n $\{a_n, b_n, c_n\}$, using the following three hypotheses.

1) At heel-strike, the vertical coordinate of the estimated heel trajectory should be equal to 0

$$Z^{\mathrm{3D}}_{\mathrm{Heel}}(ths_n) = Z^{\mathrm{2D}}_{\mathrm{Heel}}(ths_n) = 0. \tag{8}$$

2) At toe-off, the vertical coordinate of the estimated toe trajectory should be equal to 0

$$Z^{\mathrm{3D}}_{\mathrm{Toe}}(tto_n) = Z^{\mathrm{2D}}_{\mathrm{Toe}}(tto_n) = 0. \tag{9}$$

3) The heel-to-toe distance is equal to the shoe size (*Ssize*)

$$a_n + c_n = Ssize. \tag{10}$$

For each cycle n, we obtain a system of three [(7)–(9)] with three unknown variables $\{a_n, b_n, c_n\}$. Three different ways to solve those equations systems were considered. The first solving approach was to find analytically the solution at each cycle n; this is referred as the *per-cycle* (PC) *approach*. In a second time, by assuming that the sensor position remains fixed on the foot during one gait trial, it implies that $\{a_n, b_n, c_n\} = \{a, b, c\}$. Considering all cycles of a gait trial, $\{a, b, c\}$ was estimated by the median (ME) of the set of solutions $\{a_n, b_n, c_n\}$; this is referred as the ME *approach*. Finally, by using all cycles, it was also possible to consider having multiple equations with three unknowns, and that overestimated system was solved using a least square (LS) criteria, this is referred as the LS *approach*.

Finally, the following two constraints were considered to correct the 2-D and 3-D trajectories.

1) During $[tff_n\colon tto_n]$, it was assumed that the toe is in contact with the ground and therefore

$$\forall t \in [tff_n : tto_n],\ Z^{\mathrm{2D}}_{\mathrm{Toe}}(t) = Z^{\mathrm{3D}}_{\mathrm{Toe}}(t) = 0 \tag{11}$$

2) During $[ths_n\colon tff_{n+1}]$, it was assumed that the heel is in contact with the ground and therefore

$$\forall t \in [ths_n : tff_{n+1}],\ Z^{\mathrm{2D}}_{\mathrm{Heel}}(t) = Z^{\mathrm{3D}}_{\mathrm{Heel}}(t) = 0. \tag{12}$$

Those corrections do not bring discontinuities to the clearance signals since the equations were solved with null values at tto_n and ths_n.

D. Foot-Clearance Parameters

Heel and toe clearance were defined as the vertical coordinates of the heel $(Z^{2D}_{\mathrm{Heel}}, Z^{3D}_{Heel})$ and the toe trajectories $(Z^{2D}_{\mathrm{Toe}}, Z^{3D}_{Toe})$. Although the full time-trajectory patterns were obtained, several basic statistical features were extracted to characterize foot clearance patterns through simple and interpretable parameters. These foot-clearance parameters were based on the local maximum and minimum of heel and toe clearance and were computed for each cycle measured by the system (see Fig. 2).

E. Experimental Validation

In this study, 12 healthy adults (9 Males, 3 Females, mean age 32 ± 7 years, mean height 176 ± 8 cm, and mean weight 71 ± 15 kg) were asked to walk five times at a slow, self-selected (also referred as normal), and fast speed, in a 15-m corridor while wearing the two Physilog units on their feet. The middle 5 m of the corridor, where gait could be considered as steady state, were tracked by a reference optical motion capture system (Mocap) with submillimeter accuracy [13], including seven cameras (Vicon, U.K.). The Mocap tracked the position of four reflective markers placed manually on the internal and external side of the shoe at the toe and heel extremities of subject's shoe according to Fig. 1. Shoe's heel and toe trajectories and related foot-clearance parameters estimated from Mocap were considered as a reference data (REF) and used for the validation of the Physilog-based system. The protocol was approved by the local ethical comity.

F. Data Analysis

The shoe size (*Ssize*) was obtained directly from the measure of the distance between the heel and toe markers and used for the heel and toe trajectory estimation based on the Physilog system. To compare the extracted parameters at each recorded gait cycle within the frame limited by the Mocap volume, the clearance pattern given by the Mocap was temporally delayed to match clearance pattern estimated with the Physilog, using the maximum of cross correlation between the two clearance patterns. That provided juxtaposed clearance curves, as in Fig. 2. The same delay was applied to the toe clearance pattern. The accuracy and precision were then computed as the mean and standard deviation (STD) value of the difference between foot-clearance parameters extracted with the Mocap reference system (REF), each of the algorithms (3-D and 2-D), and for each approach of solving sensor's position (PC, ME, and LS). The accuracy and precision were reported in millimeters (absolute value) and in percentage of average parameter values (relative value). The reference itself was assessed through the difference between the parameters extracted on the internal and external side of the shoe. Bland and Altman plots were investigated to estimate the limit of agreement between the proposed system and reference.

Finally, walking velocity was estimated using the same inertial sensors configuration [14] to check significant changes between low, normal, and fast speed. Two-sample t-tests were performed on the speed and foot-clearance parameters to investigate the significance of foot clearance changes with speed, and observe the influence of walking speed on the error in foot clearance estimation.

III. Results

A. Comparison With the Reference System

Fig. 2 shows a good correspondence between Z^{3D}_{Heel} and $Z^{\mathrm{REF}}_{\mathrm{Heel}}$ (respectively Z^{3D}_{Toe} and $Z^{\mathrm{REF}}_{\mathrm{Heel}}$) during a typical recorded gait cycle. Four parameters were extracted from these patterns. Heel pattern reached its maximal value (MaxHC) right after toe-off. Before heel-strike, a local minimum and a maximum of heel clearance were sometimes observed (see Fig. 2), but it was not consistent in all subjects; so, it was not considered in the analysis. Regarding toe clearance, right after toe-off, a first local maximum was reached (MaxTC1). It corresponded to the highest position of the foot during swing phase. Then, toe clearance reached a minimum (MinTC) around mid-swing time, and a second maximum (MaxTC2) prior to heel-strike.

TABLE I
Accuracy (Mean) and Precision (STD) of Foot-Clearance Parameters With 3-D and 2-D Model and Automatic Estimation of Sensor Location Using PC, ME, and LS Approaches, Compared to Motion Capture (REF)

			Accuracy (mean)		Precision (STD)		
			mm	%	mm	%	Samples
MaxHC	REF	ext/in	10.5	3.9	10.6	4.0	378
	3D	PC	43.4	16.2	23.9	8.9	
		ME	47.6	17.7	25.6	9.6	
		LS	40.6	15.1	22.5	8.4	
	2D	PC	45.9	17.1	25.1	9.4	
		ME	48.1	17.9	24.0	8.9	
		LS	42.0	15.7	22.6	8.4	
MaxTC1	REF	ext/in	4.0	10.7	5.4	14.4	169
	3D	PC	21.0	56.0	14.1	37.6	
		ME	25.6	68.3	17.7	47.0	
		LS	20.5	54.5	14.5	38.6	
	2D	PC	27.8	74.0	15.3	40.7	
		ME	30.4	81.1	16.2	43.2	
		LS	27.3	72.6	15.1	40.1	
MinTC	REF	ext/in	4.0	15.5	4.4	16.7	154
	3D	PC	-14.3	-54.8	9.5	36.4	
		ME	-12.7	-48.7	9.0	34.5	
		LS	-12.7	-48.8	9.1	35.0	
	2D	PC	-0.9	-3.6	13.5	51.7	
		ME	0.2	0.6	12.7	48.5	
		LS	0.4	1.7	12.6	48.1	
MaxTC2	REF	ext/in	-7.5	-5.1	6.1	4.2	182
	3D	PC	-20.2	-13.8	19.6	13.4	
		ME	-22.0	-15.1	18.0	12.3	
		LS	-23.6	-16.2	17.8	12.2	
	2D	PC	-9.6	-6.6	13.7	9.4	
		ME	-10.4	-7.1	14.1	9.7	
		LS	-13.9	-9.5	13.7	9.4	

Values are expressed in millimeter and % of average parameters. REF ext/In corresponds to the intrinsic error of reference system obtained by the difference between external and internal side of the shoe.

Table I provides a quantitative one-by-one comparison of the foot-clearance parameters obtained with the 2-D and 3-D models, the different solving approaches (PC, ME, and LS), and the reference system (REF). Due to the limited capture volume of the reference system and the variation of heel and toe clearance patterns among the subjects, the sample size for the different parameters was not always the same but ranged between 154 and 378 cycles. MaxHC was obtained with an error of 40.6 $\pm$ 22.5 mm for the 3-D and LS approach and 42 $\pm$ 22.6 mm for the 2-D and LS approach. The best absolute accuracy and precision (expressed as the mean $\pm$ STD of the set of difference with the reference system) were observed for MinTC, with 0.4 $\pm$ 12.6 mm and -12.7 ± 9.1 mm, respectively, for the 2-D and 3-D models solved with the LS criteria. The other toe-clearance parameters, namely MaxTC1 and MaxTC2, showed an absolute accuracy between 13.7 and 19.6 mm depending on the different models and approaches. However, when looking at the relative error, we observed that MaxHC and MaxTC2 showed the best

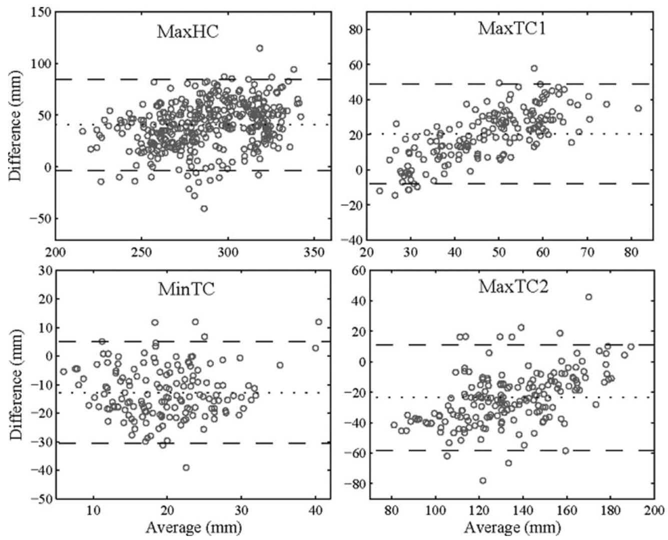

Fig. 3. Bland and Altman plots of the mean (dotted line) ± 1.96 STD limit of agreement (dashed line) of the difference between the 3-D model with LS approach and reference for foot-clearance parameters.

TABLE II
FOOT-CLEARANCE PARAMETERS AT DIFFERENT WALKING SPEEDS

		Slow			Normal		Fast		
		mean	STD	p	mean	STD	mean	STD	p
Speed (m/s)		0.82	0.10	0.00	1.19	0.20	1.62	0.15	0.00
MaxHC (cm)	REF	25.3	2.3	0.00	27.6	2.1	28.7	2.2	0.00
	3D_LS	30.2	3.1	0.00	31.5	3.3	31.2	3.4	0.52
	Error	5.0	1.7	0.00	3.9	2.1	2.5	2.5	0.00
MaxTC1 (cm)	REF	3.5	0.9	0.00	4.1	0.7	3.8	0.7	0.10
	3D_LS	5.6	1.9	0.00	6.5	1.5	5.3	1.7	0.00
	Error	2.1	1.4	0.08	2.5	1.2	1.5	1.6	0.00
MinTC (cm)	REF	2.5	0.7	0.06	2.7	0.7	2.7	0.8	0.88
	3D_LS	1.1	0.7	0.05	1.4	0.7	1.7	1.1	0.11
	Error	-1.3	1.0	0.94	-1.3	0.8	-1.0	1.0	0.15
MaxTC2 (cm)	REF	13.5	1.8	0.00	15.0	1.6	16.4	1.5	0.00
	3D_LS	10.7	2.4	0.00	12.9	2.4	14.5	2.6	0.00
	Error	-2.8	1.7	0.01	-2.1	1.8	-1.9	1.8	0.64

Significant change of parameters compared to normal (i.e., self-selected) speed is shown with the p value.

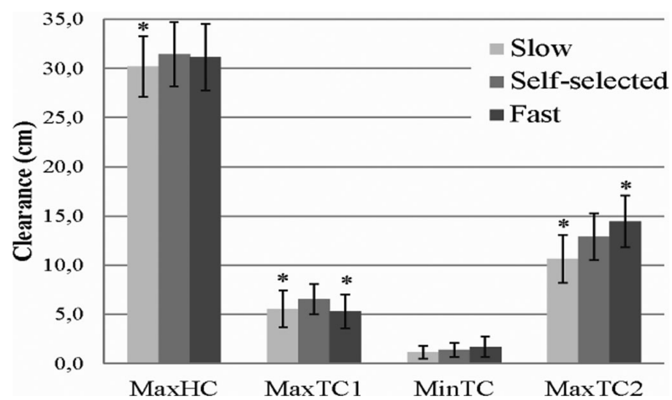

Fig. 4. Foot-clearance parameters at slow, self-selected, and fast walking speed. *Significant differences with self-selected speed ($p < 0.01$).

performances with a minimal random error below 10%, whereas this random error was between 30% and 40% for MaxTC1 and MinTC, due to the small quantity being measured. The intrinsic variations of the heel and toe clearance reference estimation were evaluated by the difference obtained between the markers placed on the internal and external side of the shoe (REF, ext/in in Table I). Those intrinsic variations were 4.0 ± 5.4 mm for MinTC and 10.5 ±10.6 mm for MaxHC.

Results were comparable among the different solving approaches (see Table I). Regarding the precision in particular, which can be interpreted as the random error, slightly better results were obtained with the LS criteria for MaxHC, MinTC, and MaxTC1 on the 3-D model. Only MaxTC1 showed a better precision with the PC approach (14.1 mm) compared to the LS approach (14.5 mm). Results obtained with the 2-D model showed lower performances in terms of precision than with the 3-D model, except for MaxTC2. Therefore, in the following, only the 3-D model with the LS approach (3-D_LS) was used for further analysis.

Fig. 3 shows the Bland–Altman plot for all parameters obtained with 3-D_LS against the reference and the limit of the 95% confidence interval (±1.96 SD) around perfect agreement. We can observe systematic biases in accordance with the accuracy measures of Table I. Moreover, Fig. 3 shows that the differences between the reference and the proposed system increase as the average of MaxTC1 increases, whereas opposite tendency is observed for MaxTC2.

B. Influence of Walking Speed on Foot-Clearance Parameters

Table II provide the values of speed and foot-clearance parameters for instructed walking speed. The walking speed of subjects was significantly different ($p < 0.01$) between slow (0.83 ± 0.14 m/s), fast (1.46 ± 0.35 m/s) and normal (i.e., self-selected) speed (1.18 ± 0.26 m/s). The variation of the different foot-clearance parameters with speed was investigated through the mean and STD value of each parameter (see Table II).

The influence of speed on the error for estimating foot-clearance parameters was found to be significantly higher at a slow speed for MaxHC and MaxTC2, whereas it was significantly lower at a fast speed for MaxHC and MaxTC1. The estimation of MinTC, however, was not affected by changes in walking speed ($p > 0.05$). Overall, the mean error was found to be smaller for all parameters at fastest walking speeds, while the STD error was smaller at self-selected speed for MaxTC1 and MinTC, and at slow speed for MaxHC and MaxTC2 (see Table II). Those changes can be interpreted by a higher signal-to-noise ratio compensated by a lower accuracy of the temporal detection at higher speeds.

In Fig. 4, significant changes in clearance parameters were observed for MaxTC2, which was increasing with speed. MaxTC1 was higher at normal speed, and MaxHC was smaller at slow speed. Although a tendency for an increased MinTC with speed was observed, this was not statistically significant. We observed

MinTC ranging from 1.1 cm at slow speed to 1.4 cm at self-selected and 1.7 cm at fast speed.

IV. Discussion

The primary aim of the study was to propose a wearable and wireless system with a model to obtain relevant parameters characterizing foot clearance. To our knowledge, this is the first study that used wireless inertial sensors and shows their technical validity against a reference system for estimating foot-clearance parameters. The method considers both temporal detection and kinematics estimation with models based on biomechanics of foot movements.

Overall results show a good agreement between both the 3-D and 2-D based model and the reference, and allow observing different foot clearance patterns changes with velocity in a group of healthy subjects. Those tendencies were similar to the ones observed with the reference system, showing face validity. In addition, our method for foot-clearance parameters estimation showed a better accuracy and precision than previous studies using inertial-based systems [14], [16]. Previous studies on foot clearance have shown that MinTC values in older people were similar to those found in younger people and ranges between 1.1 and 1.5 cm [4], which is congruent with the results we obtained. However, intraindividual or intercycle variability in MinTC was shown to be significantly increased in older people compared to younger [4]–[6]. Results for MinTC showed a random error of 9 mm (34.5%) compared to the reference Mocap, which showed itself a difference of ±5.4 mm (16.7%) between the internal and external marker. So, our system seems to be acceptable to observe changes of minimal toe clearance. Nevertheless, that requires further confirmation in a clinical setting. No bibliographic data were found for the other foot-clearance parameters obtained in this study. But interestingly, they show a better precision below 10% (see Table I).

This study establishes a proof of concept that the proposed methods can quantitatively assess heel and toe clearance characteristics during gait, with no relevant difference of performance. Nevertheless, we could expect that the 3-D model would perform better than the 2-D model in case of turning, which should be further evaluated with an adequate protocol. Since the full trajectory of heel and toe was obtained with the proposed method, other foot clearance-related parameters could have been investigated such as the time duration where toe clearance is below a certain threshold, or the foot velocity at minimal toe clearance as an important factor in tripping and fall risk. Using longer gait trials, and since the system assesses foot clearance at each gait cycle, it could also be used to assess the intercycle variability of foot-clearance parameters. All together, we believe that the presented method has a very promising potential for further investigations of foot clearance.

The proposed algorithm assumes a heel-strike at the initial contact and a toe-off at the terminal contact, as in normal gait and even in many type of abnormal gait [17], [18]. However, in specific diseases where this assumption is not valid, the algorithm needs adaptation. Moreover, important factors and potential sources of errors have to be carefully considered for the successful implementation of the proposed method. First, the error of sensors calibration can be improved by using more efficient sensors. Second, the double integration of gravity-free acceleration signals produces some drift which was minimized in this study by periodical updates of the signal at motion-less period (foot-flat), which validity has been recently evaluated [19]. Third, an additional source of error using our model was the time detection of the heel-strike and toe-off events. While Mariani *et al.* [20] proposed a validated inertial sensors-based time detection algorithm, other sensors such as pressure insoles could be used to increase the accuracy [21], [22], with the drawback of having more sensors. Fourth, the location of the sensor was prone to error since it was automatically estimated during gait. In the PC approach, this location estimation does not require multiple gait cycles. Nevertheless, we still observed a better robustness with solving approaches using the information of all cycles together (ME and LS). Finally, other sources of error comes from the manual placement of the markers on the shoe, and from our rigid single segment model of the foot, whereas its shape is modified during stance due to the shoe and soft tissue deformation and the rotation of metatarsal joint.

One of the main advantages of the proposed system is the possibility to perform gait analysis out of the laboratory and in natural conditions. The system being lightweight and wireless, it is easy to use and attach on feet. Gait parameters are automatically computed in a few seconds by the proposed algorithm after data transfer to the computer. All participants reported that the wireless system was convenient to wear and did not disturb their walking. Our method offers new applications for the clinical assessment of mobility associated with different pathologies or conditions, such as frailty in elderly persons [9], or neurorehabilitation studies focused on foot clearance alteration with obstacle avoidance [23], without requiring complex system such as optical motion capture. The proposed system has been consequently used for gait evaluation on a cohort of more than 1800 elderly persons, and results will be further analyzed.

V. Conclusion

New methods have been proposed and described for estimating heel and toe clearance using foot-worn wireless inertial sensors. The position of the sensor on foot was automatically estimated and foot-clearance parameters were extracted and validated against a reference motion capture system. This study provides new insight into foot clearance signature at different walking speeds in a healthy population. The results prove that small distances can be estimated with inertial sensors with adequate models and hypothesis. The proposed system adds new relevant features for the spatiotemporal gait analysis and offers a promising tool for the routine clinical assessment of walking outside a laboratory.

Acknowledgment

The authors would like to express their gratitude to Ms. C.-L. Hoskovec, Mr. P. Morel, and Mr. J. Gramiger for their help and assistance in measurements.

References

[1] W. P. Berg, H. M. Alessio, E. M. Mills, and C. Tong, "Circumstances and consequences of falls in independent community-dwelling older adults," *Age Ageing*, vol. 26, no. 4, pp. 261–268, Jul. 1997.

[2] J. H. van Dieën, M. Pijnappels, and M. F. Bobbert, "Age-related intrinsic limitations in preventing a trip and regaining balance after a trip," *Safety Sci.*, vol. 43, no. 7, pp. 437–453, Aug. 2005.

[3] D. A. Winter, "Foot trajectory in human gait: A precise and multifactorial motor control task," *Phys. Therapy*, vol. 72, no. 1, pp. 45–53, Jan. 1992.

[4] R. Begg, R. Best, L. Dell'Oro, and S. Taylor, "Minimum foot clearance during walking: Strategies for the minimisation of trip-related falls," *Gait Posture*, vol. 25, no. 2, pp. 191–198, Feb. 2007.

[5] R. S. Barrett, P. M. Mills, and R. K. Begg, "A systematic review of the effect of ageing and falls history on minimum foot clearance characteristics during level walking," *Gait Posture*, vol. 32, no. 4, pp. 429–435, Oct. 2010.

[6] D. T. H. Lai, R. K. Begg, S. Taylor, and M. Palaniswami, "Detection of tripping gait patterns in the elderly using autoregressive features and support vector machines," *J. Biomech.*, vol. 41, no. 8, pp. 1762–1772, Jan. 2008.

[7] U. Lindemann, B. Najafi, W. Zijlstra, K. Hauer, R. Muche, C. Becker, and K. Aminian, "Distance to achieve steady state walking speed in frail elderly persons," *Gait Posture*, vol. 27, no. 1, pp. 91–96, 2008.

[8] R. T. Harbourne and N. Stergiou, "Movement variability and the use of nonlinear tools: Principles to guide physical therapist practice," *Phys. Therapy*, vol. 89, no. 3, pp. 267–282, Mar. 2009.

[9] W. Zijlstra and K. Aminian, "Mobility assessment in older people: New possibilities and challenges," *Eur. J. Ageing*, vol. 4, no. 1, pp. 3–12, Feb. 2007.

[10] K. Aminian and B. Najafi, "Capturing human motion using body-fixed sensors: Outdoor measurement and clinical applications," *Comput. Animation Virtual Worlds*, vol. 15, no. 2, pp. 79–94, May 2004.

[11] A. M. Sabatini, C. Martelloni, S. Scapellato, and F. Cavallo, "Assessment of walking features from foot inertial sensing," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 3, pp. 486–494, Mar. 2005.

[12] S. J. M. Bamberg, A. Y. Benbasat, D. M. Scarborough, D. E. Krebs, and J. A. Paradiso, "Gait analysis using a shoe-integrated wireless sensor system," *IEEE Trans. Inf. Technol. Biomed.*, vol. 12, no. 4, pp. 413–423, Jul. 2008.

[13] H. M. Schepers, H. F. J. M. Koopman, and P. H. Veltink, "Ambulatory assessment of ankle and foot dynamics," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 895–902, May 2007.

[14] B. Mariani, C. Hoskovec, S. Rochat, C. Büla, J. Penders, and K. Aminian, "3D gait assessment in young and elderly subjects using foot-worn inertial sensors," *J. Biomech.*, vol. 43, no. 15, pp. 2999–3006, Nov. 2010.

[15] A. Kerr, D. Rafferty, P. Dall, P. Smit, and P. Barrie, "Using an optical proximity sensor to measure foot clearance during gait: Agreement with motion analysis," *J. Med. Devices*, vol. 4, no. 3, pp. 031004-1–031004-9, 2010.

[16] D. T. H. Lai, R. Begg, E. Charry, M. Palaniswami, and K. Hill, "Measuring toe clearance using a wireless inertial sensing device," in *Proc. Int. Conf. Intell. Sensors, Sensor Netw. Inf. Process.*, Dec. 2008, pp. 375–380.

[17] L. Allet, S. Armand, R. A. de Bie, A. Golay, D. Monnin, K. Aminian, J. B. Staal, and E. D. de Bruin, "The gait and balance of patients with diabetes can be improved: A randomised controlled trial," *Diabetologia*, vol. 53, no. 3, pp. 458–466, Nov. 2009.

[18] A. Salarian, H. Russmann, F. J. G. Vingerhoets, C. Dehollain, Y. Blanc, P. R. Burkhard, and K. Aminian, "Gait assessment in Parkinson's disease: Toward an ambulatory system for long-term monitoring," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 8, pp. 1434–1443, Aug. 2004.

[19] I. Skog, J.-O. Nilsson, and P. Handel, "Evaluation of zero-velocity detectors for foot-mounted inertial navigation systems," in *Proc. Int. Conf. Indoor Positioning Indoor Navig.*, Sep. 2010, pp. 1–6.

[20] B. Mariani, H. Rouhani, X. Crevoisier, and K. Aminian, "Quantitative estimation of foot-flat and stance phase of gait using foot-worn inertial sensors," to be published.

[21] C. M. Senanayake and S. M. N. A. Senanayake, "Evaluation of gait parameters for gait phase detection during walking," in *Proc. IEEE Conf. Multisensor Fusion Integ. Intell. Syst.*, Sep. 2010, pp. 127–132.

[22] S. Barnett, J. L. Cunningham, and S. West, "A comparison of vertical force and temporal parameters produced by an in-shoe pressure measuring system and a force platform," *Clin. Biomech. (Bristol, Avon)*, vol. 16, no. 4, pp. 353–357, May 2001.

[23] B. Galna, A. T. Murphy, and M. E. Morris, "Obstacle crossing in people with Parkinson's disease: Foot clearance and spatiotemporal deficits," *Human Mov. Sci.*, vol. 29, no. 5, pp. 843–852, Oct. 2010.