IRT-SD-SLE: An Improved Real-time Step Detection and Step Length Estimation using Smartphone Accelerometer

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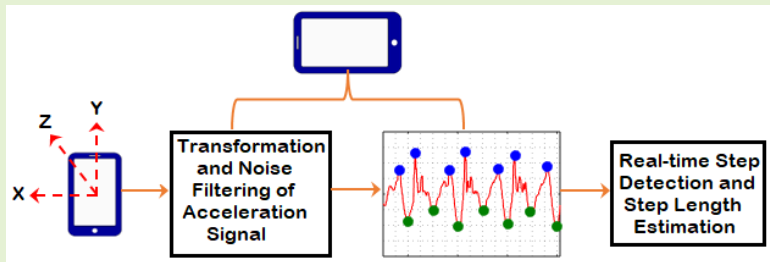
***Abstract*—Smartphone sensor-based pedestrian dead reckoning (PDR) systems provide a viable solution to the problem of localization in an infrastructure-less area. Step detection (SD) and step length estimation (SLE), being two fundamental operations of the PDR based localization technique, have drawn many researchers' attention in the recent time. Most of the existing SD and SLE methods proposed over the years, however, provide either server- or cloud-based solution that consume additional network bandwidth and suffer from increased transmission delay. Moreover, non-availability of the inertial sensors like gyroscope, magnetometers etc. at every smartphone makes majority of the existing SLE methods less applicable to such devices. To address the above-said issues, in this paper we focus on devising an improved SLE method that would detect the pedestrian's steps and subsequently estimate the step length in real-time by processing the accelerometer data at the device itself. Our proposed method transforms the measured acceleration values along the Earth coordinate system and also applies sliding window meaning to mitigate the negative effects of the smartphone's orientation and gravitational bias on the accuracy of SD and SLE. The performances of our proposed method are evaluated in terms of accuracy for ten different users by taking the device in two different postures (handheld and trouser pocket) under two different walking modes (normal and fast) to demonstrate its efficacy. Moreover, our proposed method obtains more than 80% average accuracy for SD and also obtains more than 75% accuracy (median) for SLE for all participants under four different scenarios considered here.**



***Index Terms*— step detection, step length, sensor, smartphone, accelerometer, machine leaning, accuracy.**

I. Introduction

PEDESTRIAN'S step detection and step length estimation are crucial for designing the localization and navigation systems utilized for offering various location-based services [1, 2]. Such systems could be effectively used in applications such as, guide for blind, assisted living, emergency rescue, and so on. Satellite-signal based localization, which exploits either global navigation satellite system (GNSS) or global positioning system (GPS), works well in outdoor areas. But such localization techniques cannot provide satisfactory localization performance in indoor areas or urban canyons since direct satellite signals cannot reach those areas. In order to overcome this difficulty, many indoor localization systems based on radio frequency technologies such as, Wi-Fi, ultra-wide band (UWB), wireless sensor networks, radio frequency identification (RFID), Long Range (LoRA), and so on have been proposed in the literature [3]. Among the various localization algorithms existing in literature, time delay-based localization schemes that depend on time-of-arrival (ToA) or time-difference-of arrival (TDoA) measurements, cannot determine the user's location without knowing the positional co-ordinates of the access points (APs) or beacons [4, 5, 6]. Fingerprint based localization algorithms, on the other hand, require a database of fingerprints collected at several known

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locations within the field of localization in the offline phase and determine the user's location in online phase by taking the location of offline fingerprint that matches best with the online fingerprint [7, 8, 9].

However, these localization systems require availability of certain infrastructure made up of the concerned RF technology in the area of localization for their proper working. Moreover, such localization systems, in general, provide the location estimate of a static user or object rather than a moving one. Low-cost inertial sensor based pedestrian dead reckoning (PDR) method that does not need availability of any infrastructure in the neighboring areas, is another powerful solution to indoor localization and navigation [10, 11]. Integration of the inertial sensors like accelerometer, gyroscope etc., with the smartphones available nowadays has motivated the researchers to develop smartphone sensor-based PDR localization system. Step detection (SD) and step length estimation (SLE), on the other hand, are the two fundamental operations of the PDR based localization systems since by adding the pedestrian's estimated step length to his/her initial location successively, pedestrian's current location can be easily determined. Design and implementation of an accurate SD and/or SLE method, thus, has become an important field of research.

Although a significant number of researches on the inertial sensor based SLE techniques have been proposed in literature over the past decade, majority of such works collect data from the sensors mounted on some body parts and process them either at some remote server or cloud to determine the step length [12, 13]. Only a few SD and SLE methods, which process and analyze the sensor measurements collected from the built-in sensors at the smartphone itself in real-time, do exist in the literature. Another important issue which has been overlooked by most of the researchers is the negative effect of the smartphone's orientation on the performances of SLE methods with respect to the Earth coordinate system (ECS). It basically depends on the placement position of the smartphone. Even though very few existing SLE methods have considered the above-mentioned issue, they use some inertial sensors (which is not usually available in most of the smartphones), to provide some reliable results irrespective of the device's orientation. *The availability of accelerometer in every smartphone along with the lack of existence of some suitable real-time SD and SLE techniques relying on the accelerometer only in the literature, have motivated us to focus on designing an improved real-time smartphone accelerometer-based step detection and step length estimation scheme in this paper*. Our proposed method works on the sensor measurements at the device itself rather than sending them to a remote server or cloud for necessary processing. This feature of our proposed technique further extends its applicability for emergency navigation where Internet connectivity may not be ensured. The contributions of our proposed work are listed below.

- Design of a smartphone-based improved step length estimation technique to reduce both the usage of network bandwidth and the transmission delay. The proposed approach works in real-time at the device itself.
- Solution based solely on the accelerometer sensor, which exists on every smartphone available nowadays.
- Mitigation of the negative effect of smartphone's orientation on the performances of SLE method by transforming raw acceleration data along the ECS.
- Adoption of a sliding window meaning based low-pass filter by the proposed method to remove the gravitational component and other noises from the acceleration magnitude.
- Evaluation of the proposed system and its comparison with the other contemporary techniques in terms of step detection accuracy and step length estimation accuracy by placing the smartphone in two different positions (hand-held or in trouser pocket) under two different walking modes (normal and fast) to demonstrate the efficacy of the proposed system.

The paper is structured as follows. We review the various existing SD and SLE techniques in Section 2. Section 3 presents our proposed system. In Section 4, we evaluate and compare our proposed method in terms of accuracy by placing the smartphone in two different positions under two different walking modes. The concluding remarks along with future research direction are given in Section 5.

II. Related Work

Many step detection and step length estimation techniques using either the inertial sensors attached to some body parts or smartphone's built-in sensors have been proposed in the literature over the past few decades. State-of-the-art review of such techniques are provided in this section.

A. Step Detection Techniques

The existing SD techniques based on smartphone's inertial sensor usually employ peak-valley detection procedure [15, 16, 29], zero-point detection procedure [17] or some machine learning model [20]. Although the peak-valley detection or zero-point detection-based SD techniques are comparatively simple and have low computational overhead, detection of proper peak-valley sequences by such techniques depends on the use of some threshold and their performances also get affected by the user's walking pattern as well as the sensor's placement position. To improve the SD accuracy a combination of both peak-valley detection and zero-point detection are applied by Zhang et al. in [18]. In [19], Yao et al. combines zero-crossing detection with the dynamic time wrapping based prediction of peak points for accurate detection of the step boundaries. Abiad et al. in [20], have proposed a machine-learning based step detection method that is designed to detect the steps for various types of human gait and also to work effectively irrespective of the sensor placement on human body, step mode, hand motion mode etc.

B. Step Length Estimation Techniques

Most of the inertial sensor based existing SLE techniques are based on some biomechanical model or machine learning method. In some cases, the empirical relation between the step length and sensor measurements is also used. In [21], Ho

Lee et al., proposed a motion-aware step length estimation technique processing measurements collected from a smart phone's built-in sensors. In this proposed technique, the hybrid model of decision tree (DT), artificial neural network (ANN) and support vector machine (SVM) are used to identify the user's motions. Moreover, map-based in-flight calibration is used in order to analyze the user's gait characteristic as well as enhance the step length estimation. To verify the proposed algorithm various experiments have been conducted where the experimental results show the effectiveness of the proposed algorithm in computing the step length for any kind of motion. A smartphone sensors-based adaptive step length estimator that can estimate the walking distance at different walking speeds of the user is proposed by Huynh Ho et al., in [22]. The proposed method, at first, applies a fast Fourier transform (FFT)-based smoother on the collected acceleration data and then analyses them based on some step-detection rules for the purpose of detecting the walking steps. In [23], Martinelli et al, applies the weighted context to estimate the step length of the pedestrians. The continuous wavelet transform analysis is used to detect the step time boundaries, whereas a relevance vector machine is used to determine the pedestrian context probabilities by the step detection algorithm proposed in [23].

Several existing SLE models require calibrating the user-specific parameter before using it for step length estimation purposes [24 – 26]. In [27], Bylemans et al., propose an SLE model to be used on the smartphone based on the assumption that regularly used devices are in general kept in pockets. The proposed SLE method considers the step duration, the difference between two consecutive peak acceleration points and the average acceleration to determine the step length. The SLE model proposed by Mikov et al. in [28] uses the step duration in the place of the calibration parameter in Weinberg's formulae [24] in order to simplify the process. Smartphone sensor based SLE model proposed by Strozzi et al., in [29] transforms the measured acceleration into the linear acceleration before applying it to the SLE model and evaluates the performances of the proposed model under the different poses of smartphone like navigation mode, phoning mode etc. In [30], Lu et al. apply fuzzy logic to dynamically adjust the user-specific parameter of the Weinberg's SLE model [24] for the different pedestrians. The proposed SLE method uses dynamic threshold-based peak-valley detection method and provides satisfactory results under different walking modes of various pedestrian. A few researches on smartphone-based PDR system conducted by Lee and Huang [31] and also by Tian et al. [32] aim to recognize different poses of smart phone like handheld, swinging or in the pocket and their effect on the positioning results. The smartphone sensors-based step detection and step length estimation technique proposed by Yao et al., in [19] addresses the problem of recognizing pedestrian's different walking pattern using random forest algorithm.

A few researchers, on the other hand, have worked on inverted pendulum model to derive the step length [33 - 35]. An inverted pendulum-based gait model has been proposed to derive the trajectory of the center of mass (CoM) by Zijlstra and Hof in [33]. An empirical approximation of the same has been proposed in [34] to derive the step length by considering the changes in the vertical displacement of the CoM. By extending Zijlstra's proposed gait model, Lueken et al., have deduced a mathematical model that relates acceleration measurements with the proposed model to estimate the step length in [35]. The SLE model proposed by Yan et al. in [36] uses deep belief network (DBN) made up of several restricted Boltzmann machines in order to learn various features of inertial sensor measurements and fit the input data based on the probability distribution. The proposed method combines zero-crossing detection of the acceleration signal with peak-valley detection of gyro signal for step detection purposes. Long short-term memory and convolutional neural network based adaptive learning is applied to retrieve the different elements for changing and recognition activities in another stride length estimation model proposed by Shu et al. in [37]. The proposed model combines the features obtained from the learning module via some suitable fusion method to determine the stride length. The SLE model recently proposed by Vezočnik and Juric in [38] considers the magnitude of accelerometer sensor and step frequency as input. The proposed SLE model provides satisfactory results when it is evaluated by walking on a treadmill as well as a test polygon with rectangular shape. Our recently proposed foot mounted inertial sensor based SLE model that processes both accelerometer and gyroscope sensor measurements to estimate step length is presented in [39].

Most of the above-mentioned SD and SLE techniques process the sensor data collected from the body-mounted inertial sensors at the remote server or cloud rather than processing them locally. Moreover, the majority of such techniques have not considered the negative effect of the smartphone's orientation on the performances of SD and SLE methods. Thus, we aim to design an improved SD and SLE method, which would transform the collected raw acceleration data along the ECS and then further process them at the device itself to estimate the step length in this paper.

III. Proposed System

The proposed smart phone-based step detection (SD) and step length estimation (SLE) technique is composed of three parts which are sensor data collection using android sensor API (phase I), data processing (phase II) and then step detection along with step length estimation using a simplified SLE model discussed in phase III. The work flow diagram for our proposed system, which is named as *IRT-SD-SLE* is summarized in Fig. 1. The constituent parts of the proposed system are described below.

A. Phase I: Sensor Data collection

In the first phase (phase I) of our proposed system data from accelerometer and rotation vector sensor are collected in periodic manner. Android sensor application programming interface (API) provides a set of methods to collect and manage the raw data from the embedded physical sensors of a smart handheld device. The full documentation of this API is available at [40]. To collect data from some sensor of an android device, it is required to create and activate a

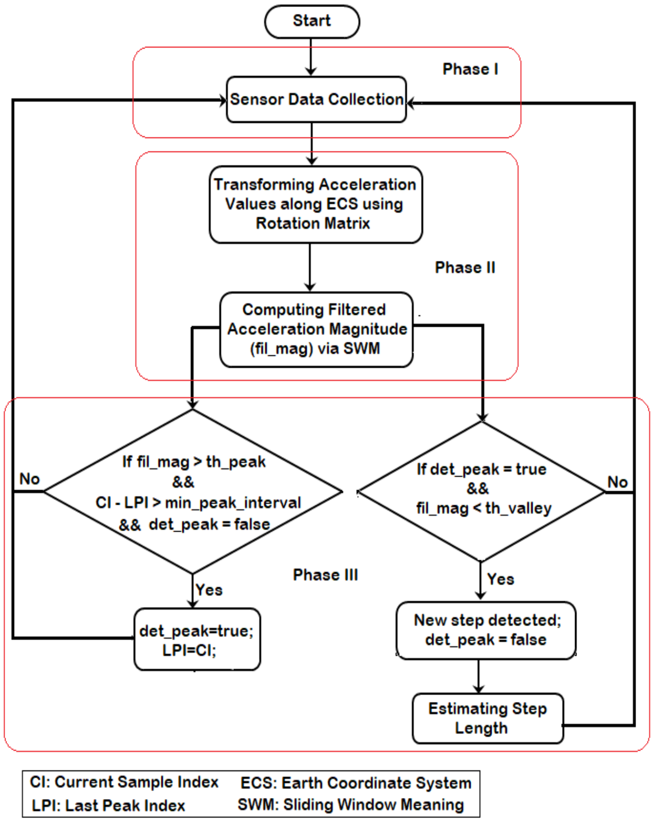

Fig. 1. Workflow diagram of the proposed system.

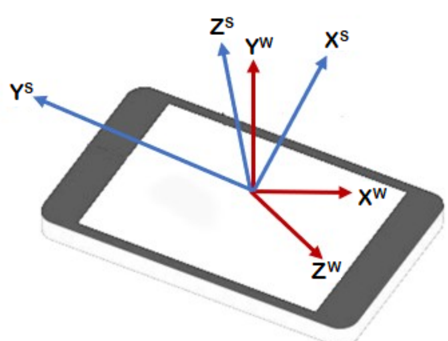

Fig. 2. Earth co-ordinate system and smartphone's body co-ordinate system denoted by $\boldsymbol{X^W}$, $\boldsymbol{Y^W}$, $\boldsymbol{Z^W}$ and $\boldsymbol{X^S}$, $\boldsymbol{Y^S}$, $\boldsymbol{Z^S}$ respectively.

listener over the needed sensor, which can be either an actual hardware sensor or virtual sensor, by making a call to the *registerListener* method. *SensorManager.registerListener(this, SensorManager.getDefaultSensor(Type_sensor), S_rate)*, where *SensorManager* is the object that lets the user to access the device's sensors, *Type_sensor* indicates the identification code associated with the needed sensor type and *S_rate* defines the sampling rate at which data is read from the specified sensor. The virtual sensor is a software-based sensor created by android operating system and it derives data from some hardware sensor. The examples of such sensors are linear acceleration, rotation vector sensor etc.

The orientation of the smartphone with respect to world reference system, i.e., Earth coordinate system (ECS) has a considerable effect on the performances of the smartphone-based PDR system, in terms of specifically step length estimation (SLE), heading determination etc., which works on the data collected from the built-in inertial sensors of the smartphone. Since the raw inertial sensor measurements are aligned with the sensor's (i.e., smartphone's) body co-ordinate system, their transformation along the ECS is an important requirement for accurate determination of the smartphone's position as well as its position displacement. A smartphone-based localization and tracking application, thus, require the device's acceleration values along the ECS for accurate estimation of the step length.

Our proposed method uses only a three-axis accelerometer whose coordinate system is the same as that of a smartphone's body coordinate denoted by $[X^S, Y^S, Z^S]$ as shown in Fig. 2. Earth coordinate system, on the other hand, is represented by $[X^W, Y^W, Z^W]$ as shown in Fig. 2. The x and y axes belonging to smartphone's body co-ordinate system (denoted by X^S and Y^S) are aligned to forward and upward directions respectively whereas z axis (denoted as Z^S) remains vertical to the phone screen as shown in Fig. 2. The same for ECS (denoted as X^W, Y^W, Z^W), on the other hand, points to the local east, north and up directions respectively as shown in Fig. 2.

To transform the acceleration values measured along the device's body coordinate system into that corresponding to ECS, it is required to know the device's orientation with respect to the ECS. The orientation of a device denoted by a pair of an angle and an axis, can be obtained by processing the measurements of the rotation vector sensor, a kind of android virtual sensor. In the above-said *listener* method, if *Type_sensor* is set to *Sensor.TYPE_ROTATION_VECTOR*, the listener method for rotation vector sensor is activated. The first three elements of the rotation vector are equal to the last three components of a unit quaternion represented as $\left\langle cos\left(\frac{\varphi}{2}\right),\ x * sin\left(\frac{\varphi}{2}\right),\ y * sin\left(\frac{\varphi}{2}\right),\ z * sin\left(\frac{\varphi}{2}\right)\right\rangle$, where φ is the angle through which the device has rotated around the axes $\langle x, y, z\rangle$. The fourth element of the rotation vector is equal to the scalar component of the unit quaternion, i.e., $cos\left(\frac{\varphi}{2}\right)$.

B. Phase II: Data Processing and Transformation

The second phase (phase II) of our proposed system processes the collected sensor data and then transforms the acceleration measurements into the corresponding values along the ECS.

Mathematical Modelling of Co-ordinate Transformation: To transform the raw acceleration data collected from the hardware sensor into the corresponding acceleration values along the ECS, it is required to compute the orientational or rotation matrix by processing the orientation measurements collected from the rotation vector virtual sensor. At first, four elements of unit quaternion ($Q = [u_0\ u_1\ u_2\ u_3]$) are obtained from the values of rotation vector sensor (denoted as RV) as follows.

$$\begin{aligned} u_0 &= cos\left(\frac{\varphi}{2}\right) = RV[3] \\ u_1 &= x \cdot sin\left(\frac{\varphi}{2}\right) = RV[0] \\ u_2 &= y \cdot sin\left(\frac{\varphi}{2}\right) = RV[1] \\ u_3 &= z \cdot sin\left(\frac{\varphi}{2}\right) = RV[2] \end{aligned} \tag{1}$$

The rotation matrix at i^{th} time slot is computed as follows.

$$O_i = \begin{bmatrix} 1-2(u_2^2+u_2^3) & 2(u_1u_2-u_0u_3) & 2(u_1u_3+u_0u_2) \\ 2(u_1u_2+u_0u_3) & 1-2(u_1^2+u_3^2) & 2(u_2u_3-u_0u_1) \\ 2(u_1u_3-u_0u_2) & 2(u_2u_3+u_0u_1) & 1-2(u_1^2+u_2^2) \end{bmatrix} \tag{2}$$

Now, the raw acceleration measured at i^{th} time slot along the sensor body framework (denoted as $Acc^S(i)$) can be transformed to the same along the ECS (denoted as $Acc^W(i)$) by applying the following equation.

$$Acc^W(i) = Acc^S(i) \cdot O_i \tag{3}$$

C. Phase III: Step Detection and Step Length Estimation

The third phase of our proposed system (phase III) aims to detect the steps taken by the pedestrian and then estimate the corresponding step length in real time as shown in Fig. 1. Our proposed step length estimation method uses, at first, a sliding window meaning based low-pass filter and then a peak-valley detection procedure to detect the steps of the pedestrian as well as estimate the corresponding step lengths. Various sub procedures of our proposed SLE technique are described below.

1) Removal of gravitational component from acceleration magnitude via low-pass filter: Removal of the gravitational components and other incorporated noises from the transformed acceleration signal is the next step towards generating a periodic acceleration signal consisting of the cyclic patterns having a pair of positive and negative peaks, which helps to detect the step cycles of the pedestrian and also to estimate the step length accurately. Our proposed method uses sliding window meaning (SWM) based filter, which computes the moving average of the previously processed acceleration signal (as presented by Cho and Park in [14]), to remove the noises from the transformed signal and to transform it into a periodic acceleration signal consisting of the cyclic patterns having a pair of positive and negative peaks. The magnitude of the transformed 3-axis acceleration data (denoted as Acc^m) at i^{th} time slot is computed as follows.

$$Acc^m(i) = \sqrt{(Acc_x^W(i))^2 + (Acc_y^W(i))^2 + (Acc_z^W(i))^2} \tag{4}$$

where $Acc_x^W(i)$, $Acc_y^W(i)$ and $Acc_z^W(i)$ denote transformed acceleration values along the X, Y and Z-axis respectively at i^{th} time slot.

The removal of various noises from the acceleration magnitude by using SWM based filter adopted by our proposed method is carried out by applying the following equation.

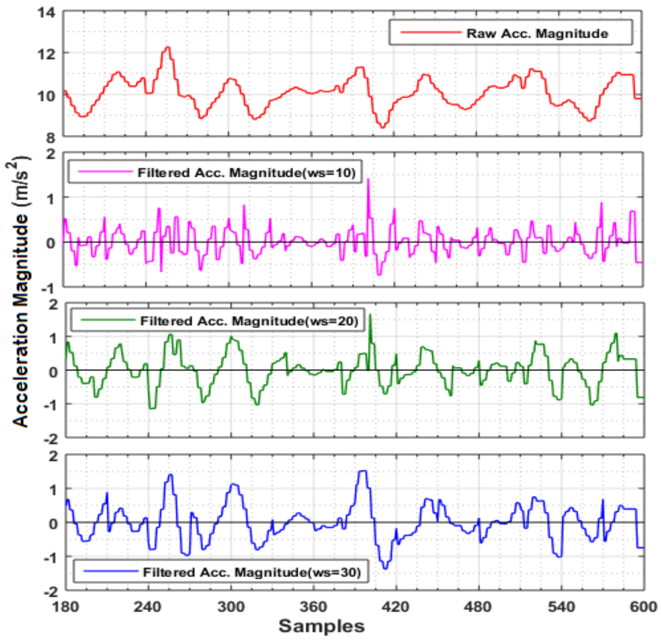

Fig. 3. Raw and filtered acceleration magnitude versus samples.

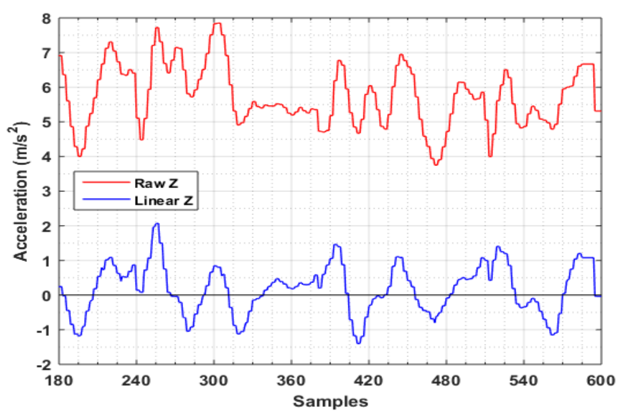

Fig. 4. Raw and linear Z-axis acceleration versus samples.

$$\begin{aligned} Acc_f^m(i) &= \left\| Acc^m(i) - \overline{Acc^m} \right\|, \\ \overline{Acc^m} &= \frac{1}{n}\sum_{i=1}^{n} Acc^m(i), \end{aligned} \tag{5}$$

where n is the window size.

As evidence of our proposed method, we have provided the signal analysis of the raw acceleration magnitude and various filtered acceleration magnitudes generated by setting the value of window size (WS) to 10, 20 and 30 respectively as given in Fig. 3. The raw acceleration signal shown in Fig. 3 is random in nature and does not contain any cyclic pattern having a pair of positive and negative peaks. On the other hand, by applying SWM-based filter, the raw acceleration signal can be transformed into a periodic signal consisting of a set of cyclic patterns having a pair of positive and negative peaks, which helps to easily identify the step cycles of the pedestrian. Fig. 3 also shows that the filtered acceleration signal gets more simplified with the increasing value of WS.

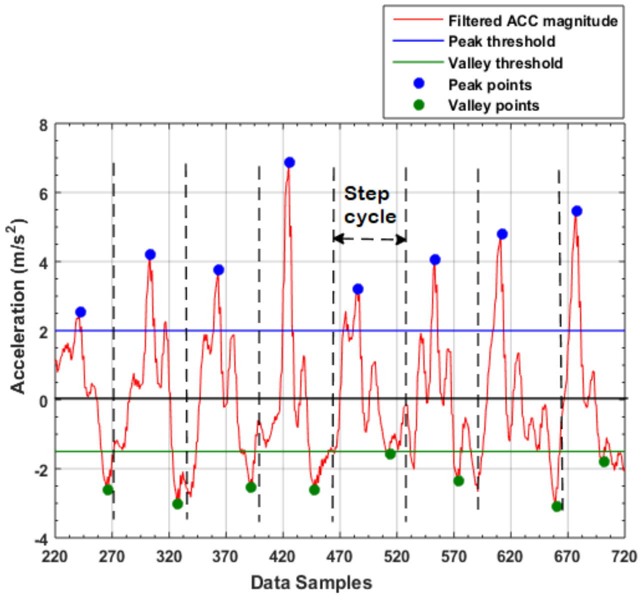

Fig. 5. Identification of step cycles using filtered acceleration magnitude with peak and valley points.

On the other hand, by subtracting the gravity ($g = 9.8$) component from the transformed z-axis acceleration, linear z-axis acceleration component (denoted as Acc_z^{lin}) at the i^{th} sample is computed as follows.

$$Acc_z^{lin} = Acc_z^w - g \tag{6}$$

As evidence of the transformation of the raw Z-axis acceleration measurement into linear Z-axis acceleration value by using the equations 1, 2, 3, and 6, the signal analysis of both raw and linear Z-axis acceleration signal is provided in Fig. 4.

2) Detection of steps using peak valley identification procedure: According to the researchers in [13], each step cycle consists of exactly one maximum or peak point followed by exactly one minimum point or valley point. To identify both maximum points and minimum points from the filtered acceleration magnitude, our proposed technique have considered two different thresholds which are peak threshold (*th_peak*) and valley threshold (*th_valley*) as shown by the flow chart given in Fig. 1. To determine the valid peak points from the set of identified maximum points, some restrictions on the interval between two consecutive peak points (denoted by the variable *min_peak_interval*) in terms of samples are imposed by our proposed method. Moreover, to identify the step cycles using a valid pair of peak and valley points, another condition variable named as *det_peak* is introduced. The value of condition variable *det_peak* is initialized to false and it becomes true upon detecting a valid peak point when the following conditions are met.

$$C1 : Acc_f^m(i) > th\_peak$$
$$C2 : i - LPI > min\_peak\_interval$$
$$C3 : det\_peak = false;$$

Here, i and LPI denotes current sample index and last peak index respectively. LPI, which is initialized to 0, is set to current sample index whenever a valid peak point is detected. On the other hand, valid valley point is found when the following conditions are satisfied.

$$C1 : Acc_f^m(i) > th\_valley$$
$$C2 : det\_peak = true;$$

The identification of the step cycles using the valid pairs of peak valley sequence within the range of data samples from 220 to 720 is depicted by Fig. 5. The values of peak threshold (th_peak) and valley threshold (th_valley) is set to 2.0 and -1.5 respectively as shown in Fig. 5, whereas min_peak_interval is set to 15 based on the reasoning that the pedestrians can take at most three steps per second [41].

3) Estimation of step length using Weinberg Model: Following the Weinberg's proposed SLE model, step length (SL) of the pedestrian is estimated by the following equation.

$$ESL_j = \beta \cdot \sqrt[4]{Acc_{z,max}^{lin}(j) - Acc_{z,min}^{lin}(j)} \tag{7}$$

where ESL_j denotes the user's estimated step length at the jth step, whereas $Acc_{z,max}^{lin}(j)$ and $Acc_{z,min}^{lin}(j)$ denote the maximum and minimum linear vertical acceleration within the jth step cycle respectively. β, which is a user dependent parameter, is required to be calibrated for each individual pedestrian. The value of β can be determined by using the measured values of maximum and minimum linear vertical acceleration as well as the actual step length in the following equation.

$$\beta = \frac{Actual\ SL}{\sqrt[4]{Acc_{z,max}^{lin}(j) - Acc_{z,min}^{lin}(j)}} \tag{8}$$

IV. Experimental Results and Analysis

Ten participants of different demographics were involved in our experimentation. Each participant had walked a linear distance of 30 meters and the experiments were carried out multiple times. Then the average experimental results for each of the ten participants are provided in subsection $IV.B$ to demonstrate the feasibility of our proposed method. We had used Galaxy $M13$ $5G$ smartphone having 2.2 GHz octa-core processor for experimentation purposes. Since calibration of parameter β is required to be done for different users before the evaluation of our proposed method, so parameter β is calibrated at first for the ten different participants.

A. Calibration of user parameter

A linear distance of 5 meters was walked by each of the ten participants to calibrate β. Based on the calculated average step length (which is obtained by dividing the traveled distance by the number of foot steps taken by the pedestrian) along with the maximum and minimum vertical acceleration within each step cycle of individual pedestrian, the value of β is estimated by using equation 8. The calibrated values of β for 10 pedestrians are provided in table I. The relationship between the parameter β and pedestrian's *body mass index*

TABLE I
CALIBRATED VALUES OF β FOR TEN PARTICIPANTS ALONG WITH THEIR BODY CHARACTERISTICS

Sl No	Height (cm)	Weight (kg)	Gender	BMI	β
1	178	75	Male	23.7	0.38
2	150	53	Female	23.6	0.43
3	169	87	Male	30.5	0.43
4	170.68	72	Male	24.7	0.40
5	162.56	58	Male	21.9	0.44
6	167.64	80	Male	28.5	0.44
7	156	56	Male	23	0.40
8	157	59	Female	23.9	0.42
9	160	64	Female	25	0.44
10	176.78	81	Male	25.9	0.45

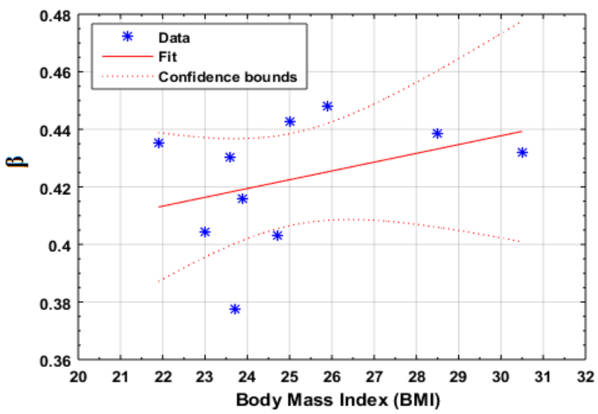

Fig. 6. Relationship between parameter β and pedestrian's body mass index.

(*BMI*) is depicted in Fig. 6. Such relationship between β and user's *BMI* would help to predict the value of β for any new user without the user's participation in the calibration process.

B. Performance Analysis

The performances of our proposed method *IRT-SD-SLE* have been evaluated and compared with the other contemporary methods including the existing method proposed by Strozzi et al. [29] in terms of *step detection* (SD) accuracy and *step length estimation* (SLE) accuracy. Apart from the existing one proposed in [29], we have also considered the other variant of our proposed method named as *IRT-SD-SLE-noECS*, which does not carry out the process of transforming the raw acceleration data along the ECS but uses SWM based filter to process them, to demonstrate the effectiveness of proposed *IRT-SD-SLE* over the latter. The working principle of *IRT-SD-SLE-noECS*, i.e., the proposed one without the use of ECS is almost same as that of *Weinberg's proposed SLE model*.

A linear distance of 30 meters on the first floor in our departmental building was selected for our experimentation. Each of the ten participants had walked along that path multiple times in four different scenarios that are resulted by placing the device in two different postures (handheld and trouser pocket) under two different walking modes (normal and fast) for analyzing the performances of the proposed technique. Average experimental results for each individual participant for step detection are provided in the tables II, IV, VI, VIII and the same for step length estimation are given in the tables III, V, VII, IX by considering the above-said four different cases. Moreover, the average and median accuracy acquired by the various methods including our proposed one under the four different scenarios for SD and SLE are shown in the tables X and XI respectively, which demonstrates the efficacy of our proposed method *IRT-SD-SLE* over the other methods under the four different scenarios. The linear path

TABLE II
ANALYSIS OF SD ACCURACY WHEN DEVICE IS HELD IN HAND UNDER NORMAL WALKING MODE

User Id	Act. Steps	Steps det. by [29]	Steps det. by IRT-SD-SLE-noECS	Steps det. by IRT-SD-SLE	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	43	26	32	32	60.47	74.42	74.42
2	49	28	63	63	57.14	71.43	71.43
3	49	30	35	35	61.22	71.43	71.43
4	51	34	38	38	66.67	74.51	74.51
5	51	31	47	47	60.78	92.16	92.16
6	45	23	36	36	51.11	80.00	80.00
7	47	33	34	34	70.21	72.34	72.34
8	47	31	52	52	65.96	89.36	89.36
9	48	26	54	54	54.17	87.50	87.50
10	46	25	42	42	54.35	91.30	91.30

TABLE III
ANALYSIS OF SLE ACCURACY WHEN DEVICE IS HELD IN HAND UNDER NORMAL WALKING MODE

User Id	Act. Dist. (m)	Dist. est. by [29] (m)	Dist. est. by IRT-SD-SLE-noECS (m)	Dist. est. by IRT-SD-SLE(m)	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	30.0	14.44	20.01	20.01	48.12	66.71	66.71
2	30.0	15.91	42.35	41.97	53.04	58.83	60.11
3	30.0	16.71	20.69	21.09	55.71	68.97	70.31
4	30.0	18.68	24.06	24.31	62.26	80.21	81.03
5	30.0	16.95	31.11	30.96	56.50	96.28	96.78
6	30.0	12.13	22.82	23.99	40.43	76.07	79.96
7	30.0	17.97	17.17	18.05	59.89	57.23	60.15
8	30.0	16.67	32.02	30.87	55.58	93.26	97.10
9	30.0	15.39	35.01	34.84	51.30	83.31	83.88
10	30.0	14.86	27.55	28.51	49.54	91.85	95.04

TABLE IV
ANALYSIS OF SD ACCURACY WHEN DEVICE IS KEPT IN POCKET (TROUSER) UNDER NORMAL WALKING MODE.

User Id	Act. Steps	Steps det. by [29]	Steps det. by IRT-SD-SLE-noECS	Steps det. by IRT-SD-SLE	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	43	31	48	48	72.09	88.37	88.37
2	48	35	43	43	72.92	89.58	89.58
3	46	32	40	40	69.57	86.96	86.96
4	41	29	55	55	70.73	65.85	65.85
5	50	35	59	59	70.00	82.00	82.00
6	46	30	32	32	65.22	69.57	69.57
7	48	33	43	43	68.75	89.58	89.58
8	47	31	33	33	65.96	70.21	70.21
9	47	33	44	44	70.21	93.62	93.62
10	45	29	34	34	64.44	75.56	75.56

TABLE V

ANALYSIS OF SLE ACCURACY WHEN DEVICE IS KEPT IN POCKET (TROUSER) UNDER NORMAL WALKING MODE.

User Id	Act. Dist. (m)	Dist. est. by [29] (m)	Dist. est. by IRT-SD-SLE-noECS (m)	Dist. est. by IRT-SD-SLE(m)	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	30.0	16.14	25.16	27.48	53.79	83.86	91.61
2	30.0	19.93	25.15	26.00	66.45	83.82	86.65
3	30.0	16.67	24.96	25.07	55.57	83.19	83.58
4	30.0	17.73	32.12	31.95	59.09	92.93	93.49
5	30.0	18.55	39.17	38.52	61.83	69.43	71.61
6	30.0	15.49	18.52	21.28	51.63	61.72	70.93
7	30.0	17.97	25.26	26.56	59.89	84.21	88.54
8	30.0	16.67	20.12	20.98	55.58	67.08	69.93
9	30.0	18.17	24.72	28.89	60.56	82.39	96.32
10	30.0	15.12	22.86	24.53	50.39	76.22	81.77

TABLE VI

ANALYSIS OF SD ACCURACY WHEN DEVICE IS HELD IN HAND UNDER FAST WALKING MODE

User Id	Act. Steps	Steps det. by [29]	Steps det. by IRT-SD-SLE-noECS	Steps det. by IRT-SD-SLE	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	36	62	26	26	27.78	72.22	72.22
2	43	63	39	39	53.49	90.70	90.70
3	39	62	51	51	41.03	69.23	69.23
4	33	61	26	26	15.15	78.79	78.79
5	42	58	50	50	61.90	80.95	80.95
6	42	65	37	37	45.24	88.10	88.10
7	40	61	33	33	47.50	82.50	82.50
8	41	59	36	36	56.10	87.80	87.80
9	41	54	34	34	68.29	82.93	82.93
10	40	57	28	28	57.50	70.00	70.00

TABLE VII

ANALYSIS OF SLE ACCURACY WHEN DEVICE IS HELD IN HAND UNDER FAST WALKING MODE

User Id	Act. Dist. (m)	Dist. est. by [29] (m)	Dist. est. by IRT-SD-SLE-noECS (m)	Dist. est. by IRT-SD-SLE(m)	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	30.0	43.23	17.16	17.17	55.89	57.18	57.24
2	30.0	42.91	23.49	24.78	56.96	78.29	82.61
3	30.0	42.31	38.11	33.46	58.96	72.96	88.46
4	30.0	43.68	16.41	16.60	54.41	54.70	55.34
5	30.0	39.05	34.66	34.58	69.84	84.47	84.72
6	30.0	44.28	23.87	25.68	52.41	79.57	85.60
7	30.0	40.70	20.90	21.64	64.34	69.67	72.13
8	30.0	40.72	22.47	22.59	64.25	74.90	75.30
9	30.0	39.16	22.69	22.99	69.47	75.65	76.63
10	30.0	40.61	20.47	21.16	64.62	68.25	70.53

TABLE VIII

ANALYSIS OF SD ACCURACY WHEN DEVICE IS KEPT IN POCKET (TROUSER) UNDER FAST WALKING MODE.

User Id	Act. Steps	Steps det. by [29]	Steps det. by IRT-SD-SLE-noECS	Steps det. by IRT-SD-SLE	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	35	54	36	36	45.71	97.14	97.14
2	42	61	32	32	54.76	76.19	76.19
3	38	57	29	29	50.00	76.32	76.32
4	34	63	36	36	14.71	94.12	94.12
5	40	61	35	35	47.50	87.50	87.50
6	41	58	33	33	58.54	80.49	80.49
7	41	62	37	37	48.78	90.24	90.24
8	41	55	48	48	65.85	82.93	82.93
9	41	57	41	41	60.98	100.0	100.0
10	38	54	48	48	57.89	73.68	73.68

within the experimental site walked by some participant while keeping the smartphone in handheld mode, is shown in Fig. 7.

Equations 9 and 10 given below define the *SD accuracy* and *SLE accuracy*, respectively.

$$SD\ Accuracy = \left(1 - \frac{|DS - AS|}{AS}\right) \times 100\%, \qquad (9)$$

where DS and AS indicate the number of steps detected by SD method and the actual number of steps taken by the pedestrian respectively.

$$SLE\ Accuracy = \left(1 - \frac{|ED - AD|}{AD}\right) \times 100\%, \qquad (10)$$

where ED denotes the estimated distance provided by the proposed technique and AD denotes actual distance travelled by the user. The value of AD in our case is 30 meters, whereas the estimated distance is obtained by successively adding the step length estimated by the SLE technique for each step taken by the user during the experimental walk.

Tables X and XI, which provide the average and median accuracy for the SD and SLE respectively acquired by various methods, show that our proposed method *IRT-SD-SLE*, i.e., the proposed one with ECS achieves better SLE accuracy compared to the state-of-the-art methods under the four different scenarios. Moreover, our proposed technique achieves better results in terms of SLE accuracy when the phone is placed in trouser pocket compared to the device's handheld position under normal walking mode. This happens because the device's orientation changes more rapidly when it is held in hand compared to when it is placed in trouser pocket. Since the results of the SLE model adopted by our proposed methods *IRT-SD-SLE* and *IRT-SD-SLE-noECS* depend on the value of user-specific parameter β which is calibrated for each participant under the normal walking mode, so they achieve better SLE accuracy under such walking mode compared to the other one as demonstrated by the results given in table XI.

On the other hand, SD accuracies for both methods *IRT-SD-SLE* and *IRT-SD-SLE-noECS* proposed here, remain the same, though their achieved accuracies are better than that of the existing method proposed in [29] as shown in table X. To remove the various noises from the acceleration signal, both methods, i.e., *IRT-SD-SLE* and *IRT-SD-SLE-noECS* use SWM based low pass filter, which is able to transform the raw acceleration signal into a proper periodic signal consisting of the cyclic patterns having a pair of positive and negative peaks in both cases. Since both methods (i.e., *IRT-SD-SLE* and *IRT-SD-SLE-noECS*) use the peak-valley detection procedure for step detection purposes, the number of steps detected by them remains the same under all scenarios. The screen shot of the android app designed for real-time step detection and

TABLE IX
ANALYSIS OF SLE ACCURACY WHEN DEVICE IS KEPT IN POCKET (TROUSER) UNDER FAST WALKING MODE.

User Id	Act. Dist. (m)	Dist. est. by [29] (m)	Dist. est. by IRT-SD-SLE-noECS (m)	Dist. est. by IRT-SD-SLE(m)	Acc. for [29] (%)	Acc. for IRT-SD-SLE-noECS(%)	Acc. for IRT-SD-SLE (%)
1	30.0	40.31	20.33	21.28	65.62	67.78	70.94
2	30.0	42.09	19.57	20.83	59.69	65.22	69.45
3	30.0	41.10	20.06	20.59	63.00	66.87	68.62
4	30.0	44.68	18.19	20.75	51.07	60.63	69.17
5	30.0	41.98	23.63	25.87	60.06	78.77	86.23
6	30.0	41.02	22.16	23.07	63.26	73.87	76.90
7	30.0	41.09	20.57	23.87	63.02	68.56	79.55
8	30.0	37.93	35.82	30.66	73.56	80.61	97.79
9	30.0	40.06	24.34	26.58	66.48	81.13	88.59
10	30.0	38.15	36.50	36.34	72.85	78.35	78.86

TABLE X
AVERAGE AND MEDIAN ACCURACY FOR VARIOUS SD METHODS UNDER FOUR DIFFERENT SCENARIOS.

Device pose and walking mode	Avg. acc. for [29] (%)	Avg. acc. for IRT-SD-SLE-noECS(%)	Avg. acc. for IRT-SD-SLE(%)	Med. acc. for [29] (%)	Med. acc. for IRT-SD-SLE-noECS(%)	Med. acc. for IRT-SD-SLE(%)
Handheld & normal walk	60.21	80.44	80.44	60.62	77.25	77.25
In pocket & normal walk	68.99	81.13	81.13	69.78	84.48	84.48
Handheld & fast walk	47.40	80.32	80.32	50.49	81.73	81.73
In pocket & fast walk	50.47	85.86	85.86	52.38	85.21	85.21

step length estimation purposes based on our proposed method *IRT-SD-SLE* is provided in Fig. 8.

V. CONCLUDING REMARKS AND FUTURE RESEARCH DIRECTIONS

A smartphone accelerometer based real-time step detection and step length estimation technique is proposed in this paper. Our proposed technique can detect the pedestrian's steps and subsequently estimate his/her step length in real-time by processing only the accelerometer measurements at the device itself to reduce the network bandwidth and transmission delay. Moreover, our proposed method attempts to mitigate the negative effect of smartphone's orientation on the SD and SLE accuracy by transforming raw acceleration data along the ECS by using rotation matrix and also adopts a sliding window meaning based low-pass filter to remove the gravitational component and other noises from the acceleration magnitude. The proposed technique employs a peak valley detection procedure that uses two thresholds and also imposes a constraint on the interval between consecutive peak points to avoid over detection of the step cycles. The performances of our proposed method are evaluated by holding the device in two most commonly used different postures under two different walking modes and also compared with the state-

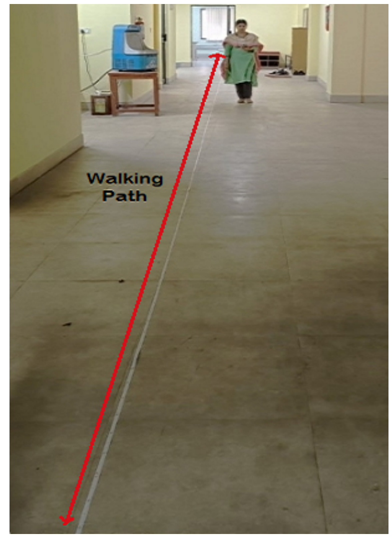

Fig. 7. Linear path walked by some participant with smartphone in handheld mode in experimental site.

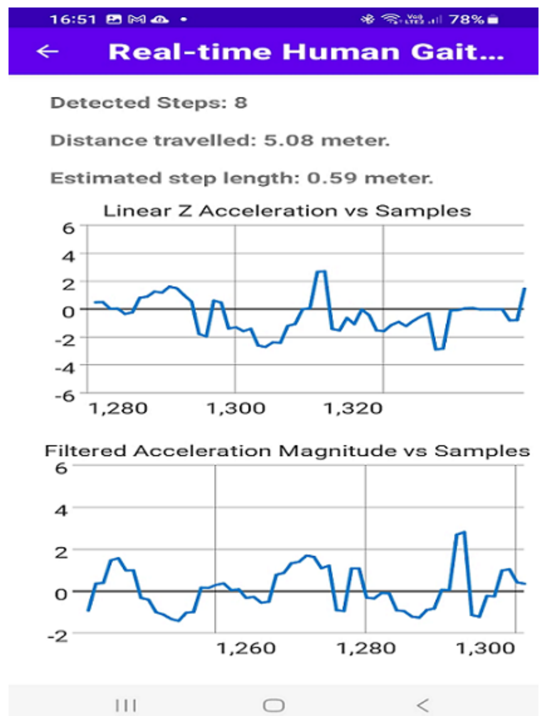

Fig. 8. Screen shot of android app designed for Real-time step detection and step length estimation based on our proposed method.

TABLE XI
AVERAGE AND MEDIAN ACCURACY FOR VARIOUS SLE METHODS UNDER FOUR DIFFERENT SCENARIOS.

Device pose and walking mode	Avg. acc. for [29] (%)	Avg. acc. for IRT-SD-SLE-noECS(%)	Avg. acc. for IRT-SD-SLE(%)	Med. acc. for [29] (%)	Med. acc. for IRT-SD-SLE-noECS(%)	Med. acc. for IRT-SD-SLE(%)
Handheld & normal walk	53.24	77.27	79.11	54.31	78.14	80.50
In pocket & normal walk	57.48	78.49	83.44	57.33	82.79	85.12
Handheld & fast walk	61.11	71.56	74.86	61.61	73.93	75.97
In pocket & fast walk	63.86	72.18	78.61	63.14	71.22	77.88

of-the-art methods including the other variant of our proposed method, which does not rely on transforming along the ECS, to demonstrate the effectiveness of the former (*IRT-SD-SLE*) over the latter (*IRT-SD-SLE-noECS*). The performance analysis in terms of SD accuracy and SLE accuracy for ten different users show that our proposed method *IRT-SD-SLE* achieves better SLE accuracy compared to the other methods considered here and both the proposed methods (*IRT-SD-SLE* and *IRT-SD-SLE-noECS*) achieve better SD accuracy compared to the existing one proposed in [29]. Furthermore, the proposed method *IRT-SD-SLE* obtains more than 80% average accuracy in terms of SD, whereas it obtains more than 75% accuracy (median) in terms of SLE for all ten participants under the four different scenarios considered here.

However, the performances of our proposed technique have been evaluated by walking a linear path only while the smartphone is held in two different positions. So, we intend to evaluate its performance by taking a curvaceous walk that includes either left or right turn as well as considering several other device postures in near future. Moreover, our proposed method cannot achieve desirable accuracy when the device is held in hand under fast walking mode. We, thus, plan to resolve this issue also in future.

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