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An algorithm for real time minimum toe clearance estimation from signal of in-shoe motion sensor

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Abstract— **An algorithm has been constructed for estimating minimum toe clearance (MTC), an important gait parameter previously proven to be a critical indicator of tripping risk. It uses data from a previously reported in-shoe motion sensor (IMS) for detecting gait events. First, candidate feature points in the IMS signal for use in detecting MTC events were identified. Then, the temporal agreement between each feature point and target MTC event was evaluated. Next, the accuracy and precision of the MTC estimated using each feature point was evaluated using a reference value obtained using a 3-D optical motion-capture system. The MTC was estimated using a geometric model and the IMS signal corresponding to the predicted MTC event. Once the best candidate feature point was identified, a real-time MTC estimation algorithm for use with an IMS was constructed. The mean values and standard deviations of measured foot motions obtained in a previous study were used for evaluating accuracy and precision. The results suggest that MTC events can be estimated by detecting the crossing point between the acceleration waveforms in the anterior-posterior and superior-inferior directions in an accuracy of 2.0% gait cycle. Using this feature point enables the MTC to be estimated in real time with an accuracy of 8.6 mm, which will enable monitoring of MTC in daily living.**

I. INTRODUCTION

Tripping is a major cause of falls in the elderly [1], and minimum toe clearance (MTC) has been proven to be a critical indicator of tripping risk [2–3]. The MTC event is important during the swing phase because it is the point at which a trip is most likely to occur [4]. At the moment of the MTC event, the toe-ground clearance is at a minimum, typically 10–30 mm. Accurate MTC measurements have only been possible using optical 3D motion capture inside the laboratory [5]; however, to reduce the risk of falling during everyday walking, there is an urgent need for monitoring the MTC in daily life.

A recent approach to addressing this need is the mounting of motion sensors in footwear. Such an "in-shoe motion sensor (IMS) system" uses a single inertial measurement unit (IMU) to acquire acceleration and angular velocity at the foot. Its usability has made it feasible to provide stable and precise gait measurement in daily life [6–7]. There are several methods for estimating MTC by using an IMU mounted on the foot. For example, Santhiranayagam et al. proposed a machine learning method using hill-climbing feature selection based on the signal from a toe-mounted IMU [8]. However, such a machine learning approach requires complicated preprocessing and lengthy calculation. Mariani et al. suggested an MTC estimation method in which the complete toe trajectory is geometrically predicted on the basis of data from an instep-mounted IMU [9]. However, this method is not practical for real-time estimation of the MTC because the measured data need to be transferred to a PC for processing before being used for MTC calculation.

We speculated that if the MTC event in a stride could be detected, it would not be necessary to predict the entire toe trajectory and then search for the MTC. It should be possible to estimate the MTC from the geometric relationship between the foot and the ground at the moment of the MTC event. This would make MTC estimation practical in real time.

We previously demonstrated that it is possible to detect the heal-strike (HS) and toe-off (TO) gait events from an IMS signal by using a simple peak detection method [10]. By the hint from the results obtained in that study, we investigated whether there is an easily detectable feature point, such as a peak, valley, or crossing point, that can be used for detecting MTC events precisely. We first searched for a feature point useful for MTC event detection and then evaluated the temporal agreement between the feature point and MTC events. Next, we evaluated the accuracy and precision of the estimated MTCs using candidate feature points on the basis of a reference value measured with a 3-D optical motion-capture system. The MTCs were calculated using a geometric model and the IMS signal at the predicted MTC event. Finally, we constructed an MTC estimation algorithm based on the best candidate feature point. In this study, we used the same datasets collected in our previous study.

II. MATERIAL AND METHODS

A. Participants

We recruited 26 participants (20 male and 6 female) for whom we collected data on their gender, age, height, weight, and shoe size. The average age was 39.3 ± 9.5 years, the average height was 169.5 ± 7.7 cm, the average weight was 67.2 ± 12.1 kg, and the average shoe size was 26.4 ± 1.0 cm. All participants could walk independently without an assistance device such as a cane, crutches, or orthotic device. They had normal or corrected-to-normal vision, no history of neuromuscular or orthopaedic disease, and no obstacles to communication. The experimental procedure was explained to all participants, and informed consent was obtained individually before the experiment. The experimental

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procedures involving human participants described in this paper were approved by the NEC Ethics Committee.

B. Experiment setup and protocol

We used the MATLAB software (Mathworks, USA) for the data processing and simulation. Fig. 1 shows the experimental scheme and shoe setup. An IMS was mounted in the insole of the shoe on the right foot, beneath the foot arch to ensure that the participants could walk naturally. Sports shoes of the appropriate size were attached tightly on the participants' feet. The data measured by the IMS were transferred to a smartphone interface and stored. The acceleration and angular velocity for three axes were directly measured: acceleration A_x (medial: +, lateral: −), A_y (posterior: +, anterior: −), and A_z (superior: +, inferior: −); angular velocity G_x (plantarflexion: +, dorsalflexion: −), G_y (eversion: +, inversion: −), and G_z (abduction: +, adduction: −). The sole-to-ground angle (SGA) roll (E_x), pitch (E_y), and yaw (E_z) of the foot for the three axes were calculated internally using a Madgwick filter [11]. The definitions of the directions are the same as those for angular velocity. The acceleration values were then corrected to the global coordinates.

Motion data obtained using a 3-D motion analysis system with ten cameras (System: Track 3, Cameras: Bonita B10, Vicon Motion Systems, UK) was used for reference. The cameras were set on both sides of an 8-m straight walking path at a height of 2.5 m from the ground, five cameras on each side.

Optical reflection markers were attached to the surface of each shoe. An example right shoe is shown in Fig. 1; one marker was located at the toe, and the others were at the midfoot and hindfoot; the markers on the other shoe were symmetrically attached. The markers at the midfoot and hindfoot were combined as a rigid body, with the gravity centre set on the marker at the heel. The foot motion could thus be represented by the motion of a rigid body. The trajectory of the rigid body was equivalent to that of the heel, which could be used to clarify the moment of an HS. The traced trajectories of the toe marker were used to clarify the movement of the toe and the moment of a TO (T_{TO}) event at the minimum of the trajectory. All participants walked along the path at a self-determined comfortable speed in four successive trials. Their gait data were captured by both the IMS and motion analysis system. The data sampling frequency was set to 100 Hz. The acceleration measurement range was ±16 g, and the angular velocity range was ±2000 degree/s in the IMS.

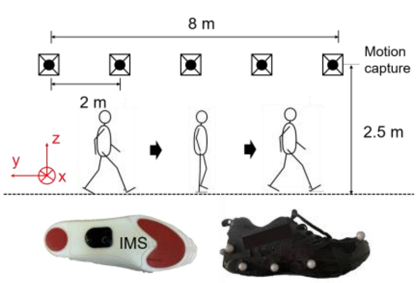

Fig. 1. Experimental scheme and shoe setup.

C. Finding IMS signal features for MTC event detection

By the hints of our previous study [10], we investigated whether there is an easily detectable feature point in real-time algorithm, such as a peak, valley, or crossing point, that can be used for detecting MTC events precisely. To determine whether there is a signal feature that can be used for reliably detecting MTC events, we first synchronized the IMS signals with the Vicon optical motion-capture system signal for each walking trial offline by using E_x obtained from both systems. Fig. 2 shows the synchronized toe and heel trajectory in the Z direction and acceleration A_y and A_z (2(a)) and angular velocity G_x (2 (b)) waveforms during approximately one gait cycle (GC). The MTC event in the reference data is at the local minimum after TO on the toe trajectory (T_{MTC}). Feature points F_y, F_{yz}, F_z, and F_{gx} can be considered candidates, where F_y is the zero-crossing point from TO to HS in A_y, i.e. the peak velocity in the anterior direction; F_z is the first zero-crossing point after TO in A_z; F_{yz} is an A_y and A_z crossing point prior to F_z; and F_{gx} is the minimum of G_x. The one that has the highest synchronicity with T_{MTC}, which is judge by the highest temporal accuracy, A_T and lowest precision, P_T values calculated by (1) and (2), is the most optimal point for MTC event detection, F_q

$$A_T = \Sigma^W{}_{w=0}(F_{a\_w} - T_{MTC\_w})/W \tag{1}$$

$$P_T = \{\Sigma^W{}_{w=0}[(F_{a\_w} - T_{MTC\_w}) - A_T]^2/W\}^{1/2} \tag{2}$$

where W means the total number of the dataset, the index "$\_w$" means the wth data in the dataset and the index "F_a" was used to represent arbitrary listed aforementioned feature points indexes.

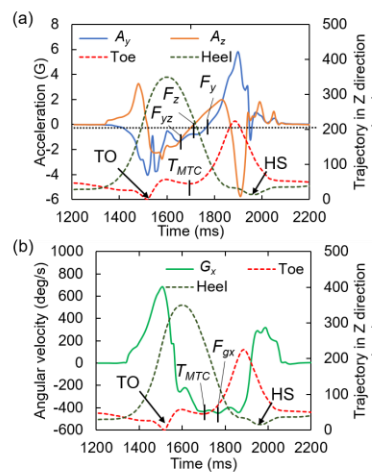

Fig. 2 Synchronized toe and heel trajectory in Z direction (a) with A_y, A_z; (b) with G_x.

D. Geometric MTC prediction model

The method for calculating MTC from the measured trajectory of an IMS mounted beneath the foot arch is shown schematically in Fig. 3. The trajectory of the marker on the toe is treated as reference data. The distance from the marker on the toe to the ground is set to zero at T_{TO}. Therefore, the true MTC (H_{MTC}) can be expressed as

$$H_{MTC} = H'_{MTC} - H_{toe}, \tag{3}$$

where H_{toe} and H'_{MTC} are the marker's measured heights at T_{TO} and T_{MTC}, respectively. Due to the thickness of the sole and the structure of the shoe, the IMS was located at a height of d (12 mm in this study) from the ground, and the marker on the toe was located at a height of M from the ground. Both are shoerelated parameters, so the estimated MTC (H^1_{MTC}) is located on a different plane than H_{MTC}; thus, when evaluating prediction accuracy, H_{MTC} must be converted into H^0_{MTC} by using offset N relevant to M and d. Precision can then be evaluated by comparing H^1_{MTC} with H^0_{MTC}.

$$H^0_{MTC} = H_{MTC} - N = H_{MTC} - (M - d) \times \cos E_x(T_{MTC}), \quad (4)$$

where $E_x(T_{MTC})$ is E_x at T_{MTC}. To obtain the height at T_{MTC} in the vertical trajectory of IMS (T), the data streams are split between strides by detecting the foot-flat points. The trajectory is then calculated by applying the zero velocity update (ZUPT) algorithm [12]. The synchronized Vicon motion-capture system data streams are also split at the foot-flat points. After that, H^1_{MTC} can be obtained from the geometric relationships shown in Fig. 3 by using

$$H^1_{MTC} = Z_S'(T_{MTC}) + d - L_{MTC}, \quad (5)$$

where $Z_S'(T_{MTC})$ is the IMS measured height at T_{TO}, and Z_S' is the Z direction trajectory Z_S corrected using the ZUPT algorithm. L_{MTC} is the perpendicular distance from the IMS to the distal end of the toe at T_{MTC}:

$$L_{MTC} = L_1 \times \sin E_x(T_{MTC}). \quad (6)$$

L_1 is the distance from the IMU in the IMS to the distal end of the toe. Its value is unknown. It could be manually measured after mounting the sensor in the shoe, but doing so would be practically cumbersome and could lead to imprecision. Instead, L_1 can be automatically calculated independent of sensor mounting by using the data captured at TO:

$$L_1 = [Z_s'(T_{TO}) + d] \;/\; \sin E_x(T_{TO}), \quad (7)$$

where $Z_s'(T_{TO})$ and $E_x(T_{TO})$ are the height and the E_x at T_{TO}, respectively. Then, H^1_{MTC} can be expressed by

$$H^1_{MTC} = Z_S'(T_{MTC}) + d - [Z_s'(T_{TO}) + d] \;/\; \sin E_x(T_{TO}) \times \sin E_x(T_{MTC}), \quad (8)$$

where all the parameters can be determined on the basis of the shoes and the measured values at T_{TO} and T_{MTC}. If we ignore the effect of the thickness of the sole (i.e. d is assumed to be 0), H^1_{MTC} can be expressed by

$$H^1_{MTC} = Z_S'(T_{MTC}) - Z_s'(T_{TO}) / \sin E_x(T_{TO}) \times \sin E_x(T_{MTC}). \quad (9)$$

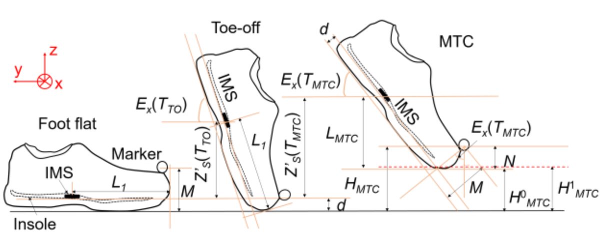

Fig. 3 Geometric MTC prediction model for IMS mounted beneath foot arch.

And therefore, the accuracy and precision of proposed algorithm for MTC estimation A_{MTC} and P_{MTC} can be expressed as,

$$A_{MTC} = \Sigma^W_{w=0}(H^1_{MTC\_w} - H^0_{MTC\_w})/W \quad (10)$$

$$P_{MTC} = \{\Sigma^W_{w=0}[(H^1_{MTC\_w} - H^0_{MTC\_w}) - A_{MTC}]^2/W\}^{1/2} \quad (11)$$

E. Algorithm for real time MTC estimation

From the results for MTC estimation that will be shown in Section III, F_q is F_{yz} and we determined that the key point of the algorithm for real time MTC estimation is to how to detect F_{yz} in real time. By observing A_y and A_z, we found that, in one gait cycle, there were many crossing points on A_y and A_z whereas F_{yz} was the nearest crossing point prior to F_z. Therefore, we constructed the algorithm as shown in Fig. 4. The real-time data stream (A_y^i, A_z^i, and E_x^i) is temporarily stored in a buffer of size N, $Buf[N]$, where i is the number in the data stream; N was set to 256 to ensure that data points over two strides could be stored, with the data for one stride being split from the total data stored. The stride split algorithm splits the data for one stride (A_y, A_z, and E_x) from the foot-flat point in the first stride ($K1$) to the one in the second stride ($K2$), which are labelled in the figure as A_{yS}, A_{zS}, and E_{xS}. A_{yS} is used for TO event detection by using the feature point proposed in our previous study [10]. E_{xS} is directly input into the MTC estimation model. A_{zS} is used to calculate Z'_S and to detect, along with A_{yS}, the MTC event. The T_{MTC} in each stride is detected by sweeping A_{yS} and A_{zS} along the temporal axis, detecting the time stamps of their crossing points in order, and temporarily recording the latest one as T_{MTC}. The appearance of F_z is monitored as well. Once F_z is detected, the sweeping is terminated, and the final recorded time stamp of the crossing point of A_{yS} and A_{zS} is taken as T_{MTC}. In the flow of MTC event detection algorithm, k means the number of data points between $K1$ and $K2$.

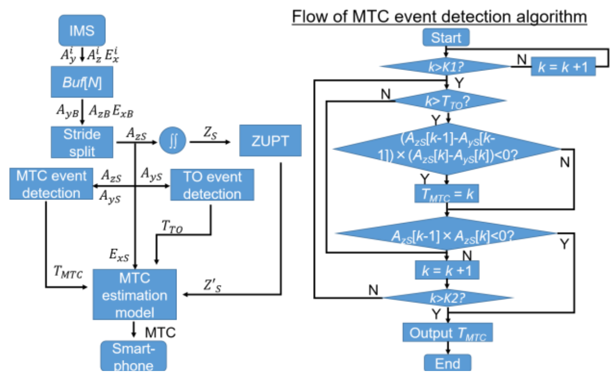

Fig. 4 MTC estimation algorithm based on F_{yz} detection.

III. Results

A. Candidates for MTC event detection

The accuracy and precision of synchronicity for the candidate points and T_{MTC} are summarized in Table I. The positive and negative values mean after and before, respectively. The MTC event occurred at 15.2 ± 2.2%GC after T_{TO} as measured using the Vicon motion-capture system. Candidate F_{yz} had the best synchronicity as it was only 1.5%GC before the reference MTC event with a precision of 2.0%GC. Although candidates F_y and F_z had precision almost the same as that of F_{yz}, they were 8.0%GC and 2.9%GC after the reference MTC event.

TABLE I. ACCURACY AND PRECISION OF SYNCHRONICITY FOR CANDIDATE POINTS AND T_{MTC}

Candi-date	Moment of MTC event (%GC)		Synchronicity (%GC)	
	Vicon system	*IMS*	A_T	P_T
F_y	15.2 ± 2.2	23.2 ± 1.7	8.0	2.3
F_{yz}		13.7 ± 1.9	−1.5	2.0
F_z		18.1 ± 1.6	2.9	2.1
F_{gx}		22.6 ± 6.3	7.4	5.2

B. Results of MTC estimation using different candidates

We took F_y, F_{yz}, and F_z as the primary candidates for MTC estimation. For each one, the corresponding MTC event was determined by extracting the corresponding temporal offset ("Accuracy" column in Table I). The results are summarized in Table II. Feature point (F_{yz} + 1.5%GC) achieved the most robust MTC estimation: a −0.3 mm difference with a precision of 8.6 mm between the true and estimated value while the precisions of the other two feature points were 9.3 and 8.8 mm. A Bland–Altman plot of the Vicon system and IMS measured MTC for the best feature point with a 95% confidence interval (CI, ±1.96 SD) around perfect agreement is shown in Fig. 5. The difference between the two systems slightly increased with the average MTC. The dotted line represents the mean value, and the two dashed lines represent the upper and lower limits of the confidence interval.

TABLE II. MTC ESTIMATIONS COMPARED WITH REFERENCE VALUE

Feature point	MTC (mm)		A_{MTC} (mm)	P_{MTC} (mm)
	Vicon system	*IMS*		
F_y – 8.0%GC	22.4 ± 6.6	22.3 ± 11.2	−0.1	9.3
F_{yz} + 1.5%GC		26.5 ± 10.1	−0.3	8.6
F_z – 2.9%GC		26.5 ± 10.7	0.4	8.8

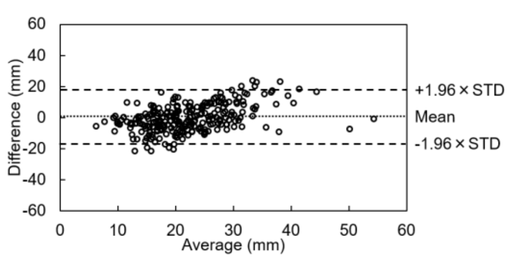

Fig. 5 Bland–Altman plot comparing agreement of Vicon and IMS measured MTC using best feature point (F_{yz} + 1.5%GC).

IV. DISCUSSION AND CONCLUSION

Using results obtained in a previous study, we have constructed an online algorithm for estimating minimum toe clearance (MTC) that uses data on gait event detection obtained from an in-shoe motion sensor. The predicted MTC had a precision of 8.6 mm, slightly improved than that obtained in a previous study [9]. The MTC event was synchronized with the moment of the acceleration vector was 45 degree with both the vectors in the anterior and inferior directions. This finding differs from that of De Asha et al., who suggested that MTC was synchronized with the peak velocity in the anterior direction (F_y) [13]. We found that F_y was 8.0 ± 2.2 %GC after MTC. We also found that F_{yz} occurred around 13.7%GC after TO. According to the gait phase defined by Neumann [14], this feature point can also be used for identifying the feet adjacent event, i.e. the start of the mid-swing phase.

Begg et al. [3] demonstrated that a histogram of the skewness of MTC in multiple strides can be used for predicting falls if the estimation precision is at least 5 mm. Our future work includes improving the algorithm to achieve higher precision. It also includes testing the applicability of the algorithm to elderly people and people with neuromuscular or orthopaedic disease in a clinical setting.

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