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Research article

A novel wearable biofeedback system to prevent trip-related falls

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A R T I C L E I N F O

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A B S T R A C T

Real-time gait monitoring of older adults and gait-impaired individuals while providing real-time biofeedback has the potential to help reduce trip-related falls. A low or unsuccessful Minimum Toe Clearance (MTC) is considered a predictor of tripping risk. Thus, increasing the MTC can be a key component in minimizing the likelihood of tripping. This paper discusses a proof-of-concept wearable system that estimates the MTC in real-time using two Time-of-Flight (ToF) sensors and provides auditory biofeedback to alert users if they have a low MTC during everyday walking activities. Ten healthy female adults were asked to perform two experiments: 1) walk at a predetermined speed to evaluate the proposed real-time MTC detection algorithm, and 2) walk in four conditions: baseline, biofeedback with no distraction, biofeedback with distraction 1 (talking on the phone), and biofeedback with distraction 2 (playing a simple mobile game). The average MTC values were significantly greater during all feedback conditions than the baseline, indicating that the proposed system could successfully warn users to increase their MTC in real-time.

1. Introduction

FALLS are a significant concern to the healthcare system, contributing to 85% of injury hospitalizations among older Canadian adults aged 65 and older [1]. Falls can lead to severe injuries, hospitalizations, and gait limitations that negatively impact daily living activities, social relationships, and overall quality of life [2]. A study conducted by Blake et al. revealed that trip-related falls accounted for over 50% of the falls in older adults [3]. A trip can occur when an unexpected force or obstacle disrupts the swinging motion of the foot during walking, causing the body to swing forward suddenly and lose balance [4]. When an individual cannot recover from a loss of balance caused by a trip, it can result in a fall [4]. The Minimum Toe Clearance (MTC) has been suggested as a critical factor to consider for fall prevention [5]. The MTC is the smallest vertical distance between the toe and ground during the swing phase of the gait cycle [6]. At this gait event, the swinging foot moves at a high velocity, and the body weight is supported solely by the contralateral leg and foot [6].

When the MTC is low, it can lead to tripping and ultimately falls, especially when walking on uneven ground surfaces or coming in contact with unanticipated obstacles [7]. Older adults have been observed to have a low MTC due to reduced cognitive awareness, shorter step length, slower walking velocity, or decreased range of motion, which can lead to an increased risk of falling [8,9]. Individuals who experience gait abnormalities from musculoskeletal and neurological conditions such as stroke, Parkinson's disease, or

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Fig. 1. Design components of the proposed wearable biofeedback system, where **(a)** shows the ToF sensors attached to the running shoes, and **(b)** shows the box containing the microcontroller, piezo buzzer, batteries, and electronic components.

multiple sclerosis tend to reduce their MTC due to foot drop or shuffling gait [10]. Since low MTC can be used to predict tripping gait patterns, increasing the MTC while reducing its variability can provide a possible strategy to reduce the tripping risk in these populations [11,12].

Wearable sensors are widely-used as monitoring systems to provide measurements about an individual's vital signs or body movements without being confined to a research lab [13–16]. When wearable systems are used for gait analysis, realistic data is obtained because the experiments are conducted in real-life settings such as hospitals, patient's homes, or the community [13]. The most common wearable sensors for gait analysis include the accelerometer, gyroscope and force sensors, as they are inexpensive, lightweight, and relatively accurate [17]. A few studies have investigated the use of wearable systems to provide real-time gait monitoring for patients with gait impairments. Arens et al. proposed an exosuit that uses inertial sensors to provide real-time gait metrics such as circumduction, foot clearance, and stride length for post-stroke patients [18]. Lin et al. developed a smart insole integrated with an array of textile-based pressure sensors and inertial measurement units to measure the plantar pressure and gait parameters [19]. Tay et al. proposed a gait monitoring system for Parkinson's disease patients that tracks gait movements and body posture with an accelerometer, gyroscope, and compass while also providing voice biofeedback to guide users if the system detects abnormal gait movements [20].

In our previous paper [21], the accuracy of the proposed system was compared with other wearable systems that used different technologies to measure gait parameters. The results revealed that the proposed system had the lowest mean error compared to other systems after applying angle and offset compensation [21]. It was concluded that the proposed system can detect the foot clearance parameters with high accuracy, minimal hardware and simple calculations, making it a viable option to use for biofeedback purposes [21].

Although many wearable systems have been developed to monitor different gait parameters in real-time, to the best of our knowledge no study has investigated the use of Time-of-Flight (ToF) sensors and auditory biofeedback to monitor the MTC in real-time and provide alerts if the user's MTC is low. Therefore, the two objectives of our study include the following: 1) design a proof-of-concept wearable system that can detect the MTC in real-time using ToF sensors and provide auditory feedback to increase MTC height and 2) evaluate the effectiveness of the proposed system as a warning tool. The MTC data is compared pre- and post-feedback to evaluate whether the system effectively increased the MTC height in feedback conditions.

2. Materials and methods

2.1. System design

Fig. 1 (a) and (b) displays all the components used to develop the wearable biofeedback system. Two VL53L0X laser Time-of-Flight (ToF) sensors (SensorDots, Victoria, Australia) were secured on custom-made 3D printed mounts near the lateral toe and heel for both shoes (two sensors per foot), as shown in Fig. 1 (a). The ToF sensors were placed at least 50 mm from the ground to ensure that the entire distance range was captured during various foot motions. The system was battery-powered and used the Teensy 3.6 microcontroller (PJRC, Sherwood, OR, USA) with an SD card reader to control and store the sensor data at a sampling rate of 33Hz. Auditory biofeedback was delivered through a piezo buzzer (Adafruit Industries, New York, NY, USA) that produced beeps at 3 kHz. The electronic components were placed in a box on the participant's waist, as shown in Fig. 1 (b). Ribbon cables were used to connect the electronic components in the box with the ToF sensors on the shoe. The cables had a length of 2.7 m and were taped to the participant's leg during the experiment.

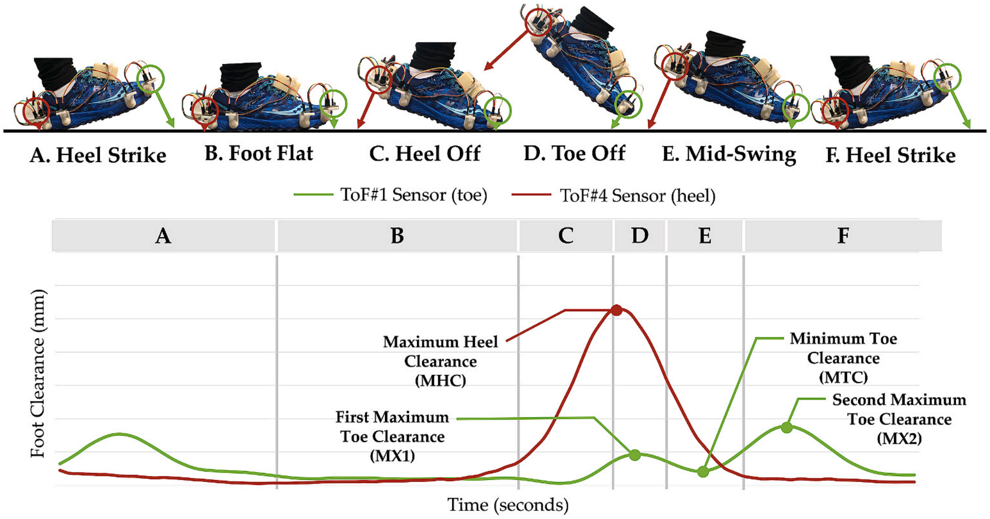


Fig. 2. An illustration of the key foot clearance parameters measured by the toe and heel sensors of the proposed system as the foot moves through the gait cycle. Sections A to F represent each phase of the gait cycle [21].

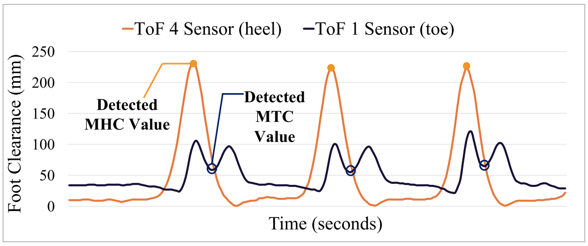


Fig. 3. An example of a typical foot clearance signal measured by the ToF 1 and ToF 4 sensors.

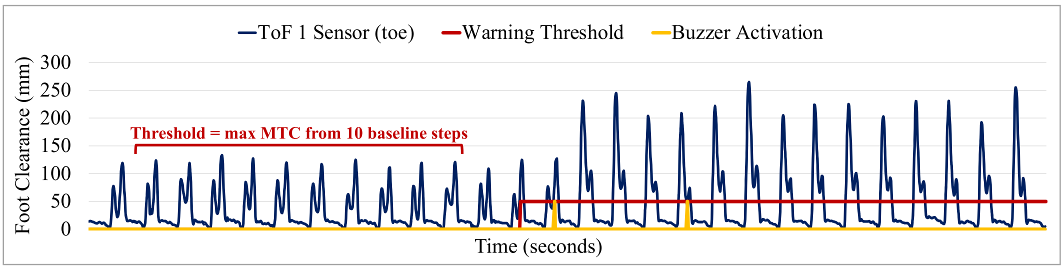


Fig. 4. Illustration of the biofeedback strategy used for the proposed warning system.

2.2. Real-time minimum toe clearance detection

The MTC was estimated in real-time using the distance measurements provided by the ToF sensors. Based on our recent study on offline data [21], ToF 1, located at the toe, can measure three foot clearance parameters: MTC, first Maximum Toe Clearance (MX1), and second Maximum Toe Clearance (MX2). ToF 4, located at the heel, can provide information about the Maximum Heel Clearance (MHC). Fig. 2 illustrates how the key foot clearance parameters are measured using the ToF sensors at the toe and heel [21]. The true foot-to-ground distance value is calculated using Arami's method [22] which is explained in more detail in our previous paper [21].

In this paper, we propose a real-time algorithm for detecting these gait parameters. For this purpose, the distance data was calibrated, filtered, and corrected in real-time to minimize the amount of noise being evaluated by the algorithm. The MHC was first detected by the algorithm since the MHC always occurs before the MTC in a non-pathological gait pattern, illustrated in Fig. 3. The MHC was detected by comparing the current distance value with the previous value and evaluating whether the slope between the two values was negative or positive. A threshold value of 15 mm was used to exclude small peaks resulted from the noise. Once the MHC was found, the algorithm searched for an intersection between ToF 4 and ToF 1 signals as we observed that the MTC usually occurred

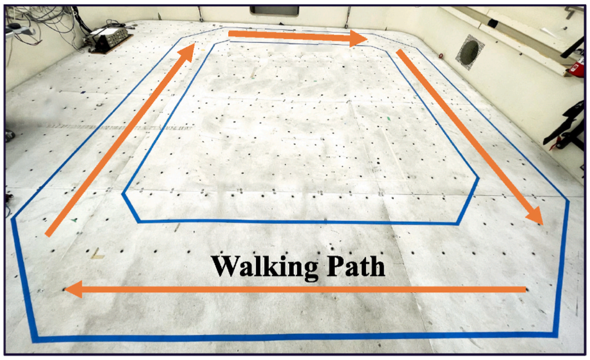


Fig. 5. The lab setup which illustrates the path walked on by the participants for both experiments.

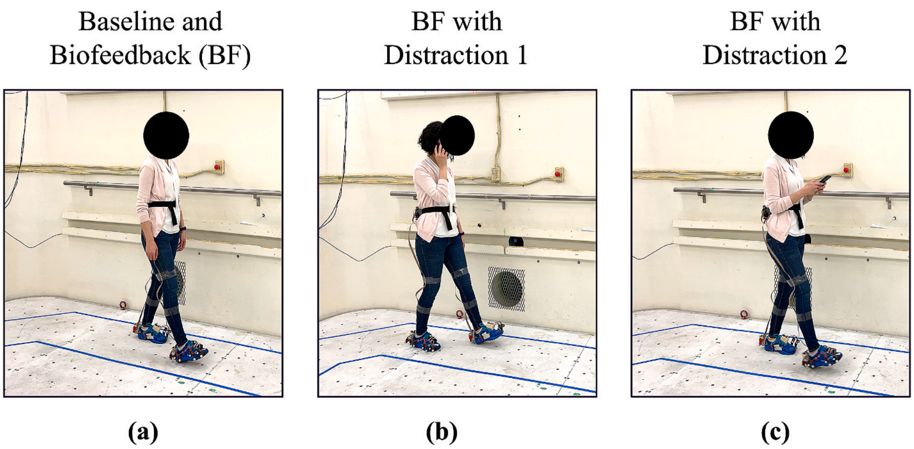


Fig. 6. A demonstration of the different conditions for Experiment 2: **(a)** baseline and biofeedback (BF), **(b)** biofeedback with distraction 1 (BF + D1), and **(c)** biofeedback with distraction 2 (BF + D2).

very close or at this intersection during the swing phase of the gait cycle. This intersection point happens when the foot changes its orientation from plantar flexion to dorsiflexion during mid-swing. The ToF 1 value at the intersection point was detected as the MTC. Fig. 3 shows an example of a typical foot clearance signal measured by ToF 1 and ToF 4.

2.3. Biofeedback strategy

The biofeedback strategy that was implemented to encourage participants to increase their MTC while walking is illustrated in Fig. 4. The participants were asked to walk at a normal speed with the metronome for ten steps to set the customized threshold value for the warning system. The initial ten baseline MTC values were calculated and the maximum MTC value was selected as a personalized threshold for the participant. Separate thresholds were calculated for the left and right feet. Auditory biofeedback was activated during each stride if the participant's MTC on either foot was lower than the personalized threshold of each foot. This encouraged the participants to raise their feet in their upcoming strides to increase their MTC and decrease the tripping risk. In Fig. 4, it can be observed that the buzzer activated two times, shown with the yellow line, to encourage the subjects to increase their foot clearance. The red line indicates the personalized threshold value of the participant.

2.4. Experimental protocol

The study involved ten (n = 10) healthy female participants aged 31.1 ± 12.1 years (mean ± SD), with an average height of 165.1 ± 7.5 cm and a weight of 60 ± 6.9 kg. The participants did not have gait-related impairments, musculoskeletal conditions, or neurological disorders. All participants reported that their dominant limb was their right foot.

The study consisted of two experiments and was conducted in the Challenging Environment Assessment Laboratory (CEAL) at the KITE Research Institute - Toronto Rehab (TRI) - University Health Network (UHN). The study was approved by the University Health Network Research Ethics Board and each participant provided informed written consent before taking part in the study. Participants were instrumented with the wearable biofeedback system and asked to perform both experiments. The walking trials for both

Table 1
Overall improvements in mean and median MTC values for baseline versus biofeedback condition.

	Normal Speed						Fast Speed					
	BF		BF + D1		BF + D2		BF		BF + D1		BF + D2	
	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right	Left	Right
Mean MTC Increase (%)	227	321	212	335	182	261	83	122	63	109	76	107
Median MTC Increase (%)	243	327	224	337	194	260	85	123	65	107	77	104

experiments took place at level ground on the path shown in Fig. 5 and were conducted at three predetermined walking speeds set by a metronome: 60 beats per minute (BPM) for slow walking, 90BPM for normal walking, and 120BPM for fast walking. In Experiment 1, participants walked at each predetermined speed for 3 min to evaluate the real-time MTC detection algorithm.

In Experiment 2, participants were asked to walk in four conditions: baseline, biofeedback (BF), biofeedback with distraction 1 (BF + D1), and biofeedback with distraction 2 (BF + D2). Fig. 6 (a) to (c) demonstrates how the baseline, BF + D1, and BF + D2 experiments were performed. Each condition was performed at normal and fast speeds and lasted 3 min each. The conditions were completed in the same order for all participants. The biofeedback threshold was calculated when walking at normal speed. For the BF + D1 condition, participants were asked to hold a cellphone to their ear to simulate a scenario of talking on the phone while walking. During this condition, the researcher asked the participant general questions to facilitate a conversation. While performing D1, participants were asked to respond to the biofeedback cues by maintaining a “raised foot” walking pattern at the metronome speed. For the BF + D2 condition, they were asked to play a simple game on the cellphone to simulate a scenario of being fully engaged and distracted on the phone while walking. D2 was considered to be more challenging than D1. Participants were not trained or given specific instructions on how to raise their feet prior to Experiment 2.

2.5. Data analysis

The ToF data was calibrated using the Least-Square (LS) method [23] to correct any possible offset introduced by the device. The signals were filtered in real-time using a moving average filter with a window size of 4 samples to reduce the noise before using the MTC detection algorithm. The foot angle was also compensated in real-time using Arami’s method [22] to obtain a more accurate distance value during MTC detection. The data was collected from both left and right feet. The total number of steps collected from all participants for all conditions for Experiment 2 were 4574 and 4011 for normal speed and 5142 and 5139 for fast speed, from the left and right foot, respectively. The first and last steps were excluded for each trial.

Statistical analyses were performed using the JMP Pro Software (Statistical Discovery, SAS, Cary, NC, USA). Since the MTC data was not normally distributed, a non-parametric analysis of variance (ANOVA) (Kruskal-Wallis test) was used. A two-way repeated measures ANOVA was performed for Experiment 2 with gait speed and condition (baseline, BF, BF + D1, BF + D2) as fixed factors. The Kruskal-Wallis non-parametric multiple comparisons test was used to determine specific statistical differences between pairs of means. Statistical significance was considered when $p < 0.05$.

3. Results

The overall improvements in the mean and median MTC values after using the biofeedback system at normal and fast speed are presented in Table 1. When providing feedback to the participants in the BF condition at normal speed, their mean MTC increased by 227% and 321% for the left and right foot, respectively, considering all ten subjects. The biofeedback condition had a significantly greater mean MTC than the baseline condition ($p < 0.0001$) at normal speed for both feet, demonstrating that the participants responded well to the feedback system due to their increased foot clearance. The mean MTC also increased from the baseline condition when distractions were added to the biofeedback, increasing 212% and 335% for BF + D1 and increasing 182% and 261% for BF + D2 for the left and right foot, respectively. It was observed that the mean MTC decreased as the distractions became more challenging and required more attention. When comparing the three biofeedback conditions (BF, BF + D1, and BF + D2) at normal speed, it was found that all three conditions were significantly different from each other ($p < 0.0001$) for the left foot. Similar results were found for the right foot, except for BF and BF + D1, which were not significantly different ($p = 0.0524$). In the fast speed scenario, all biofeedback conditions were significantly different from the baseline ($p < 0.0001$) for both feet. For the left foot, the three biofeedback conditions were significantly different from each other. The right foot had similar results, except that BF + D1 and BF + D2 were not significantly different ($p = 0.2542$). This demonstrates that users can respond very differently to the system when distracted and highlights the biofeedback system’s importance in warning the users to raise their MTC when distracted by environmental triggers.

Table 1 also demonstrates that the MTC values were more improved at normal speed than the fast speed. It is worth noting that the participants had a higher MTC during the fast speed baseline condition, which might be why the improvement for the fast speed was less than the normal speed. Another reason could be the participants’ greater control over their gait pattern at normal speed than fast speed. It is also interesting to note that the right foot had a consistently greater mean MTC than the left foot for all conditions, which could be because all participants reported that their right leg was their dominant limb.

Fig. 7 (a) and (b) illustrates the difference in MTC means between the normal and fast speeds for both feet. The baseline MTC was significantly higher for the fast speed compared to normal speed for both feet, emphasizing that participants tended to increase their

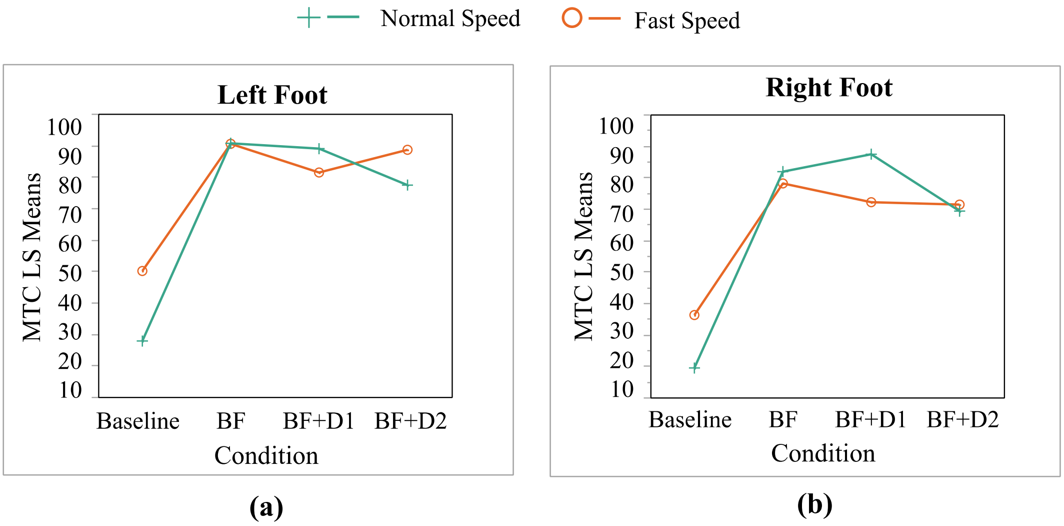


Fig. 7. Least squares (LS) means plot of the MTC at normal and fast speed for the baseline, BF, BF + D1, and BF + D2 conditions for **(a)** left foot and **(b)** right foot.

Table 2
Mean MTC ± standard deviation for each subject and condition at normal speed.

Sub#	Baseline		Biofeedback (BF)		BF + D1		BF + D2	
	Left Foot	Right Foot	Left Foot	Right Foot	Left Foot	Right Foot	Left Foot	Right Foot
1	17.09 ± 4.49	11.43 ± 3.61	51.22 ± 11.95	44.01 ± 10.69	40.95 ± 13.84	39.62 ± 9.45	39.93 ± 11.88	31.18 ± 10.92
2	31.75 ± 5.66	32.45 ± 6.39	102.19 ± 25.55	119.18 ± 24.24	82.11 ± 21.08	120.45 ± 24.72	85.26 ± 23.69	119.22 ± 26.06
3	20.32 ± 7.89	23.55 ± 5.43	134.57 ± 20.06	109.34 ± 18.95	170.89 ± 25.50	143.68 ± 25.45	125.45 ± 30.08	94.03 ± 22.78
4	28.02 ± 6.59	14.00 ± 4.58	103.62 ± 13.00	125.05 ± 17.65	118.87 ± 15.30	137.16 ± 21.56	84.26 ± 13.01	93.94 ± 17.39
5	33.91 ± 12.39	26.19 ± 7.21	101.32 ± 11.73	82.32 ± 11.47	98.67 ± 15.89	83.19 ± 9.91	80.93 ± 17.08	64.69 ± 13.91
6	30.81 ± 9.78	7.28 ± 3.02	60.98 ± 7.23	45.35 ± 7.10	58.12 ± 7.75	47.60 ± 6.64	67.81 ± 14.92	52.57 ± 12.65
7	23.36 ± 4.23	20.24 ± 5.41	90.67 ± 17.80	32.62 ± 10.92	72.25 ± 8.46	31.66 ± 9.37	76.24 ± 13.91	35.21 ± 9.16
8	13.85 ± 6.40	10.55 ± 4.28	76.77 ± 10.80	74.84 ± 10.57	74.80 ± 9.12	84.32 ± 11.20	74.16 ± 11.17	77.38 ± 14.64
9	41.62 ± 10.25	20.18 ± 4.48	83.09 ± 7.90	74.52 ± 11.48	80.51 ± 10.00	72.86 ± 11.35	82.82 ± 14.32	62.92 ± 18.20
10	33.58 ± 8.54	21.53 ± 5.93	91.66 ± 21.95	81.57 ± 24.90	59.71 ± 18.30	55.41 ± 19.39	57.86 ± 18.61	45.33 ± 18.48

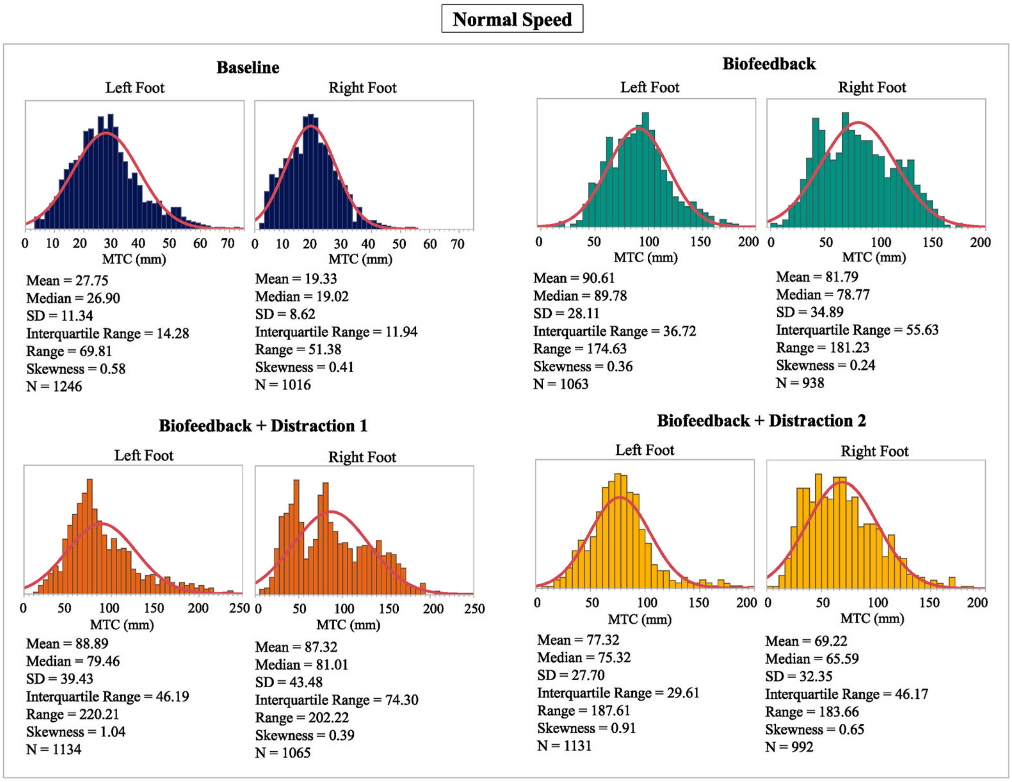
Table 3
Mean MTC ± standard deviation for each subject and condition at fast speed.

Sub #	Baseline		Biofeedback (BF)		BF + D1		BF + D2	
	Left Foot	Right Foot	Left Foot	Right Foot	Left Foot	Right Foot	Left Foot	Right Foot
1	32.92 ± 8.27	22.49 ± 4.41	49.94 ± 7.55	50.36 ± 11.30	52.75 ± 10.65	38.70 ± 8.58	63.34 ± 14.42	37.24 ± 9.84
2	41.96 ± 7.26	44.50 ± 8.31	98.52 ± 20.50	138.60 ± 30.14	83.97 ± 19.71	126.49 ± 23.80	96.84 ± 25.09	131.00 ± 31.90
3	52.12 ± 10.80	32.66 ± 8.70	131.09 ± 22.17	93.47 ± 19.72	123.97 ± 23.55	104.11 ± 21.72	125.46 ± 26.66	86.27 ± 19.61
4	74.31 ± 12.70	61.48 ± 13.36	117.72 ± 27.15	NA	101.91 ± 28.07	NA	108.54 ± 24.84	NA
5	68.30 ± 11.30	74.43 ± 11.93	96.93 ± 11.85	86.00 ± 12.12	98.52 ± 17.66	74.11 ± 12.29	76.97 ± 17.28	63.56 ± 14.46
6	50.75 ± 11.31	11.67 ± 4.82	70.78 ± 16.28	49.30 ± 14.37	71.40 ± 15.93	49.75 ± 13.75	63.50 ± 18.47	49.70 ± 13.75
7	42.97 ± 9.46	20.45 ± 5.33	86.75 ± 15.53	47.83 ± 18.97	58.66 ± 14.73	46.27 ± 20.62	102.42 ± 26.09	64.49 ± 21.38
8	38.19 ± 9.98	22.74 ± 5.28	89.35 ± 11.82	72.53 ± 12.06	83.43 ± 12.72	69.61 ± 12.94	88.01 ± 12.49	83.83 ± 20.23
9	54.27 ± 12.63	22.57 ± 5.08	99.13 ± 13.95	78.57 ± 10.59	73.89 ± 10.27	87.42 ± 14.08	85.33 ± 13.43	72.01 ± 15.95
10	40.94 ± 10.16	33.57 ± 6.27	70.30 ± 19.87	75.73 ± 22.77	63.04 ± 16.61	55.59 ± 15.80	63.34 ± 14.42	57.08 ± 19.91

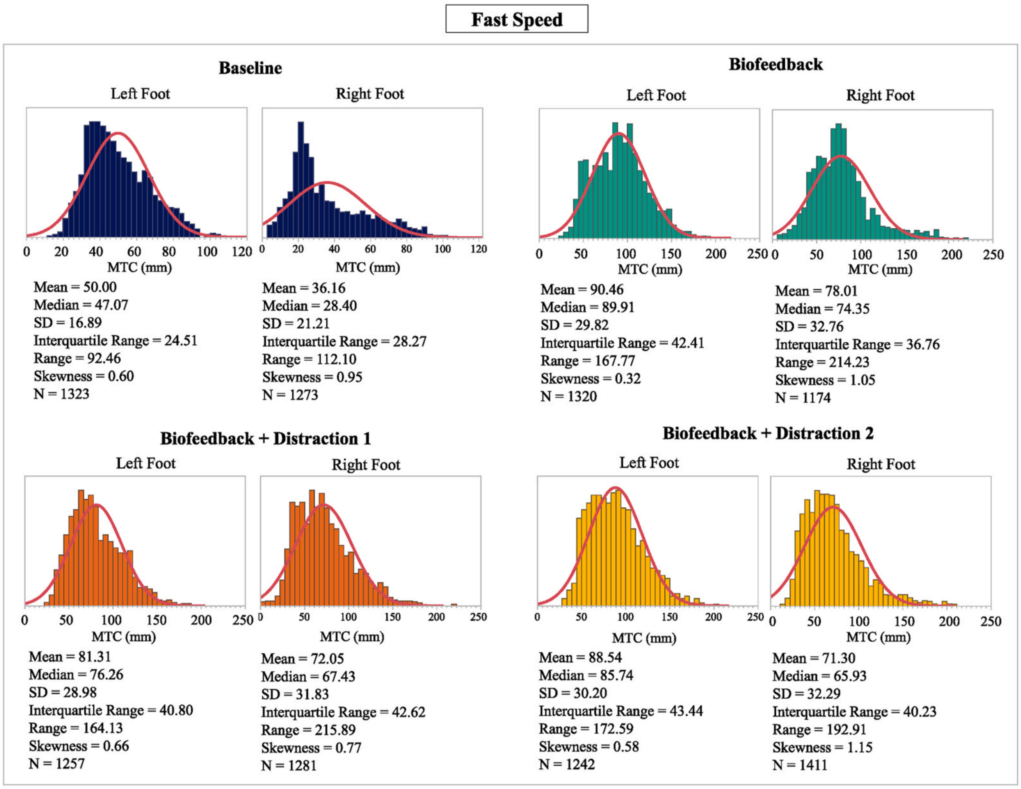
Note: NA denotes that the data was unavailable due to system error.

MTC when walking faster. The MTC during the BF condition was not significantly different for both feet. Fig. 7 (a) and (b) also shows that the MTC data from the BF + D1 condition were significantly different between the right and left foot. For the BF + D2 condition, the left foot's MTC mean was significantly different but the right foot's MTC mean was not. The interaction between condition and speed was also significant, indicating that the effect of condition (baseline, BF, BF + D1, BF + D2) statistically depends on walking speed.

The mean and standard deviation for each subject and walking condition are summarized in Table 2 and Table 3 for normal and fast speed. Overall, it can be observed that MTC variability, represented by the SD values, increases for each biofeedback condition at



(a)



(b)

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Fig. 8. MTC histograms for all subjects at the four walking conditions (baseline, biofeedback (BF), BF + distraction 1, and BF + distraction 2) for **(a)** normal speed and **(b)** fast speed.

normal and fast speed.

Fig. 8 (a) and Fig. 8 (b) display the MTC histograms of all subjects for each condition and foot for normal and fast speed, respectively. Overall, it was observed that the histograms deviate from a normal distribution for most conditions, and several distributions are skewed to the right. The histogram of the BF and BF + D1 condition for the right foot appears to have a multimodal distribution, indicating that there may be multiple "styles" of walking. One reason for this could be the large difference in the age range of the study population for each condition.

The MTC fluctuations for Subject 1 and Subject 7 are shown in Fig. 9 (a) for normal speed and Fig. 9 (b) for fast speed to illustrate examples of considerable MTC variation that occurs stride to stride for a single participant. For both speeds, it can be seen that Subject 1 successfully maintained her MTC above her personalized threshold for both feet. For cases where the MTC went lower than the threshold, it is evident that the participant quickly responded to the biofeedback prompt and raised her MTC in future steps. On the other hand, Subject 7 had difficulty maintaining her MTC above the personalized threshold for both feet. During the study, it was observed that Subject 7 found it challenging to divide her attention between both feet when responding to the biofeedback. Therefore, as shown in Fig. 9 (a), Subject 7 could successfully raise her left foot above the threshold but was unsuccessful with her right foot.

4. Discussion

The proposed algorithm presents a novel and robust strategy to detect the MTC points for non-pathological gait as it is not influenced by variations in a typical gait cycle. Fig. 10 (a) illustrates an example of a gait cycle with a clear MTC, while Fig. 10 (b) demonstrates a case where the MX1 or MX2 peaks are not prominent, resulting in a gait cycle without a well-defined MTC. The trajectories in Fig. 10 (b) were observed when participants walked with a higher MTC, which often occurred during fast speed, biofeedback, and distraction conditions. The benefit of the proposed algorithm is that it can detect the MTC even when it is not clearly defined and does not heavily rely on a specific gait cycle trajectory to detect the MTC. This feature may be advantageous for detecting the MTC on atypical gait patterns.

The purpose of this study was to determine if the biofeedback system could be used to warn users that their MTC was low and prompt them to raise their feet to increase their MTC. The purpose of incorporating distractions and a fast walking speed was to investigate whether biofeedback would be an effective warning tool to minimize tripping risk when participants perform everyday activities or walk in a hurry. The results demonstrated that the mean MTC significantly increased for the biofeedback and distraction conditions for both normal and fast speeds, indicating that the biofeedback successfully prompted.

participants to increase their MTC. Since the mean MTC was similar for BF and BF + D1 while walking at normal speed, it showed that the participants were able to maintain a raised foot while performing a simultaneous activity that was slightly challenging. However, when participants performed distraction 2, which was more challenging than distraction 1, their MTC was lower than the BF and BF + D1 conditions. The lower MTC indicated that participants found it more difficult to divide their attention between responding to the biofeedback while also fully engaging in distraction 2. Although the system successfully increased the MTC with biofeedback, the biofeedback also increased the MTC variability. The increase in variability could be due to the uncertainty of using only auditory biofeedback. Since participants were not provided upper threshold boundaries, they were allowed to raise their feet as high as they desired, increasing the MTC variability in each stride. The variability increased further when adding distractions to the biofeedback, which could be due to their attention being divided among several tasks simultaneously. Fig. 11 (a) to (j) illustrates the increased MTC variability that occurs for the biofeedback and distraction conditions versus the baseline condition. The difference between the MTC of two consecutive steps was calculated to highlight the large differences that occur when participants suddenly lift their foot higher as a response to the biofeedback. The baseline data looks consistent with minimal spikes; however, the biofeedback data has significantly larger spikes, illustrating the greater variability in those conditions.

5. Limitations and future work

The proposed wearable system was tested on healthy subjects as it was intended as a proof-of-concept in this study. It is understood that additional factors may need to be considered when testing on other age groups such as the elderly. Future studies will have a larger sample size that includes different age groups and gait impairments to test the effectiveness of the warning system on a representative population.

Another limitation of this study was that the data was only collected from female participants. This choice was made because the ToF sensors were mounted on a specific pair of women's running shoes. While this limits the study's generalizability, the initial outcomes provided insight into the system's ability to serve as a warning tool during everyday activities. Future research will include different genders to investigate how differences in gait between genders can affect the study results. Age and pathological gait can play a significant factor in how individuals respond to the biofeedback and introduce large variations in the gait cycle, affecting the accuracy of the MTC detection algorithm. In the future, the performance of the biofeedback system should be tested in populations with gait impairments and older adults to test the effectiveness of the system as a warning tool.

The algorithm proposed in this study can be improved to detect the MTC with higher accuracy by increasing the sampling rate. Users with gait impairments may have atypical trajectories during the swing phase, resulting in gait cycles without a defined MTC

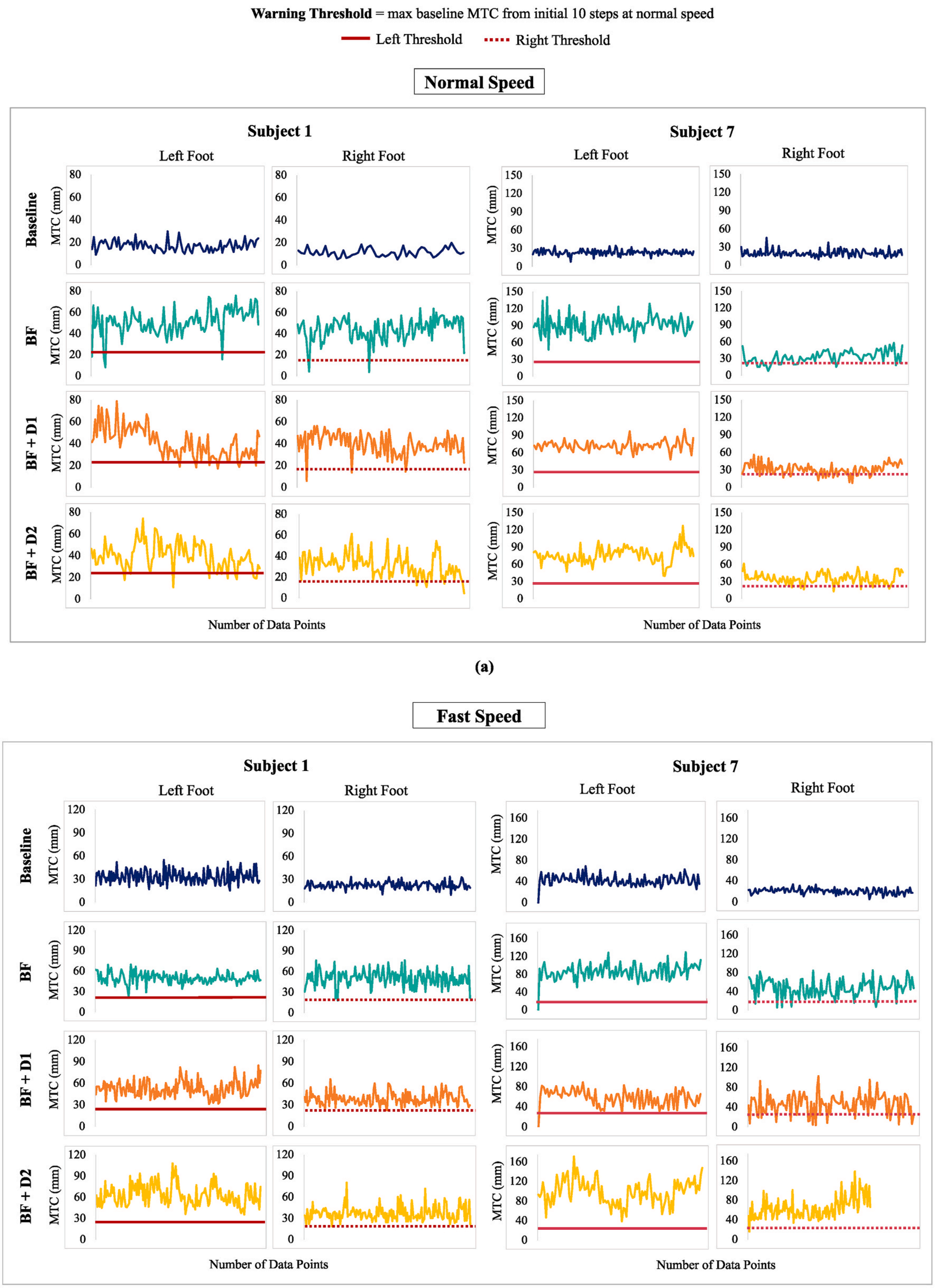

Fig. 9. MTC fluctuations for Subject 1 and Subject 7 during the baseline, BF, BF + D1, and BF + D2 conditions at **(a)** normal speed and **(b)** fast speed.

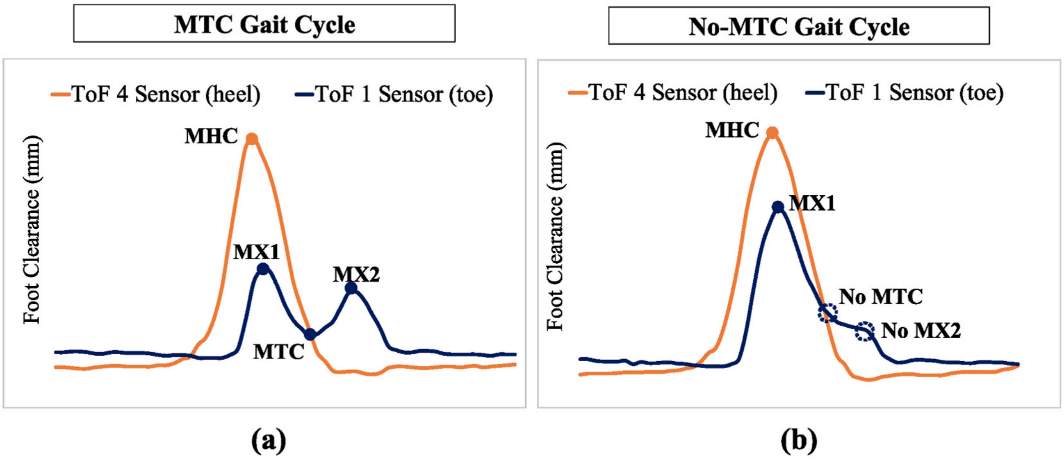

Fig. 10. An illustration of the difference between **(a)** a gait cycle with a well-defined MTC and **(b)** a gait cycle without an MTC present.

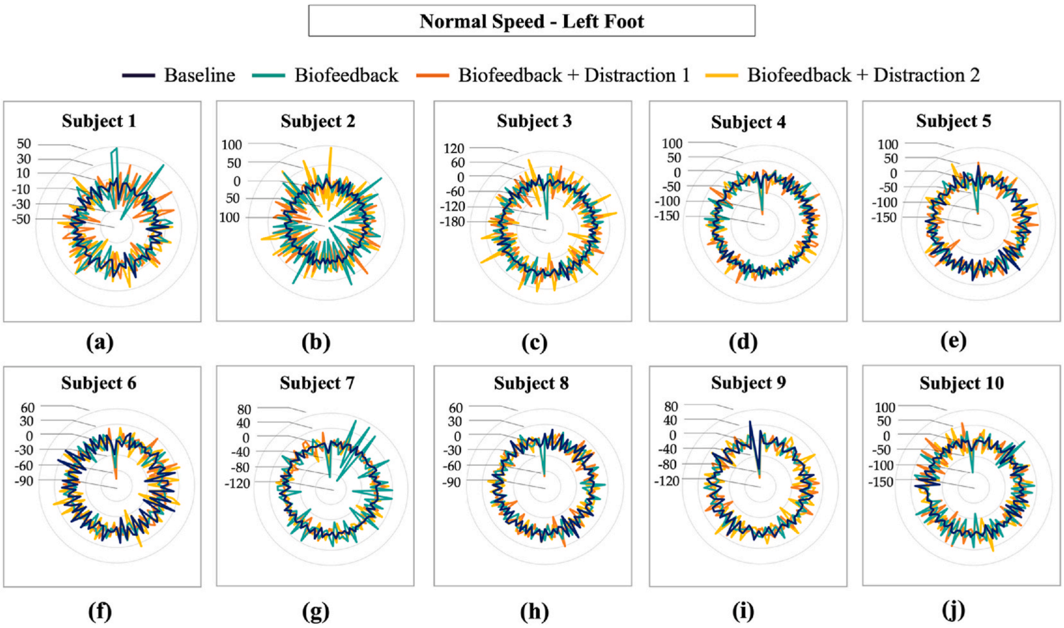

Fig. 11. A radar chart that illustrates the MTC variability for **(a–j)** Subject 1 to 10, respectively, in each warning system condition by plotting the difference between two consecutive MTC values for the left foot.

event, which could challenge the current MTC detection algorithm. In the future, other gait features such as foot velocity or pressure may need to be incorporated to account for those gait differences and be able to detect gait parameters reliably.

6. Conclusion

This study aimed to develop and evaluate a warning system that can be used during everyday activities of older adults and gait-impaired individuals to monitor their MTC in real-time and provide auditory alerts if the user's MTC is low. This paper proposed a new MTC detection algorithm that uses ToF sensors to measure the MTC in real-time. Auditory biofeedback was activated with a piezo buzzer if the participant's MTC went below their personalized threshold. The results showed that participants could successfully increase their MTC for all feedback conditions with and without distractions, but greater MTC variability was also observed for the feedback conditions. The study also demonstrated that ToF sensors could be useful for future gait monitoring systems to measure the MTC in an accurate and simple manner. The proposed system has the potential to be incorporated into rehabilitation training or assistive technologies to monitor low MTC and minimize the risk of trip-related falls.

Ethics statement

This work was approved by the University Health Network Research Ethics Board (Ethics Approval Number: 19–6161.3).

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Informed consent statement

Informed consent was obtained from all participants involved in the study. Participants also consented to have their images published.

CRediT authorship contribution statement

Shilpa Jacob: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Geoff Fernie:** Conceptualization, Funding acquisition, Resources, Supervision, Writing – review & editing. **Atena Roshan Fekr:** Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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