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Maqbool, HF, Husman, MAB, Awad, MI orcid.org/0000-0002-0367-0187 et al. (4 more authors) (2019) Heuristic Real-Time Detection of Temporal Gait Events for Lower Limb Amputees. IEEE Sensors Journal, 19 (8). pp. 3138-3148. ISSN 1530-437X

https://doi.org/10.1109/JSEN.2018.2889970

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2018.2889970, IEEE Sensors Journal

Heuristic real-time detection of temporal gait events for lower limb amputees

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***Abstract*— This article presents a complete system and algorithm to estimate temporal gait events during stance and inner-stance phases using a single inertial measurement unit (IMU) in real-time. Validation of the proposed system was carried out by placing the foot-switches (FSW) directly underneath the foot. The performance of the system was assessed with eleven control subjects (CS), one unilateral transfemoral amputee (TFA) and one unilateral transtibial amputee (TTA) while performing level ground walk and ramp activities. The experimental results showed reasonable agreement in timing differences of all the gait events in both groups when compared against the reference system. However, high data latency was observed for TFA in the case of Foot-Flat Start (FFS) and Heel-Off (HO). The slight variation in the positioning of IMU on the shank and the foot-switches underneath the foot and the difference in the kinematics of CS and lower limb amputees are probable reasons for large variations in the time difference. Overall, detection accuracy (DA) was found to be 100% for Initial Contact (IC), FFS and Toe-Off (TO), and 98.3% for HO. In addition, a high correlation was observed between estimated stance phase duration (SPD) from IMU and the SPD from FSW data. The proposed system showed high accuracy in the detection of temporal gait events which could potentially be employed in the gait analysis applications and the finite-state control of lower limb prostheses/orthoses.**

***Index Terms*— Gait events, lower limb amputees, Gyroscope, Accelerometer, real-time**

The study is linked to the research supported by EPSRC (EP/K020463/1).

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I. Introduction

GAIT Analysis is a useful assessment tool to evaluate and assess the rehabilitation progress of patients with gait disorders or facilitate for decision making in developing a control system for lower limb prostheses, orthoses and exoskeletons. Timing information of the gait events can be used to switch the controller states using a finite state machine to provide the necessary control actuations either for damping resistances in actively microprocessor controlled prostheses or actuation action in the powered prostheses while the amputees are in ambulatory action. Estimation of the temporal gait events/phases has been used for the assessment and control in functional electrical stimulation (FES) and prosthetics/orthotics systems [1-5]. Initial contact (IC) and toe-off (TO) are the main key gait events commonly used to segment the gait cycle into stance and swing phases. Temporal (time-based) parameters such as stride time, stance and swing duration can be computed from IC and TO. Foot-Flat (FF) and heel-off (HO) can provide additional insight in the analysis of inner-stance phases and can provide useful information to evaluate other gait parameters such as asymmetry during the inner-stance phases, stride length and walking speed [6]. In clinical applications, the information from these events were utilized to assess the improvement of patients with neurological disorders and to assess the gait symmetry of amputees [7-9]. By detecting the temporal gait events, stance phase can be segmented into different phases namely loading-response, foot-flat and push-off. The importance of identifying the gait sub-phases in a control scheme such as in state machine is to enhance users' control over the prostheses/orthoses to provide necessary stability and safety required during general ambulation [1, 6, 10-12].

A common laboratory method for identifying the temporal gait events includes the motion capture system and force platform. Although the motion capture-based event detection provides accurate and rich information, they are expensive, require a large space and are restricted to the indoor laboratory space. Alternatively, inertial sensors such as accelerometers and gyroscopes attached at different body locations have been used to estimate the time-based gait events/phases [13] and can also be embedded into prosthetic/orthotic systems.

Control algorithms using heuristic rule-based, wavelet transformation and machine learning methods have been implemented successfully to estimate the temporal gait

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events/phases utilizing information from inertial sensors [3, 14-19]. Most of the previous studies divided the gait cycle into stance and swing phases by estimating IC and TO. There are very few studies that focused on the gait events of the inner-stance phase [6, 10, 11, 20, 21]. A preliminary work related to the detection of temporal gait events has already been carried out in our previous work [22, 23]. Mariani et al. [20] presented the quantitative estimation of stance and inner-stance phase gait events, termed as heel-strike (HS), toe-strike (TS), HO and TO using an inertial measurement unit (IMU) placed on the forefoot. The performance was assessed with 42 subjects (healthy subjects and patients with ankle complications). The results showed good accuracy and precision in terms of time differences when compared against the reference system, however, the system was tested offline and for level ground walking only. Muller et al. [11] presented a gait phase estimation algorithm to detect four gait events in real-time, termed as IC, complete foot contact (heel + toe), HO and TO using a wireless IMU, placed on the instep of each foot. The performance was assessed with 14 Control Subjects (CS) and 5 above knee amputees while performing level ground walking at slow, normal and fast speeds. However, high data latency was reported for both control subjects and above knee amputees. Boutaayamou et al. [21] developed an algorithm to identify HS, TS, HO and TO using two accelerometers placed on the foot. The system was validated offline with seven control subjects.

Mannini et al. [6] presented an online machine learning approach to estimate four gait events termed as foot strike (FS), FF, HO and TO using foot-mounted gyroscopes. The performance was evaluated with nine healthy subjects while performing level ground walking (LGW) activities at five different speeds. The detection latency was less than 100 ms for FS, FF and TO whereas for HO the probability of having more than 100 ms was 25%. Lambrecht et al. [10] presented a real-time gait event detection of IC, FF, HO and TO using kinematic data in combination with a biomechanical model. Three threshold-based algorithms were developed in real-time and evaluated with seven healthy subjects while walking on an instrumented treadmill at three speeds. Timing accuracy and precision were found to be smaller in the detection of IC, FF and TO, however, the results of HO detection showed high variability.

To the authors' knowledge, recent studies have been confined to detecting gait events using foot-worn IMU and no study investigated the detection of inner-stance phase gait events while placing IMU on the shank for CS and lower limb amputees (LLA). The aims of the current study are, therefore,

- To develop a low-cost portable gait monitoring system capable of estimating stance and inner-stance phase temporal gait events in real-time.
- To evaluate the system performance for lower limb amputees during level ground walking and ramp activities.

II. Methodology

A. Subjects

Eleven able-bodied male subjects (mean age: 29.2 ± 1.7 years; mean weight: 75 ± 16.2 kg; mean height: 172.2 ± 6.1 cm) without any physical or cognitive abnormalities took part in this study. One male TFA (age: 53 years old; weight: 66 kg; height: 166.1 cm) and one male transtibial amputee (age: 51 years old; weight: 71 kg; height: 180.3 cm) also participated in this study. The amputees had no neurological or orthopaedic disorder apart from their amputation and did not use any ambulation aid while performing activities of daily living (ADLs). Further details of LLA are shown in Table I. The experimental procedures carried out in this study were approved by the Institutional Ethical Review Board.

TABLE I
Details of Lower Limb Amputees

Sub.	Prosthetic Knee	Prosthetic Foot/ankle	Cause of Amputation	Year of Amputation
TFA	3R80 Ottobock	Odyssey K2 College Park Venture	Trauma (Chronic infection on the knee)	2009
TTA	--	Soleus College Park	Trauma (Road traffic accident)	2003

B. Experimental Protocol

Participants were asked to wear a gait event detection system comprising an IMU, a base unit including a printed circuit board which integrates a wireless microcontroller, power unit and other electronic components such as voltage regulator, operational amplifiers and resistances. The footprint of the IMU board was small (21 mm × 16 mm), so it can be virtually mounted anywhere on the body or embedded into the assistive devices. In this study, the system was placed on the lateral side of the shank using a flexible Velcro strap. An IMU (MPU 6050, InvenSense Inc.) based on MEMS (Micro Electro Mechanical Systems) technology was used in this study. It has six degrees of freedom, consisting of a three-axis accelerometer and a three-axis gyroscope embedded in a single chip. Full scale values can be selected as ±2g, ±4g, ±8g and ±16g for the accelerometer and ±250 deg/s, ±500 deg/s, ±1000 deg/s and ±2000 deg/s for the gyroscope. Measurement range of ±4g and ±500 deg/s with the accuracy of 0.12 mg and 0.015 deg/s was selected for the accelerometer and gyroscope respectively in this study. Fig. 1 shows the experimental setup where the shank angular velocity in the sagittal plane and the acceleration along the longitudinal axis of the shank (z-axis) was recorded by a gyroscope and an accelerometer respectively using inter-integrated circuit (I2C).

Piezoresistive based FlexiForce sensors (Tekscan Inc., Boston, MA, US) A201, 25lb were used to validate the timing information of the gait events obtained from the kinematic source (IMU).Since the sensor is flexible and has negligible thickness (0.008 in.), it can be placed directly underneath the foot or can be fixed into fabric like insole. In this study, they were directly positioned underneath the foot

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at four different locations as shown in Fig.1. Data from the IMU and footswitches (FSW) were recorded and then transmitted to a PC through wireless communication. Finally, the timing difference between the events detected from the IMU and the foot-switches was evaluated.

For amputees, the system was mounted on both legs whereas for CS it was placed on one side i.e. either right or left. Once the participants were familiarized with the system, they were requested to walk on a flat surface (six meters long) at their self-selected slow, normal and fast speeds and walking up and down a four meter long inclined surface with 5^o inclination. CS walked barefoot while amputees walked with their normal daily shoes. Details of the participants' average walking speeds are shown in Table II. Walking speed of eleven CS was averaged for each activity whereas for LLA, walking speed of both legs (prosthetic and intact) was averaged.

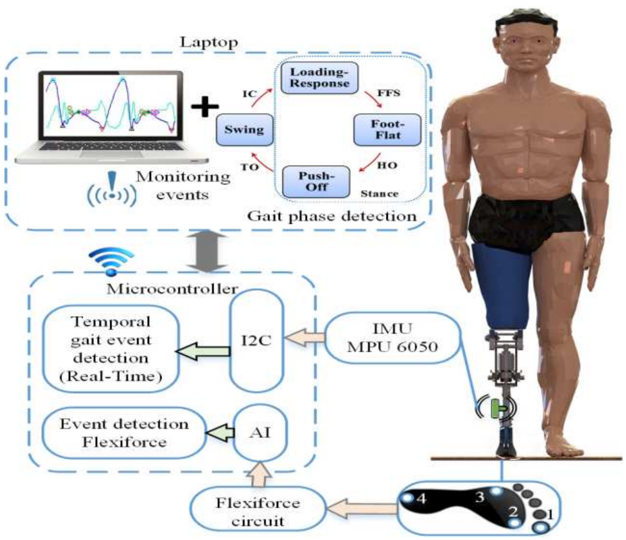

Fig. 1. Experimental Layout: Placement of foot-switches on 1-Toe, 2-1st Metatarsal, 3-5th Metatarsal and 4-Heel, AI: Analog input, I2C: Inter-Integrated circuit

TABLE II
PARTICIPANTS AVERAGE WALKING SPEED
MEAN ± STANDARD DEVIATION (M/S)

Sub.	Slow	Normal	Fast
CS	0.96 ± 0.12	1.21 ± 0.12	1.50 ± 0.17
TFA	0.77 ± 0.01	1.09 ± 0.01	1.30 ± 0.05
TTA	0.65 ± 0.06	0.92 ± 0.05	1.45 ± 0.02

III. ALGORITHM DESCRIPTION AND IMPLEMENTATION

The shank angular velocity signal exhibits peaks and troughs in a gait where the two troughs correspond to two main gait events namely IC and TO. TO and IC events occur before and after a maximum positive peak in a swing phase known as Mid-Swing (MSW) and these events have been identified accurately in our previous work [24]. To detect MSW, the following two conditions need to be met; 1) the magnitude of angular velocity should be greater than 100 deg/sec and 2) the slope must be positive.

For IC detection following conditions need to be met; 1) MSW is identified, 2) the slope must be negative and 3) in a window of 80 ms, if there are maxima with the magnitude difference of angular velocity greater than 10 deg/sec, then mark the latest minimum as IC otherwise select the previous minimum as IC [24]. For TO, the rules used were the same as mentioned in Table III. A maximum peak in the stance phase when the shank angular velocity is approximately zero is identified as Mid-Stance (MST) [25]. Two inner-stance phase gait events namely foot-flat start (FFS) and heel-off (HO) were detected before and after the MST using the acceleration signal. FFS1 and FFS2 before MST were considered as potential candidate points for FFS whereas HO1 and HO2 were considered potential candidates for HO after the MST. Fig. 2 shows the description of all the temporal gait events detected using gyroscope and accelerometer signals. Acceleration signal shows some peaks at and after IC and later shows almost a flat signal. The angular velocity signal during HO starts to decrease with dorsiflexion until TO happens.

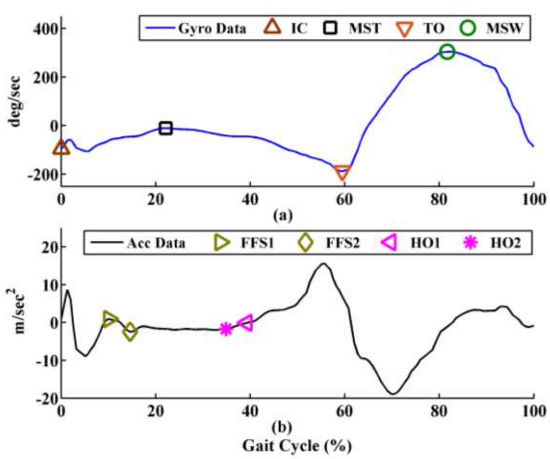

Fig. 2. Temporal gait event detection based on (a) Gyroscope, (b) Accelerometer

Preliminary data were recorded from CS and a TFA at a sampling rate of 100 Hz to develop the gait event detection algorithm. A second order Butterworth low-pass filter with a cut-off frequency of 10 Hz was used to filter the raw IMU data. IC and TO events were identified using the same rules implemented in our previous research [24], however, a couple of changes were made: 1) threshold value of angular velocity was set to 80 degrees/sec instead of 100 degrees/sec to avoid missing of MSW for small walking steps, especially at the beginning of a trial and 2) the condition of 80 ms window to detect IC was removed as the first local minimum after MSW was marked as actual IC for more than 98% of the entire IC events detected. Once IC is marked on the gyroscope signal, the algorithm begins the search for a maximum peak (FFS1) and a minimum peak (FFS2) in the acceleration signal after a time-counter of 40 ms passed. Once these potential points are identified for FFS using

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acceleration signal, the algorithm starts to search for the maximum gyroscope peak in the stance phase.

The angular velocity signal in stance phase shows more noise artifacts than the swing phase especially when the foot is in contact with the ground, therefore, an automatic tuning of the counter was incorporated to identify the real peak for MST. This time-counter was set based on the magnitude of MSW from gyroscope signal for each swing phase (see MST detection details in Table III). In addition, the angular velocity signal must be in ascending mode. Once MST is identified and a time-counter of 30 ms was passed, two conditions were implemented such that angular velocity signal should be in descending mode while acceleration signal is in ascending mode. Later, two possibilities were considered to identify HO: 1) the threshold value of acceleration signal such as $|A_N - A_{N-1}| \geq 0.1$ m/sec^2 and 2) zero crossings of the acceleration signal (see details in Table III). All the threshold values and rules were determined empirically using preliminary data from both IMU and FSW and found reliable when later assessed with eleven CS, one TFA and one TTA. Table III shows the rules of temporal gait event detection in details and Fig. 3 shows the samples of event detection system in real-time for TFA and TTA prosthetic side during the normal walk.

TABLE III
RULES OF TEMPORAL GAIT EVENT DETECTION BASED ON GYROSCOPE SIGNAL (GYRO) AND ACCELERATION SIGNAL (ACC)

Events	Signal	Rules
MSW	$Gyro$	a) Slope is positive b) $w_n > 80$ deg/sec c) Mark the maximum peak as MSW
IC	$Gyro$	a) MSW is identified b) Slope is negative c) $w_n < 0$ d) Mark the first minima as IC
FFS	Acc	a) IC is identified b) Counter is set to 40 ms c) Mark the maximum peak as FFS1 and minimum peak as FFS2
MST	$Gyro$	d) FFS2 is identified e) Slope is positive f) Counter adjustment (magnitude of gyro in deg/sec) If 320 < MSW > 260 ; counter = 70 ms else if MSW < 260 ; counter = 90 ms else counter = 50 ms; Default value g) Mark the immediate local maxima as MST
HO	Acc	a) MST is identified b) Counter is set to 30 ms c) Gyroscope signal is descending d) Zero crossing, mark HO1 e) If $\|A_N - A_{N-1}\| \geq 0.1$ m/sec^2, mark HO2
TO	$Gyro$	a) IC is identified b) Slope is negative c) Counter is set to 300 ms d) $w_n < -20$ deg/sec e) Mark the local minima as TO

A_N: Current and A_{N-1}: Previous Samples of ACC

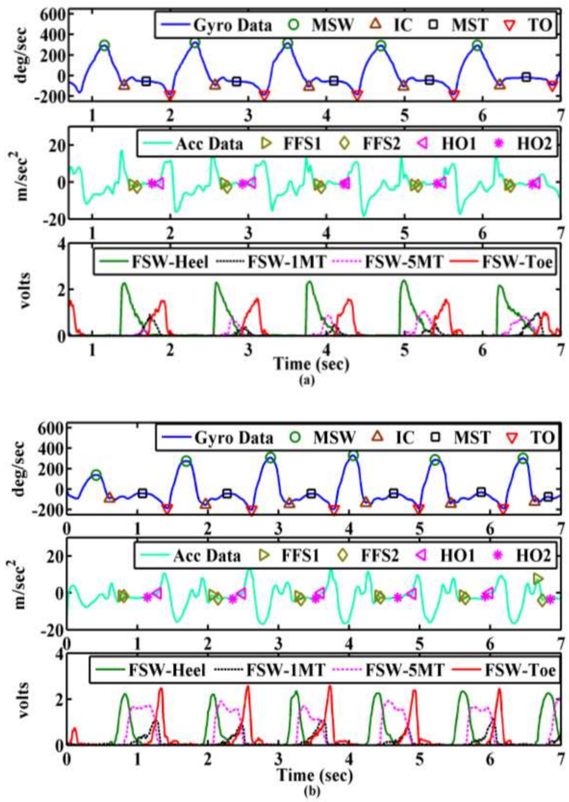


Fig. 3. Samples of temporal gait event detection of the prosthetic side of TFA (a) and TTA (b) during the normal walk. Top: Gyroscope signal, Middle: Accelerometer signal, Bottom: FSW signals, MT: Metatarsal

IV. DATA RECORDED AND ANALYSIS

Each trial was repeated five times for each subject and for each activity and the number of strides varied between the subjects. For level ground walking, the range was between 4-6 strides per trial whereas for ramp activities it was 2-3 strides per trial in both groups. A total number of strides recorded for CS were 717, 116 and 142 during LGW, ramp ascending (RA) and ramp descending (RD) respectively. For TFA and TTA, a total number of strides were 124, 21 and 25 and 125, 21 and 29 during LGW, RA and RD respectively.

The timing differences (TD) of the events detected from both sensors (IMU and FSW) were evaluated using (1) and then averaged, where T_{IMU} and T_{FSW} correspond to the timings of the gait events identified from the IMU and the reference system (FSW). Threshold values (T) of the FSW were set to (T ≥ 0.1 volts) for IC and FFS and (T ≤ 0.1 volts) for HO and TO, respectively.

$$TD = T_{IMU} - T_{FSW} \tag{1}$$

Data analysis includes both starting and stopping positions for each trial, however, data with incomplete steps were excluded. The mean difference (MD) and standard deviation (SD) were calculated for all the participants. Pearson correlation coefficient ‘r’ of stance phase duration (SPD) to see the correlation between detecting the stance phase time using IMU data and FSW data was also calculated in both groups.

Data were also assessed statistically using two-tailed independent samples t-test to determine the significance between the control subjects and each individual amputee participant. In addition, Bland-Altman plots were also produced to see the timing agreement between the two sensors (IMU and FSW). The distributions of the timing differences were shown graphically in Fig. 4.

V. Results

The evaluation of the proposed system in terms of MD and SD all expressed in milliseconds (ms) for temporal gait event detection for all the activities and for all the participants is shown in Table IV. Averaged measurements showed positive and negative values where the former indicate a delay in the detection whereas the latter indicate an early detection when compared against FSW. The results given in Table V and Fig. 4 showed that IC events were detected late and TO events were detected earlier in general across all the subjects with few exceptions where an early detection of IC was observed for TTA prosthetic side. FFS was evaluated by comparing the potential points (FFS1 and FFS2) with the beginning of 1^{st} and 5^{th} Metatarsals FSW. Results of FFS and HO showed variation in terms of early or late detection when compared against FSW across all the subjects. In this study, the MD and SD for IC and TO were 16 ± 9 ms and -16 ± 15.9 ms during LGW, 18.8 ± 11.6 ms and -17.2 ± 21.3 ms during RA and 17 ± 11 ms and -22.7 ± 19.4 ms during RD respectively for all CS. LLA also showed promising results for IC and TO. FFS2 and HO2 were found to be more suitable candidates for FFS and HO based on the overall statistical results across all the subjects in both activities as shown in Table IV. Results shown in Table V were considered as statistically significant at $p < 0.05$.

A. Distributions of time differences

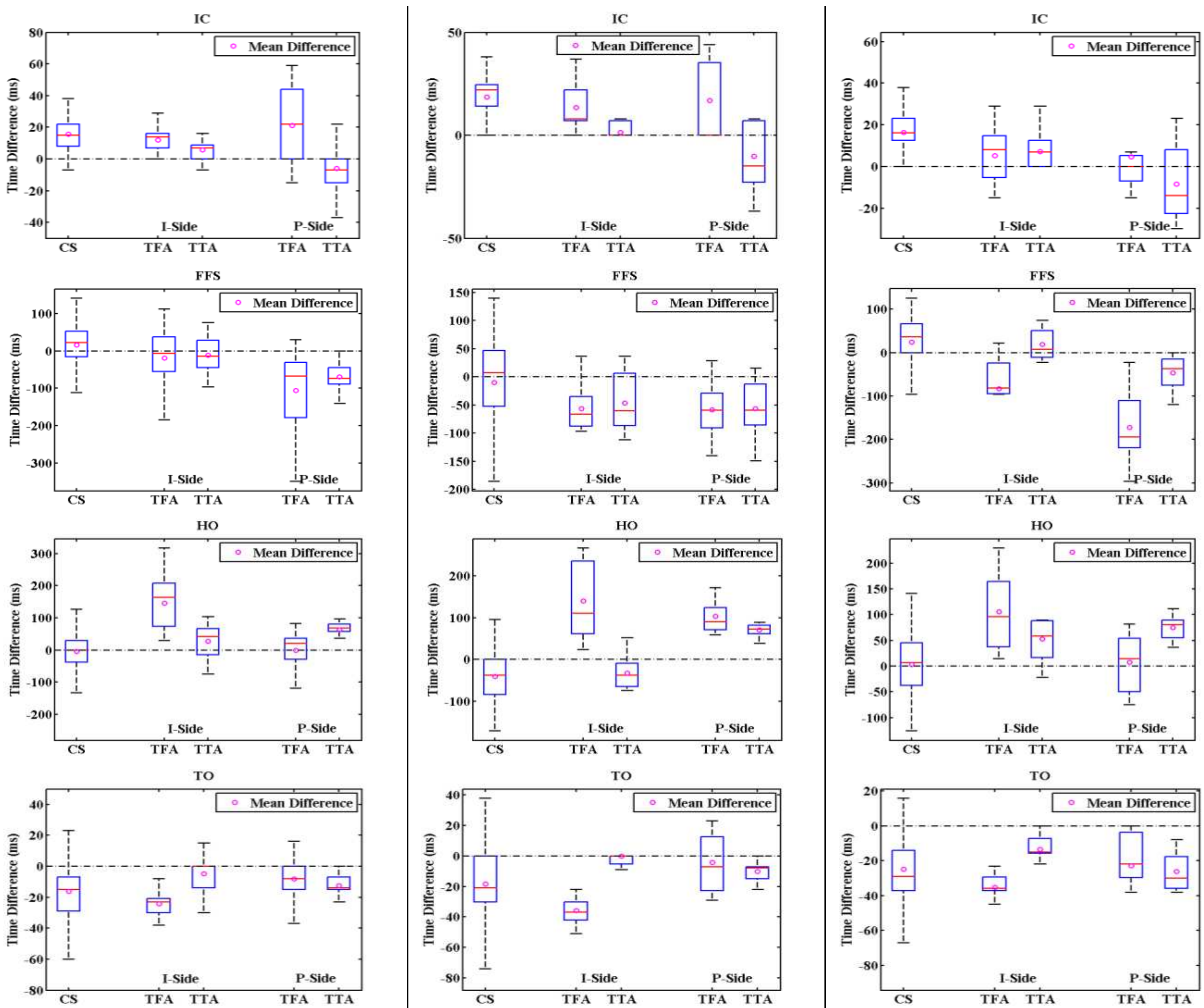
The distribution of time differences (TDs) of all temporal gait events is presented graphically in Fig. 4. An equal number of maximum available events across all the participants were considered for all the activities to avoid any bias in the boxplots. For a slow, normal and fast walk, 24, 21 and 18 events were considered respectively for each IC, FFS, HO and TO whereas for RA and RD, 11 events were considered respectively. The overall temporal gait events for the eleven control subjects, one TFA and one TTA (both legs for amputees) during LGW were 3780 (i.e. IC=945, FFS= 945, HO=945 and TO= 945) and 660 each for RA and RD, respectively. The overall variation in TDs showed positive values for IC and negative values for TO about the zero reference line. FFS and HO results showed a high variation in TDs across the subjects and for each activity. For IC, the amputees' prosthetic side showed high TD range and inter quartile range compared to the CS and the intact side of the amputees as shown in Table IV. Statistical results in Table V also showed significance ($p < 0.05$) when data were compared between control and prosthetic side of each amputee. The high range of variation in TD for CS was due to the number of control subjects (11 in this study).

TABLE IV
Time Differences of Temporal Gait Events Detected by Kinematic (IMU) and Kinetic (FSW) Method
Mean Difference ± Standard Deviation (ms)

Activity	Subject	IC	FFS1	FFS2	HO1	HO2	TO
LGW	CS	16 ± 9	-21.3 ± 49.8	16.5 ± 51.7	77.7 ± 61.6	-3.6 ± 49	-16 ± 15.9
	TFA-I	12 ± 9.5	-54.5 ± 75	-18.5 ± 75	262 ± 100	141 ± 73	-23.8 ± 8
	TFA-P	21.8 ± 20	153 ± 103	-105 ± 95	114 ± 60	1.7 ± 53	-7.5 ± 15.5
	TTA-I	5.7 ± 6.7	-45.4 ± 50	-6.3 ± 45	195 ± 88	29.4 ± 50	-4 ± 9.5
	TTA-P	-5.7 ± 16	-112 ± 35	-67.7 ± 34	175 ± 53	64 ± 24.6	-12.8 ± 6.7
RA	CS	18.8 ± 11.6	-56 ± 62.7	-14.9 ± 64	67 ± 64	-42.8 ± 57	-17.2 ± 21.3
	TFA-I	18.3 ± 17	-94.5 ± 45	-55.8 ± 39	287.5 ± 146	151 ± 91	-34 ± 8.3
	TFA-P	20.6 ± 22.3	-114 ± 43.5	-63.3 ± 44.5	202.5 ± 82.5	94.4 ± 40	-2 ± 17.6
	TTA-I	1.9 ± 7.5	-69 ± 59.7	-33.5 ± 62	178.6 ± 77	-38.6 ± 38	-3 ± 11
	TTA-P	-10 ± 14.7	-114 ± 49	-55.3 ± 64	252 ± 83	65.7 ± 27	-11.6 ± 7.6
RD	CS	17 ± 11	-20 ± 54.4	23 ± 53.7	148.6 ± 77	5.7 ± 52.6	-22.7 ± 19.4
	TFA-I	6 ± 14.1	-135 ± 69.8	-101 ± 69	279.2 ± 207	113.6 ± 72	-36.6 ± 16.3
	TFA-P	3.8 ± 17	-234 ± 118	-162 ± 112	123.3 ± 92.4	17.3 ± 62	-30.6 ± 26.7
	TTA-I	6 ± 7.3	-20.5 ± 31.5	24.5 ± 32	237.5 ± 50	58.3 ± 35	-11.6 ± 8
	TTA-P	-11.8 ± 16.4	-90 ± 61	-29 ± 64	187 ± 47.6	69.7 ± 29	-22.8 ± 10

TABLE V
ASSESSMENT OF MEAN TD BETWEEN CONTROL AND AMPUTEE GROUPS DURING LGW AND RAMP ACTIVITIES USING T-TEST, * INDICATE SIGNIFICANCE, GE: GAIT EVENTS, P: PROSTHETIC, I: INATCT

Activity	GE	CS V TFA (P)	CS V TFA (I)	CS V TTA (P)	CS V TTA (I)	TFA (P) V TTA (P)	TFA (I) V TTA (I)
LGW	IC	.03	.003	.000	.000	.000	.000
	FFS	.000	.001	.000	.000	.006	.508*
	HO	.551*	.000	.002	.000	.000	.000
	TO	.000	.000	.002	.000	.04	.000
RA	IC	.017	.006	.123	.625	.002	.01
	FFS	.001	.006	.001	.001	.927*	.636*
	HO	.000	.000	.000	.342*	.000	.000
	TO	.32*	.000	.018	.524*	.312*	.000
RD	IC	.180*	.097*	.002	.101*	.13*	.708*
	FFS	.000	.001	.000	.169*	.000	.001
	HO	.074*	.000	.000	.000	.001	.04
	TO	.048	.000	.001	.124*	.674*	.001



(a) LGW (b) RA (c) RD

Fig. 4. Distribution of time differences in temporal gait events during (a) LGW, (b) RA and (c) RD in both groups. I: Intact, P: Prosthetic

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B. Correlation and agreement between IMU and FSW

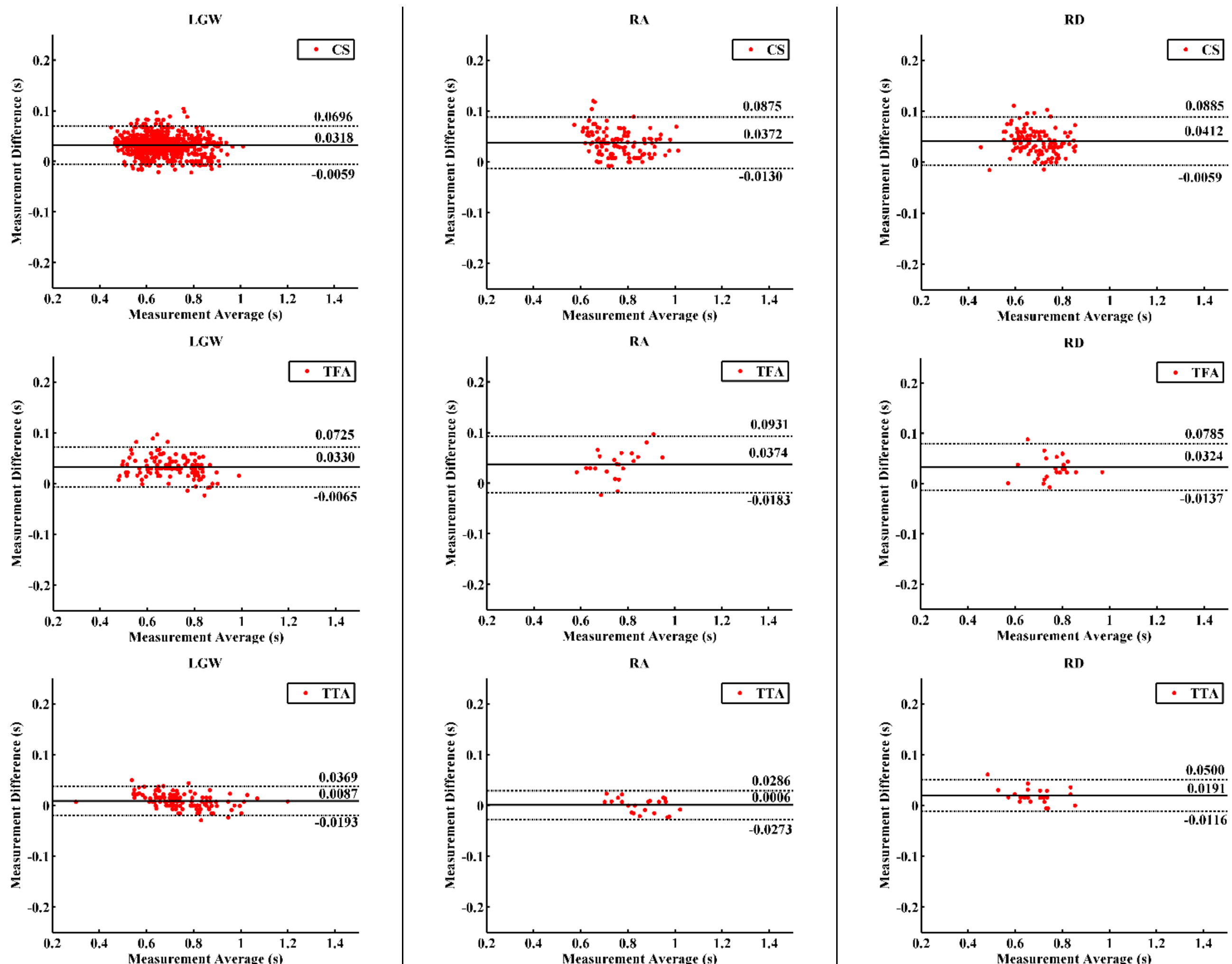
To further indicate the correlation between the estimated SPD (the difference between IC and TO estimated by IMU) and the SPD estimated from the reference FSW system, Pearson correlation coefficient was calculated. For CS, a correlation coefficient of 0.98, 0.97 and 0.96 were found for LGW, RA and RD respectively. SPD data of both legs (i.e. prosthetic and intact) were combined for LLA to calculate correlation coefficient during each activity. For TFA, a correlation coefficient of 0.98 was found for LGW whereas it was 0.96 for both RA and RD. For TTA, a correlation coefficient of 0.99 was found for each activity. In addition, to see the timing agreement of SPD between two quantitative measurements (IMU and FSW), Bland-Altman plots were produced as shown in Fig. 5. On each plot, the difference in timing between both methods is plotted against their average. The results indicate that most of the data lie within 95% confidence interval with very few data being outside this interval such as shown for CS and TFA during LGW. For CS, the mean difference of SPD was 0.031 s, 0.037 s and 0.041 s for LGW, RA and RD, respectively. For TFA, the mean difference of SPD was 0.033 s, 0.037 s and 0.032 s and for TTA, it was 0.008 s, .0006 s and 0.019 s during LGW, RA and RD, respectively.

C. Detection accuracy (Reliability)

Detection accuracy (DA) or success rate was calculated to assess the overall performance of the proposed system. It was calculated using equation (2):

$$DA\ (\%) = \frac{\text{true positive events detected by IMU}}{\text{total number of events detected by FSW}} * 100 \qquad (2)$$

A true positive event was defined as the detection of an actual gait event corresponding to its appearing phase. In total, 9654 (6894, 1290 and 1470 during LGW, RA and RD respectively) temporal gait events were detected by the reference system across all the subjects where events comprise IC, FFS1, FFS2, HO1, HO2 and TO. Fig. 6 shows the DA for all the temporal gait events in both groups. For CS, HO1 and HO2 were missed 30 and 21 times out of 1184 respectively yielding a DA of 97.5% and 98.2%.



(a) LGW (b) RA (c) RD

Fig. 5. Bland-Altman plots of SPD calculated between reference data (FSW) and estimated data (IMU) for CS (top), TFA (middle) and TTA (bottom) during (a) LGW, (b) RA and (c) RD. Positive times reflect delays of the IMU method with respect to the FSW method. A solid black line indicates mean error and dotted lines represent the 95% confidence interval (mean ± 1.96 SD)

For TFA and TTA, HO1 and HO2 were missed three times each and yielded a DA of 98.6% for each event across all the activities. IC, FFS1, FFS2 and TO events showed 100% DA during LGW, RA and RD in both groups. Overall (OA), DA values for HO1 and HO2 were found to be 97.76% and 98.3% respectively across all the activities in both groups.

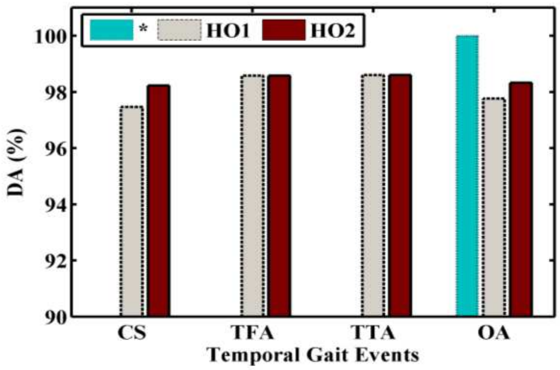


Fig. 6. Detection Accuracy, *: IC, FFS1, FFS2, TO, OA: Overall

VI. Discussion

A portable gait kinematic monitoring system was developed with capability to detect the temporal gait parameters accurately and reliably during ADLs for purpose of inclusion into robotic gait devices, which can be a useful tool to be utilized in clinical or laboratory measurements. The portable ambulatory system was used to identify temporal gait events in stance and inner-stance phases. The system is based on a single IMU placed on the shank and is capable of measuring angular velocity and linear accelerations in the sagittal plane. The system is capable of identifying four gait events, IC, FFS, HO and TO in real-time. The gyroscope signal was used to identify IC and TO as it showed good results in our previous work [24] whereas the accelerometer signal was used to identify FFS and HO. The gyroscope signal did not provide any indication of detecting these events when compared with FSW. The evaluation of the proposed system has been carried out with eleven control subjects, one unilateral transfemoral amputee and one unilateral transtibial amputee during ADLs. Evaluating the time difference accuracy between the proposed system and the reference system in eleven CS indicated the MD ± SD of 16 ± 9 ms, 16.5 ± 51.7 ms, -3.6 ± 49 ms and -16 ± 15.9 ms for IC, FFS, HO and TO respectively during LGW,18.8 ± 11.6 ms, -14.9 ± 64 ms, -42.8 ± 57 ms and -17.2 ± 21.3 ms for IC, FFS, HO and TO respectively during RA and 17 ± 11 ms, 23 ± 53.7 ms, 5.7 ± 52.6 ms and -22.7 ± 19.4 ms for IC, FFS, HO and TO respectively during RD. For LLA, MD range was -11.8 to 21.8 ms for IC, -162 to 24.5 ms for FFS2, -38.6 to 151 ms for HO2 and -36.6 to -2 ms for TO for all the activities.

Mariani et al. [20] reported a MD ± SD of 1 ± 13 ms for HS, -4 ± 37 ms for TS, 4 ± 54 ms for HO and -3 ± 13 ms for TO while evaluated with 42 subjects during level ground walk at a self-selected speed. The authors in [11] reported an overall MD ± SD of about 50 ± 50 ms and 100 ± 70 ms for IC and TO respectively. The complete contact event delay was found to be more than 200 ms for both CS and above knee amputees. The range of MD for HO was approximately ± 70 ms in both groups. The success rate (detection accuracy) was found to be about 98 % in both groups while wearing shoes [11]. The authors in [21] reported an overall MD (accuracy) ± SD (precision) of 1.3 ± 7.2 ms, -4.2 ± 10.9 ms, -3.7 ± 14.5 ms and -1.8 ± 11.8 ms for HS, TS, HO and TO respectively. Mannini et al. [6] reported high variability for FF (about 50 ms) and HO (about 60 ms) compared to FS and TO. Pappas et al. [1] reported a detected delay of 70 ms for both IC and FF, 35 ms for TO and 40 ms for HO while evaluating with ten healthy subjects and six subjects with different gait pathologies during treadmill walking. The authors also concluded that the data latency to detect these events did not exceed 90 ms [1]. However, all these studies estimated the gait events while placing wearable sensors on the foot. There is no previous study in the literature which investigated the temporal gait events of inner-stance phase while placing IMU on the shank or pylon for CS and LLA to our knowledge; hence, a direct comparison of the current study cannot be made with previous research.

Reliability of the proposed system was assessed by calculating the DA which was found to be 100 % for IC, FFS and TO in both groups. For HO, an overall DA was found to be 98.3%. Timing agreement of SPD between IMU and FSW was also observed by producing Bland-Altman plots. The results showed high agreement as most of the data lie within 95% confidence interval as shown in Fig. 5. In general, the data were found statistically significant when compared between CS and each LLA during LGW except for one instance (HO detection) where no significance was observed when data for CS and TFA prosthetic side were analyzed. For ramp activities, TFA prosthetic side was statistically found to be significant against CS and TTA except for a few instances as shown in Table V.

According to previous studies, the placement of IMU on the shank has some advantages over placing on thigh and foot. For instance, there will be less amount of skin and muscle movements on the shank compared to the thigh [26] and less signal variability between the subjects for shank signal compared to the foot [27]. Sessa et al. [28] conducted a pilot study for the gait event detection (IC and terminal-contact) using inertial measurement units at shank and foot. The performance of the system was evaluated for normal walking and with some deviations to the natural walking pattern on different surfaces. Based on the results, the shank was found to be the optimal location to place the sensors. Hamdi et al. [29] presented a study of lower limb activity recognition while using 4 IMUs (at thigh, shank, foot and the pelvis). The authors concluded that the features obtained from shank contributed mostly for the activity recognition compared to the IMUs on other locations.

The present study showed reliable accuracy and precision for timing difference evaluation of IC and TO for all the activities in both groups as shown in Fig. 4. In general, prosthetic side of both amputees showed higher MD compared to their intact side and CS. High TD and high SD were observed in the case of FFS and HO for all the participants in particular for TFA. High data latency for FF and HO was also reported in [6]. In this study, TFA was applying more load on his contralateral limb to compensate for the prosthetic limb while pushing his body forward. Early HO was observed in

TFA. This may be explained due to the vaulting during the gait cycle to provide clearance for the prosthetic side. Consequently, spending more time on his forefoot during the stance phase.

The gait events were detected using the IMU based on the minima and maxima peaks, which is detected based on the change in the angular velocity and accelerometer signals pattern not on the values of the IMU readings. Also, the footswitches were used as on/off switch sensor to detect if there is a contact between the foot and the ground or not and then indicate the gait events. The measurement accuracy of the proposed system is based on the time difference of the detected events in milliseconds between IMU and footswitches while the IMU's gyroscope and accelerometer accuracy measured in degree/s and g (m/s^2) respectively. The main sources of error in this proposed system which may affect time difference accuracy are: IMU and foot switches placements, alignment and the processing speed of the algorithm.

One of the limitations of the proposed algorithm is the prior detection of MSW, as the rest of the temporal gait events will not be detected until the onset of MSW event is identified. Another limitation of the algorithm is that the detection of IC is necessary to detect the subsequent events in the stance phase. Although the detection accuracy of IC was 100%, it may be missed for any possible reason or disturbance in the walking pattern. The other concern may be related to the threshold and counter values adjustment to identify the correct gait events. Although the same threshold and counter values were used in this study in both groups during LGW and ramp activities, these parameters would most probably need tuning for other activities of daily living such as a path that includes turning and/or start/stop effect or walking on uneven terrains. In general, the algorithm compares the current sample with the previous sample to identify an actual event; therefore, at most one sample delay (about 10 ms) is expected to detect each event. Low number of amputee participants is also one of the limitations of this study.

The overall data latency lies within a range of about ± 55 ms for IC and TO across all the subjects in this study. For FFS and HO, data latency was in a range of approximately ± 100 ms in case of CS and TTA, however, TFA showed high data latency with -162 ms as the maximum early detection for FFS and 151 ms as the maximum delay for HO. This is due to the lack of knee and ankle control in TFA. A study by Peterka and Louglin [30] showed that the dynamic behavior of human stance control could be accounted for by sensorimotor feedback-control mechanism and include a time delay of 150-200 ms in response to several perturbations and in various environmental conditions. Data latency in the proposed system depends on many factors: The RF wireless module speed, the environment infrastructure such as indoor, outdoor, and environmental condition etc., the microcontroller and algorithm processing speed. In addition, lack in control of the prosthetic knee and ankle-foot from the amputee during some ADLs, gait asymmetry and the prosthetic foot compliance with the ground affect the timing accuracy of the proposed system.

A heuristic algorithm in real-time to detect temporal gait events for stance and inner-stance phases with the corresponding system is presented. By detecting these temporal gait events, stance phase can be divided into sub-phases such as loading-response, foot-flat and push-off as shown in Fig. 1 which can provide added intuition in gait analysis applications. One of the advantages of the proposed system is the use of only one IMU to identify all the temporal gait events in LGW and ramp activities.

VII. Conclusion

This study presented a low-cost portable system to detect temporal gait events in real-time using the information from an IMU (accelerometer and gyroscope) placed on the shank. Based on the validated results, the temporal gait events can be detected accurately using the proposed system in both groups of control subjects and amputees while performing different ADLs. Experimental results showed 100% detection accuracy for IC, FFS and TO and 98.3% for HO across all the activities in both groups. The proposed system could potentially be used in gait analysis applications and the control of lower limb prostheses/orthoses. The efficacy of the proposed system will be assessed with a large number of participants specially, lower limb amputees and on varying terrains in the future.

Acknowledgment

This work is linked to the research supported by EPSRC (EP/K020463/1). The authors would like to acknowledge the relevant staff of the prosthetic department in the Seacroft hospital (Leeds, United Kingdom) for their collaborations. The authors would also like to thank the volunteers who participated in this study.

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APPENDIX

LIST OF ABBREVIATIONS

Acronym	Definition
Acc	Accelerometer
ADLs	Activities of Daily Living
CI	Confidence Interval
CS	Control Subjects
DA	Detection Accuracy
FES	Functional Electrical Stimulation
FF	Foot-Flat
FFS	Foot-Flat Start
FSW	Foot-Switches
Gyro	Gyroscope
HS	Heel-Strike
HO	Heel-Off
IC	Initial Contact
I2C	Inter Integrated Circuit
I	Intact
IMU	Inertial Measurement Unit
LLA	Lower Limb Amputees
LGW	Level Ground Walking
MD	Mean Difference
MT	Metatarsal
MST	Mid-Stance
MSW	Mid-Swing
OA	Overall
P	Prosthetic
PO	Push-Off
RA	Ramp Ascending
RD	Ramp Descending
SD	Standard Deviation
SPD	Stance Phase Duration
T	Threshold
TD	Time Differences
TFA	Transfemoral Amputee
TO	Toe-Off
TS	Toe-Start/Strike
TTA	Transtibial Amputee

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JSEN.2018.2889970, IEEE Sensors Journal

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