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Smart Phone Based Sensor Fusion by Using Madgwick Filter for 3D Indoor Navigation

Md. Abid Hasan[1] · **Md. Hafizur Rahman**[2]

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Abstract

In this paper, we proposed an enhanced pedestrian dead reckoning (PDR) system based on sensor fusion schemes using a smartphone. PDR is an effective technology for 3D indoor navigation. However, still, there are some obstacles to be overcome in its practical application. To track and simulate pedestrian's position, which is confronted by environmental errors, walls, Bayesian errors, and other obstacles, our proposed PDR system enables estimation of stride based on the vertical accelerometer data and orientation from sensor fusion technique of magnetic angular rate and gravity sensor data by Madgwick filter. This localization system is independent of the received signal strength-based fingerprinting system. In addition, to estimate the current floor level, we make use of barometer information. To collect ground truth accurately and efficiently a prototype is implemented with the benchmark. We perform the same distance estimation for four different pedestrians to evaluate the accuracy of the proposed system. The real indoor experimental results demonstrate that the proposed system performs well while tracking the test subject in a 2D scenario with low estimation error (< 2 m). The 3D evaluation of the system inside a multi-story building shows that high accuracy can be achieved for a short range of time without position update from external sources. Then we compared localization performance between our proposed system and an existing (extended Kalman filter based) system.

Keywords Activity recognition · Indoor navigation · MARG sensor · Madgwick filter · Enhanced PDR

1 Introduction

Indoor positioning is an open challenge for the researcher to context-based applications that frequently rely on user movements. Wireless sensor network (WSN) based numerous type of applications like home activity recognition to battlefield surveillance is experimentally

✉ Md. Abid Hasan
abid1084@gmail.com; abid@aiub.edu

Md. Hafizur Rahman
hafizur.raj@gmail.com

[1] Department of EEE, American International University-BD, Dhaka, Bangladesh

[2] Department of EEE, City University-BD, Dhaka, Bangladesh

performed using wearable sensor device in recent year [1, 2]. In the case of GPS signal degraded area, PDR is a promising method for indoor localization [3]. Inertial measurement unit (IMU) system based-indoor positioning and indoor navigation system (IPIN) with WAN has obtained greater importance to solve this problem. In PDR step detection, stride length estimation, and heading information are the prominent determinants. Estimation of stride length and accurate heading are main challenges without an external reference like GPS, Wi-Fi, RF signals for pedestrian with a handheld device. Radiofrequency bacon, transmitted from a fixed known position can be utilized to overcome the drawback of the IMU sensors [4]. In Wi-Fi based IPIN system, a relative comparison of traveled distance with the assumed stride length can be used to estimate INS error [5]. Deficiency of reliable availability of RF signal in all environment makes the enhanced RF indoor positioning system prone to generate large positioning error [4, 6]. However, for a short range of time, the relative attitude and heading information are quite reliable [7].

Since we believe that various types of wearable sensors make system complex, costly and infelicitous to track common pedestrian, we considered a single ubiquitous device namely smartphone. They are equipped with large number of sensors, features for all aged users and being utilized for various applications including PDR for wireless indoor to indoor network system [8–10]. So, integration of MARG, with a barometer-based height determination can play an important role in PDR for all levels. Therefore this paper studies a three dimensional indoor position tracking system using the sensors available on a smartphone.

Even the finest sensor of today's market is prone to error. IMU sensors like gyroscope and accelerometer are not good enough to track absolute position as they are erroneous with not only time but also traveled distance [11]. Whereas, calibrated magnetometer provides absolute heading information. Although the data can be affected by magnetic and ferrous component nearby. So, sensor fusion is considered the most efficient and astute method for heading information. In recent year intensive research has been conducted by to draw back the deficiencies of one sensor by another through sensor fusion technique. Previous studies determine error state by using a conventional Kalman filter but in this research, a new and dynamic filter is used for heading error state estimation designed by Sebastian O. H. Madgwick. Instead of the recursive predictive algorithm, a more effective gradient descent algorithm is used in the Madgwick filter (MF). Heading angle, estimated by the MF from MARG sensor fusion is more effective and accurate rather than from Kalman based algorithm [12].

In [13–16] authors have proposed Kalman filter-based error state algorithm for foot-mounted PDR system to track the pedestrian position. Accelerometer reading is used to detect successive step by zero phase update (ZUPT) method. But for handheld sensor device and smart eyeglass Hong-Yu Zhao et al. [14] later proceeded from [7], proposed an adjustment of ZUPT by a threshold-based mechanism to placidly identify every step. The main sources of error in PDR are stride and perfect heading information [11]. The stride differs from person to person because every person has a unique gait. According to [17], the average stride length of a person is approximately 0.8 m with a small deviation of ≈ 0.1 m. Yet stride varies according to the surrounding environment and mode of the walk even for the same person. Harvey Weinberg proposed a method to detect step length for smartphone-based PDR application [18]. This method applied vertical acceleration of pedestrian's hip, in order to determine stride. In [19] Congo-Huygens et al. modified the Weinberg formula for a hand-held smartphone where they have integrated a unit conversion as a function of step velocity. The proposed modified method significantly reduces the distance error to 5%.

The accepted fact that increment in altitude results in atmospheric pressure drop. From this relation, 3D indoor positioning is accessible by the integration of Barometer data with MARG. But environmental influences like temperature humidity and weather pattern directly affect the barometer reading which could mislead to detect the true altitude of the pedestrian. The absolute pressure reading from smartphone-based pressure sensor varies from day to day basis even on floor level as well [20]. The opening of door and window can change indoor pressure dramatically [21].

This paper presents an enhanced PDR mechanization to detect the three-dimensional human position based on the use of a smartphone, equipped with MARG and barometer. Anomalies were rectified to calibrate sensor raw data by a statistical tool (95% confidence interval). The heading problem is solved by MARG sensor fusion using MF. Accelerometer data is used both for successive step detection and stride estimation by modified Weinberg formula. We have tried to solve the height problem by barometer reading. We have integrated the above information for 3D indoor position tracking of the pedestrian. Finally, we presented a graphical comparison in terms of accuracy between our proposed and Extended Kalman filter (EKF) system based trajectories. The remainder of the paper is structured as follows: Section 2 shortly describes system architecture, stride estimation method, the existing sensor fusion algorithm, and proposed PDR system. Section 3 describe and show the total performance, outcome, and error of the model. Limitation, the scope for the next contribution and future plan is described in Sect. 4.

2 Methodology and Architecture

Our proposed system architecture-based on PDR—is shown in Fig. 1. To calibrate sensor reading, we drive a Confidence Interval (CI) to eliminate the anomalies from data. Stride estimation is one of the prominent determinants of any PDR system. Step and step length (SL) can be detected from different sensors but our step and stride event detection algorithm is based on accelerometer data that have been transformed from sensor frame to earth coordinate frame($a_{ES(XYZ)}$). Sensor fusion is a subtle process to drawback the error of one sensor by combining others. We use a gradient descent algorithm namely, MF to fuse MARG sensor data to calculate the quaternion rotation matrix, that gives a stable heading angle for each step. Barometer readings from daily basis are used to estimate the z-axis position—the vertical distance from the ground—of the user. Finally, the PDR algorithm is performed to calculate the user's 3D location in a real-time manner. A basic block diagram for this whole work is shown in Fig. 1.

2.1 Raw Data Accumulation (95% Confidence Level)

At first, sensors data-accelerometer, gyroscope, magnetometer, and barometer-were collected from Sony Z-2 with 0.01 sec sampling interval. In Bayesian probability Confidence Intervals (CI) are constructed at a confidence level [22]. In the purpose of data mining CI is a frequently used method where the level is selected by the user. In this paper, we have used 95% CI on sampling data of every second. The following equation summarizes this process:

$$c = \bar{x} \pm t\frac{\sigma}{\sqrt{n}} \tag{1}$$

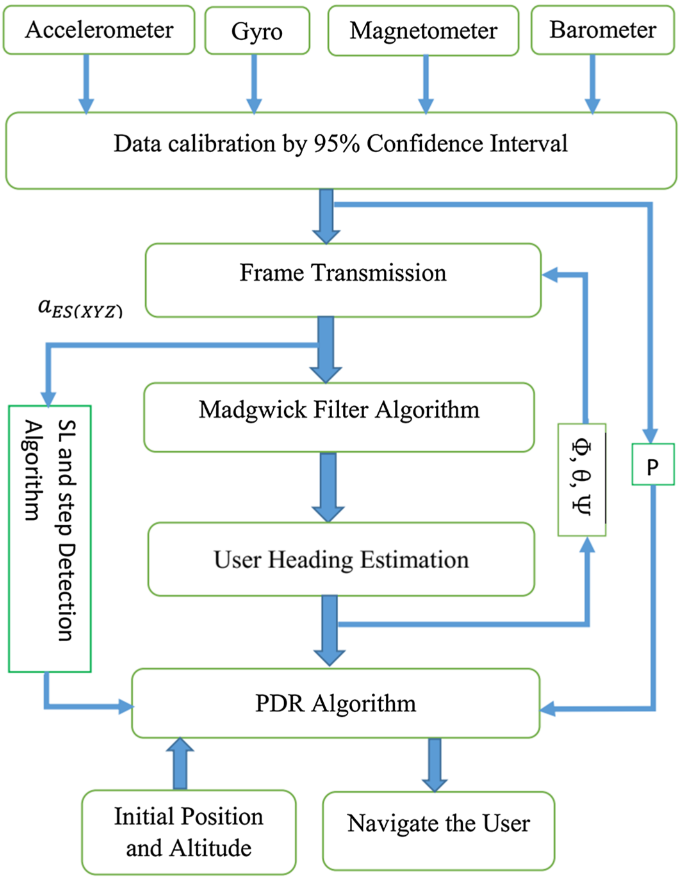


Fig. 1 Proposed system architecture

where c is the confidence interval; $\bar{x}$ is the sample mean, for 95% confidence interval and 100 sample data t is "t score" of each second,[1] σ is the standard deviation, and n is the sample number [23]. Equation 1 gives two-sided CI that brackets the sampling data from a maximum and minimum limit. Sampled data that exceed the CI level are replaced by finite differentiate method of last (Z_l) and most recent (Z_p) accepted data. We obtain the new value of anomaly is as follow (Fig. 2)

$$\bar{Z} = \frac{Z_p + Z_l}{2}. \tag{2}$$

[1] A matlab function "tinv" is used to calculate and recalculate t after each second.

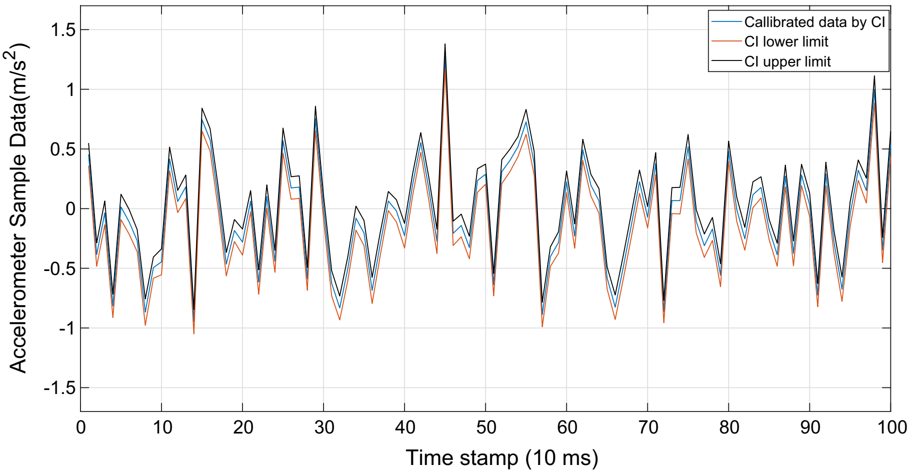


Fig. 2 Sampling data calibration by 95% CI level

2.2 Frame Transmission

To track the position on earth surface the sensor data needs to be transformed in earth coordinate frame. To transform sensor data from device frame to earth coordinate frame we have used Euler rotation theorem [24]. Vector presentation of the accelerometer raw data from 3 axis and rotation angle are constructed as follows:

$$\mathbf{V}_{acc_S} = \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix}; \quad \mathbf{V}_{angle_S} = \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix}$$

ϕ, θ and ψ are the roll, pitch and yaw of the device coordinate axes, respectively. The rotation matrix (R_{ZYX}) is calculated from Euler angles to Z-Y-X convention. If $T_c = \cos(\mathbf{V}_{Angle_S})$ and $T_s = \sin(\mathbf{V}_{Angle_S})$ both can be represented as $T_c = \begin{bmatrix} cx & cy & cz \end{bmatrix}^T$ and $T_s = \begin{bmatrix} sx & sy & sz \end{bmatrix}^T$. R_{ZYX} is computed as,

$$R_{ZYX} = \begin{bmatrix} cy \times cz & sy \times sx \times cz - sz \times cx & sy \times cx \times cz + sz \times sx \\ cy \times sz & sy \times sx \times s + cz \times cx & sy \times cx \times sz - cz \times sx \\ -sy & cy \times sx & cy \times cx \end{bmatrix}$$

Rotated transformed vector (Earth frame) is obtained by multiplying R_{ZYX} with acceleration vector as follows;

$$\begin{bmatrix} a_{ES_x} \\ a_{ES_y} \\ a_{ES_z} \end{bmatrix} = R_{ZYX} \times \mathbf{V}_{Acc_S}. \tag{3}$$

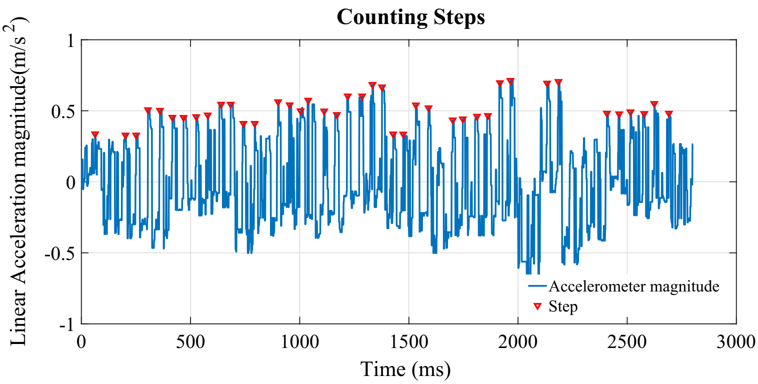


Fig. 3 Step detection and counting

2.3 Step Length and Successive Step Detection

As stated earlier this paper does not focus on step detection, instead, we use the existing technique of [7] to detect successive step for smartphone-based PDR system (Fig. 3).

According to [11] major error sources are heading information and stride length in the personal navigation system. ZUPT is applicable only for body armed sensor where device is worn on foot. Henceforth in case of handheld device Weinberg has proposed a method to detect every stride from user vertical acceleration data. The proposed Weinberg formula is

$$L \approx K \times \sqrt[4]{a_{ES_{Zmax}} - a_{ES_{Zmin}}} \tag{4}$$

where $a_{ES_{Zmax}}$ and $a_{ES_{Zmin}}$ are the maximum and minimum acceleration values on Z axis. K is considered a polynomial function of average velocity (V_{step}) of every step. For three different speed levels (low, normal, high) Ngoc-Huynh et al. have modified the factor-K as a function of magnitude of V_{step} as:

$$K_{vel} = 0.8 - 0.37V_{step} + 0.15V_{step}^2 \tag{5}$$

$$V_{step} = \sqrt{V_{stepX}^2 + V_{stepY}^2 + V_{stepZ}^2} \tag{6}$$

where V_{stepX}, V_{stepY}, and V_{stepZ} was obtained from single integration of accelerometer reading respectively for each unique step. This unit conversion procedure is used to detect step length in this research.

2.4 Madgwick Filter

Heading sensors both gyroscope and magnetometer have limitation. With time the Gyro bias increase that results in relative azimuth drift [25]. Although magnetometer reading gives absolute azimuth and long-term stability as single source magnetometer data cannot be used as heading information in harsh environments, especially indoor [26]. So, sensor fusion is the subtle process to draw back the limitation of one sensor by another. Madgwick et al. uses quaternion representation to design a new estimation-algorithm of MARG sensor orientation by applying a gradient descent algorithm. To compute the direction of gyroscope and measurement error as a quaternion derivative the algorithm allow accelerometer and magnetometer data to be used in an analytically derived and optimized gradient descent algorithmic form. The basic algorithm derivation of the MF is orientation from angular rate, orientation from a homogenous field, algorithm fusion process, magnetic distortion compensation, and algorithm adjustable parameter [12].

2.4.1 Orientation from Gyroscope

The quaternion presentation for the rate of change of the earth frame relative to the sensor frame $\dot{q}_{ES}$ can be calculated from

$$\dot{q}_{ES} = \frac{1}{2}\hat{q_{ES}} \otimes \omega_s. \tag{7}$$

where Gyroscope data, $\omega_s = [0 \quad \omega_x \quad \omega_y \quad \omega_z \quad]$, $\otimes$ denotes a quaternion product and the $\hat{}$ accent denotes a normalized vector of the unit length. The orientation[2] of the earth frame relative to the sensor frame at time t, $q_{ES}(w, t)$ can be computed by numerical integration of quaternion derivative $\dot{q}_{ES}(w, t)$ by the equation below when the previous angular estimate of orientation $\hat{q}_{ES}(est, t-1)$ is known,

$$\dot{q}_{ES}(w, t) = \frac{1}{2}\hat{q}_{ES}(est.t-1) \otimes^{s} w_t. \tag{8}$$

$$q_{ES}(w, t) = \hat{q}_{ES}(est, t-1) + \dot{q}_{ES}(w, t)\Delta t. \tag{9}$$

2.4.2 Orientation from Accelerometer and Magnetometer

A measurement in the field direction on sensor frame will allow an orientation of the earth frame relative to the sensor frame if the direction of the earth frame is known. Quaternion representation gives a formulation of an optimization problem where an orientation of the sensor, $\hat{q}_{ES}$, is calculated when prior estimate align a predefined reference direction of the field in the earth frame, ${}^{E}\hat{d}$ with the measured field in the sensor frame ${}^{s}\hat{s}$. Objective function to calculate the orientation in quaternion form is

$$f\left(\hat{q}_{ES},{}^{E}\hat{d},{}^{s}\hat{s}\right) = \hat{q}_{ES} \otimes^{E} \hat{d} \otimes \hat{q}_{ES} -^{s} \hat{s}. \tag{10}$$

Madgwick et al. have proposed a decent algorithm to optimize the aforementioned equation for n iterations resulting in an orientation estimation of $\hat{q}_{ES}(n+1)$ based on an initial guess orientation $\hat{q}^{0}_{ES}$ and a variable μ

$$q_{ES}(k+1) = \hat{q}_{ES}(k) - \mu \frac{\Delta f\left(\hat{q}_{ES},{}^{E}\hat{d},{}^{s}\hat{s}\right)}{\parallel \Delta f\left(\hat{q}_{ES},{}^{E}\hat{d},{}^{s}\hat{s}\right) \parallel}, \quad k = 1, 2, \ldots, n \tag{11}$$

computational origin of $\Delta f\left(\hat{q}_{ES},{}^{E}\hat{d},{}^{s}\hat{s}\right)$ is

[2] $\omega_{x,y,z}$: Angular velocity in corresponding direction.

$$\Delta f\left(\hat{q}_{ES},^{E}\hat{d},^{s}\hat{s}\right)=J^{T}\left(\hat{q}_{ES}(k),^{E}\hat{d}\right)f\left(\hat{q}_{ES}(k),^{E}\hat{d},^{s}\hat{s}\right). \tag{12}$$

Aforementioned Eqs. (11 and 12) are the general form of gradient decent algorithm applicable to determine orientation. Internal directional (rotation) matrix components of J and f differs for accelerometer and magnetometer. Procedure to calculate μ is proposed by

$$\mu(t)=a\parallel\dot{q}_{ES}(w,t)\parallel\Delta t, a>1 \tag{13}$$

Here $\dot{q}_{ES}(w,t)$, a are the rate of change of orientation measured by gyroscope and an augmentation of μ to count noise in homogeneous field (accelerometer and magnetometer). Equation 8–14 are taken from [12].

β is the divergence rate of $q_{ES}w$, expressed as the magnitude of a quaternion derivative and adjustable parameter of the filter. This parameter is defined by the angular quantity $\omega^{\sim}{}_{max}$, which is the maximum gyroscope measurement error of each axis. β is described by Eq. 14 where $\hat{q}$ is any unit quaternion. β is expressed in terms of $\omega^{\sim}_{maxX}$, $\omega^{\sim}_{maxY}$ and $\omega^{\sim}_{maxZ}$ (Maximum possible measurement error of a gyroscope along x, y, and z axes of the sensor frame) as:

$$\beta=\parallel\frac{1}{2}\hat{q}\otimes\begin{bmatrix}0 & \omega^{\sim}_{maxX} & \omega^{\sim}_{maxY} & \omega^{\sim}_{maxZ}\end{bmatrix}\parallel=\frac{3}{4}\omega^{\sim}{}_{max}. \tag{14}$$

2.5 Altitude Estimation

As stated earlier, the height problem can be solved by proper utilization of pressure sensor if the effect of some confronted environmental hindrances is considered. Lukas et al. have indicated at [20] that current floor estimations through barometric pressure reading of smartphone is erroneous as the reading changes with the change of temperature and humidity at the same level of the same building. And they have stated these facts as two major issues among three for erroneous current indoor localization systems. To overcome such drawbacks there are some solutions based on absolute sensor data. Reference-based methods are one of them. Because of the extra cost and deficiency of the reference sensor, this method is not suitable for this research. Instead, we can use statistical representation to predict the change in altitude between two-time intervals, presented by [27]. As the ground height varies due to change of temperature and humidity, we consider the persistent value of barometer at testbed basement, as ground truth information of that particular moment before performing any 3D experiment. Successive stair climbing evaluation is used to predict the most likely floor.

2.6 Navigation Equations

The proposed system is discerned as a relative positioning algorithm, as shown in Fig. 4. In Fig. 4, notations E_k, N_k, and h_k-the general conversion formula for atmospheric pressure-denote the east, north, and vertical directions, respectively [3, 28] are

$$E_k=E_{k-1}+I_s\times L_k\times\sin(\psi_k) \tag{15}$$

$$N_k=N_{k-1}+I_s\times L_k\times\cos(\psi_k) \tag{16}$$

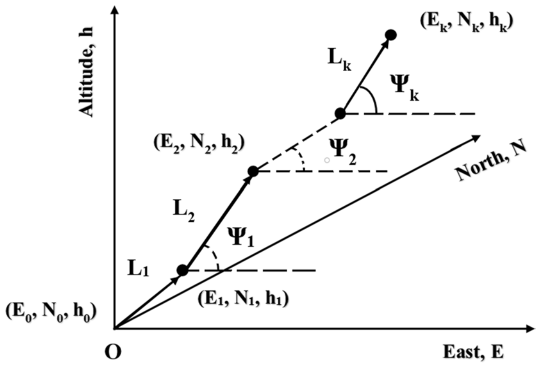


Fig. 4 Basic model for 3D navigation

$$h_k = 44{,}330\left(1 - \left(\frac{p_k}{p_0}\right)^{\frac{1}{5.255}}\right) \tag{17}$$

Here, (E_k, E_{k-1}) and (N_k, N_{k-1}) represents the East and north position in the present and immediate last known position of the object. ψ_k is the orientation (heading angle) at the current time; L_k is the stride of current successive step; I_s is number of steps. h_k is the height (altitude); P_k is the current level pressure value; P_0 is the sea level pressure value.

3 Experimental Result

In this subsection, prefatory exploratory outcomes demonstrating the accuracy of the heading, step length and position estimation using the proposed PDR system is accessed.

3.1 Hardware Description

We evaluated our proposed PDR navigation method in the institute building by using a Smart-phone. All experiments were conducted using a handhold positioned Sony mobile phone as shown in Fig. 5. This device incorporates accelerometer, gyroscope, magnetometer and a barometer. To measure the walking distance, we used a standard measuring tape.

3.2 Test and Results

The following sub-sections depict prefatory exploratory outcomes exhibiting the exactness of position estimation using the proposed system. Different walking pattern like straight line, circular shape and climbing stair were performed. The pedestrian held the phone in their hand in front of their chest and walked with normal speed (no lean, reverse walking) throughout the experiment. To extrapolate the experimental result same paths were repeated by different pedestrians. The data were post-processed using a program which was written in MATLAB.

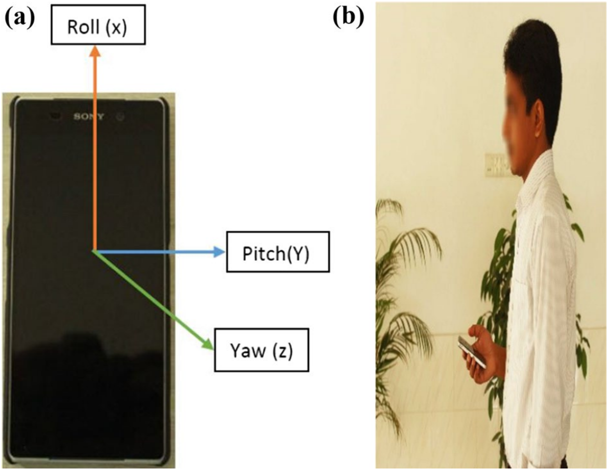


Fig. 5 Experimental setup, **a** coordinate system of the device, **b** holding mode

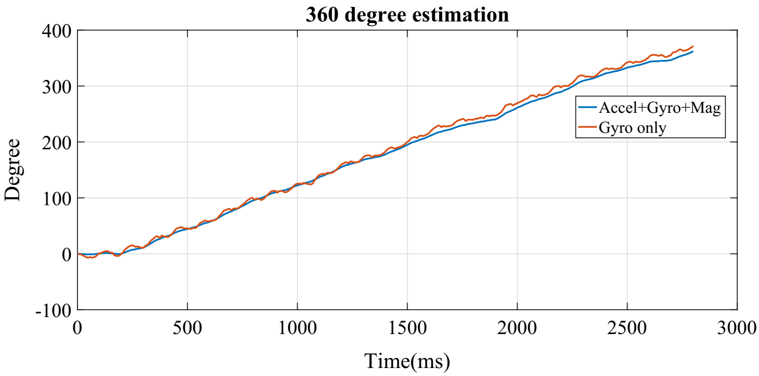


Fig. 6 Heading performance evaluation of different sensor fusion strategies

3.3 Heading Performance Evaluation

Orientation information has a pivotal impact on positioning accuracy. Heading, derived from sensor raw data is subjected to persistent error. The proposed PDR consolidate CI attributes with sensor fusion by MF algorithm for more rigid orientation information. A simple test was conducted to corroborate the heading accuracy of the enhanced PDR. At first, we placed the smart-phone pointing to magnetic north-a mechanical compass. By marking the reference with a mechanical compass, we had rotated the device 360°. Figure 6 depicts the estimation of rotation angle for two scenarios, alike, gyroscope raw data only and fusion of MARG sensors data by MF.

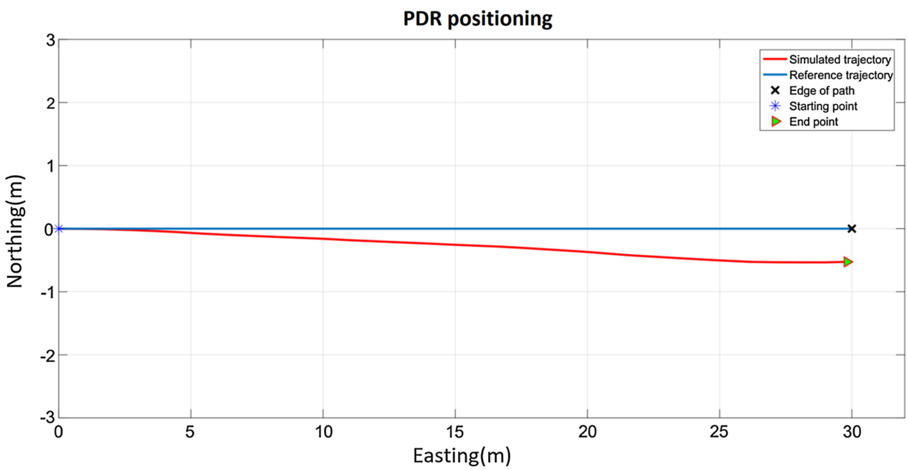


Fig. 7 Straight walking test trajectory

Table 1 Walking distance estimation summary

Test	Actual distance (m)	Avg. estimated distance (m)	Standard deviation (m)
*T*1	30	29.21	0.39
*T*2	30	29.32	0.85
*T*3	30	30.84	0.54
*T*4	30	30.05	0.36

3.4 Traveled Distance Evaluation

To validate enhancement of stride estimation by proposed modified Weinberg formula, straight-line walking experiments were conducted on 4 individual pedestrians. Every person walked the same distance i.e., 30 m. Figure 7 shows the walking trajectory of one straight line experiment.

Table 1 shows the average of estimated traveled distance and Standard Deviation for four different pedestrians. The average estimated traveled distance error is 0.48%.

3.5 Preparatory Test

Before we begin with the 3D complex walking experiments, we performed different patterns of test walk in indoor environment. In the first experiment, the person walks over a circular path (reference trajectory) of 10 diameters on a level surface. Figure 8 shows the estimated trajectory by proposed PDR system is an almost closed circle. Although the first step and the last step are not the same, with a distance error of ≈ 0.2 meter.

A 2D test (Random walking) was conducted inside the academic building of City University. The reference trajectory path was plotted in the top view of the building and the pedestrian had followed the path. The test was started from an initial point, after 450° turns

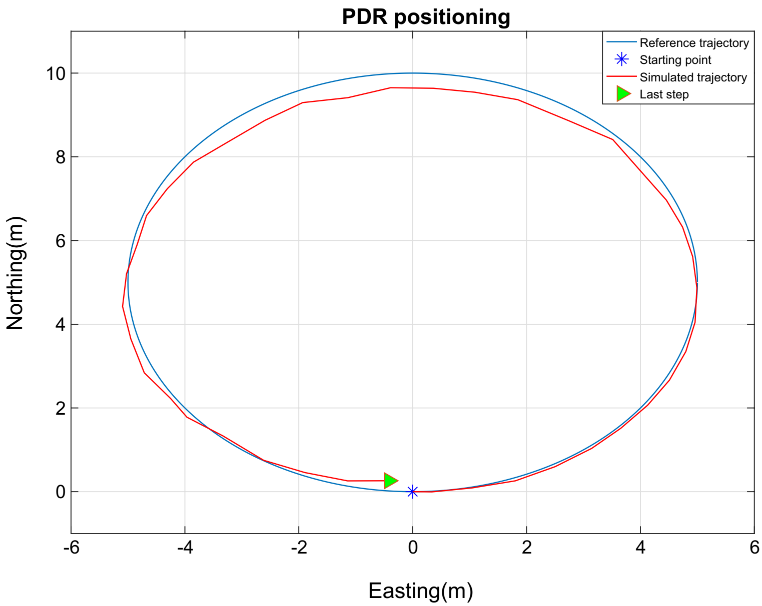


Fig. 8 Circular walking test trajectory

the user reached the endpoint. The simulated trajectory from the proposed system is represented in Fig. 9. To compare performance of the test, we plotted the simulated trajectory proposed by [7] on the same figure. From the figure it can be concluded in comfort, simulated trajectory of the proposed system is much closer to reference path than that of EKF based system trajectory.

3.6 3D Indoor Navigation

The combination of accelerometer, gyro, magnetometer, and barometer sensors module provides 3-dimensional position latitude, longitude, and altitude in X, Y, and Z-axes. Figure 10 depicts the 3D estimated trajectory of the test subject who climbed the stairs. In the experiment, the estimated trajectory resembles the reference trajectory of stairs but has north and east error (≈ 20 cm and ≈ 33 cm).

To extrapolate and compare 3D tracking at different floor inside a building by the proposed enhanced system and EKF based system [7] we have conducted different experiments. Pedestrian walked ground to second floor of the faculty building at different routes with natural walking behavior. We designed a 3D structure of test bed in AutoCad. To evaluate the overall accuracy of the PDR algorithm, reference trajectory of the actual direction of tests were plotted on the 3*D* structure. Height difference of each floor is around 3.048 m (10 feet).

Testing route of our first experiment starts from the ground floor. After a straight walk on the same floor, three consecutive rooms are passed. Ascending the stairs pedestrian reached first and second floor sequentially. Figure 11 illustrate simulated trajectories both proposed and EKF for the aforementioned route. From the figure, it can be seen that route and floor changes are well recognized. Human walking patterns create

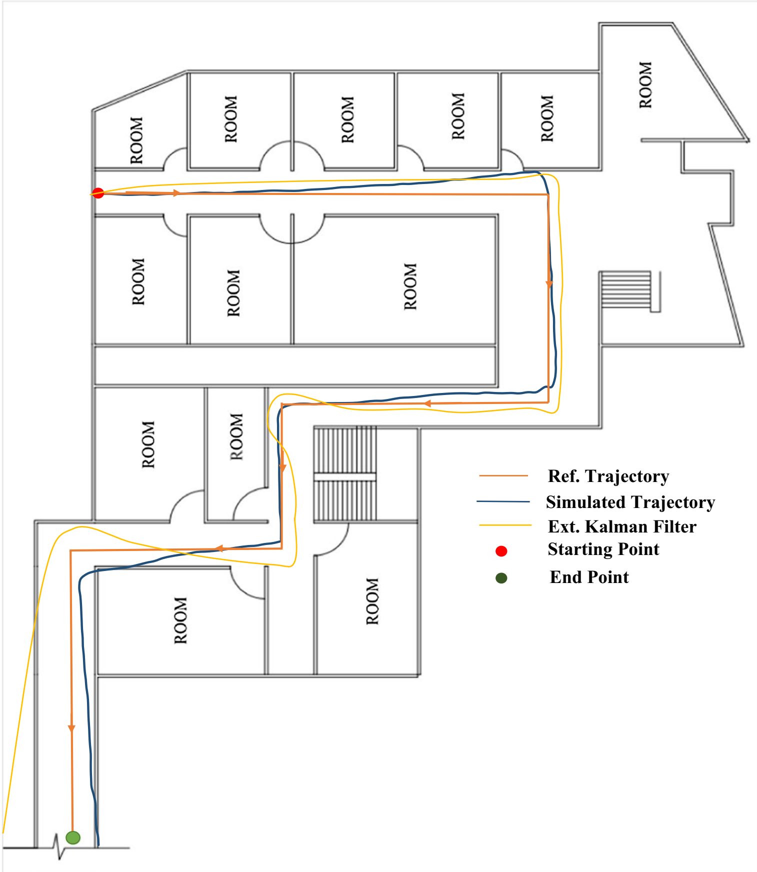
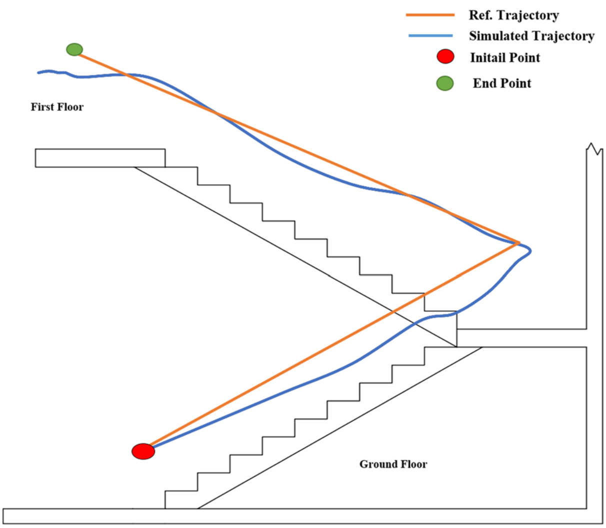


Fig. 9 Indoor test trajectory

Fig. 10 Climbing stairs



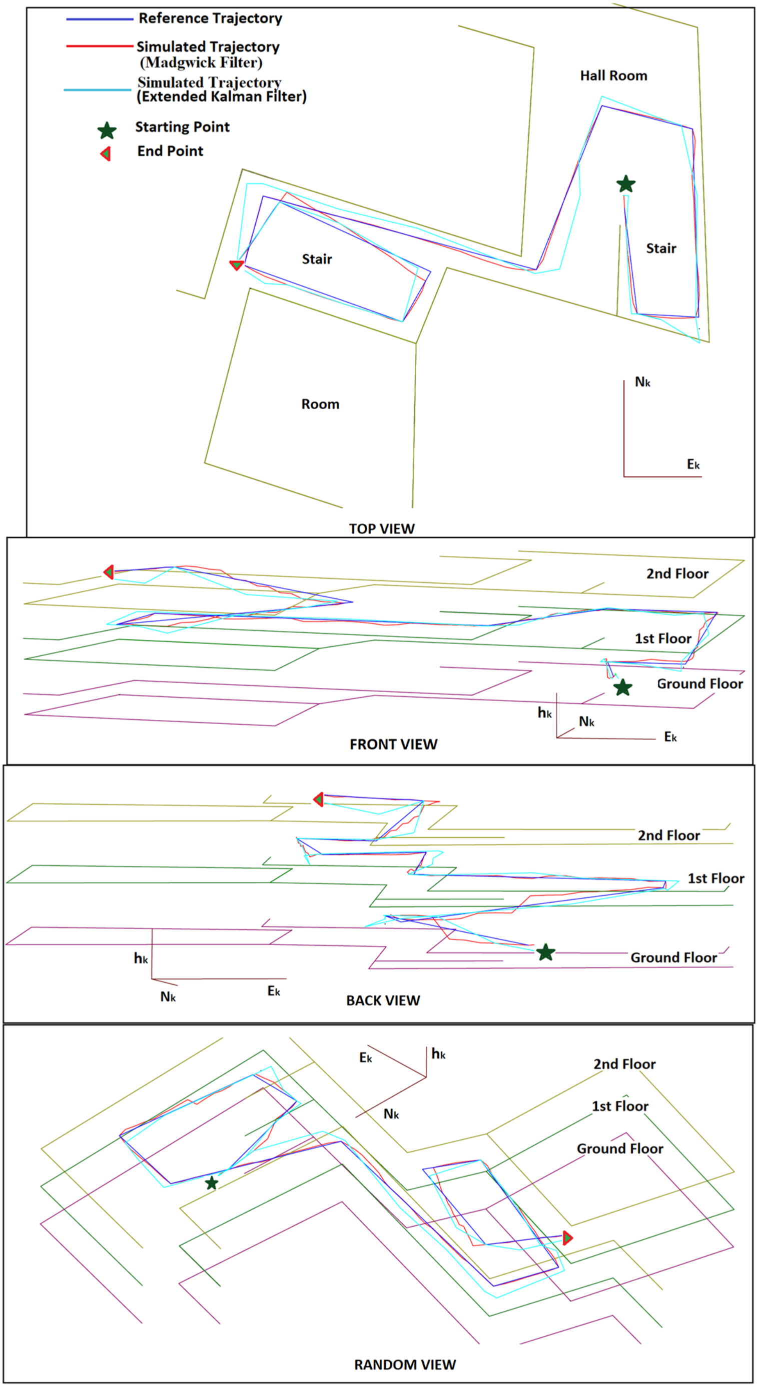


Fig. 11 Ascend from ground floor to second floor

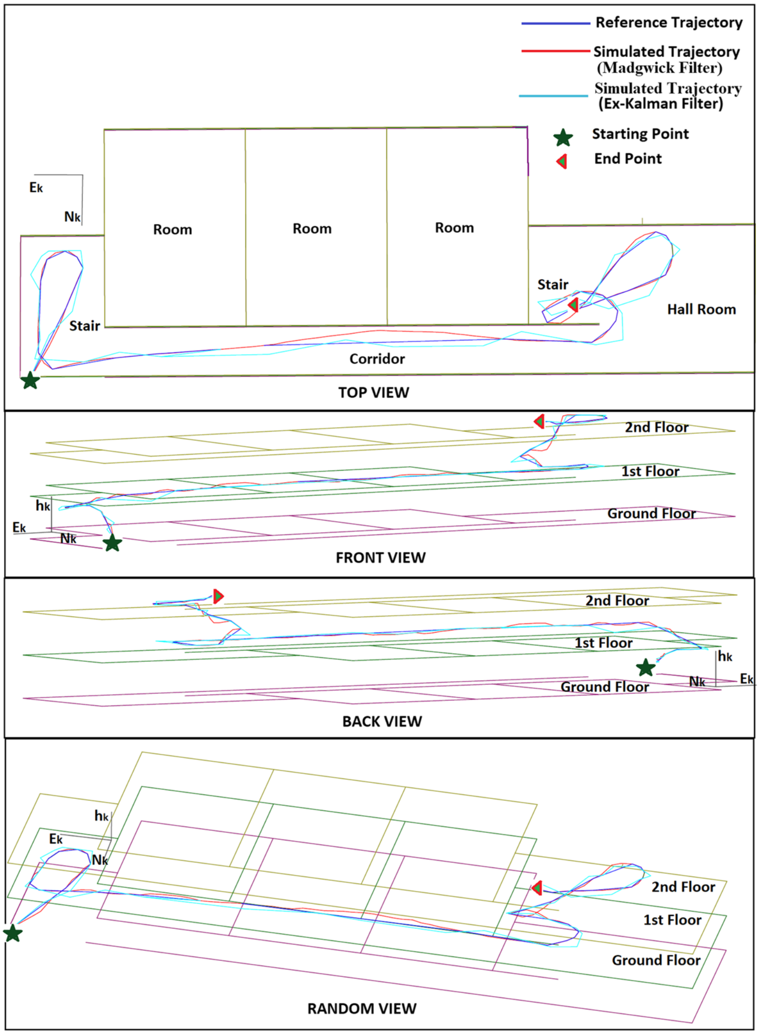


Fig. 12 Random walking at different floor

jitters in the Z-axis, that causes a structural difference between simulated and reference trajectory. However we present the simulated path trajectory form different view, that shows almost the same route as reference path. Note that the trajectory of our proposed system follows the reference trajectory more closer than the EKF one. It can be concluded with comfort that our proposed system accuracy of 3D localization is higher than the EKF based system.

In the second test, from ground floor pedestrian ascend the stair (south-west) to reach the first floor. At first-floor test subject walked randomly and explored hall room, corridor, classroom and reached the northeast corner of the building. Ascending the stair from that corner, finally test subject reached the endpoint of the route. Figure 12 depicts the simulated result of the test. From the test result, it is clearly recognizable that the proposed system can track the 3*D* position. Because of the very simple transition model

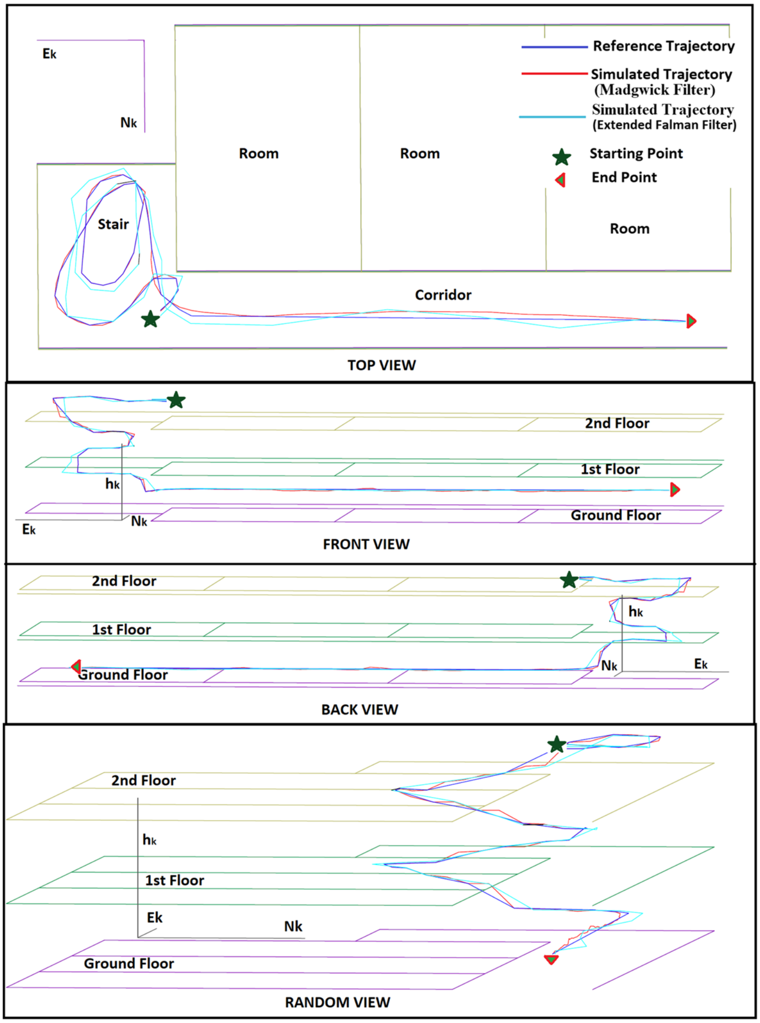


Fig. 13 Descend from second floor to ground floor

environmental modality that affects magnetic and pressure sensor reading was not considered here. That causes a small deviation of simulated trajectory from reference trajectory.

To check the capability of tracking object when falling from high to low we performed our third test. Here the initial point was selected on the second floor. The pedestrian starts from an initial point and descends stair to reach the first floor. Walking a straight line, pedestrian reached in front of the opposite stair. Finally descending stairs from same floor test subject reached endpoint at ground floor. The simulation result of the test is depicted in Fig. 13. In each of the above three experiments, it is being illustrated in the graphs that proposed enhanced PDR performance is yet mathematical compared to EKF based system.

4 Conclusion

An enhanced PDR technique based on smartphone sensor is presented. The proposed system opens the feasibility of indoor navigation by smartphone sensor without ZUPT. Positioning performance was evaluated for the indoor environment using MARG sensory integration strategies. A major source of error, caused by miss detection of unique stride is solved by a new step detection algorithm. The heading estimation is based on quaternion mechanization. The stochastic signal processing based on a gradient descent algorithm is the working principle of the applied filter. Altitude information from pressure sensor for a particular date and temperature extends the PDR navigation from 2D to 3D. Performance of the proposed PDR based estimated trajectories and recursive Kalman filter based trajectories are compared to reference trajectories. The results show that the presented algorithm is able to provide navigation information with less heading error compared to Kalman filter-based system in the short term of walk. Till the deficiency of temperature and humidity sensor left an open challenge for us to detect altitude information. The system can not follow the reference trajectory for a long duration (>5 min) of walk because of random error which introduces scatter in measured data and propagate through the simulation time. In the near future, we will integrate temperature and humidity sensor to estimate acute altitude and explore the applicability of the proposed system for a long term of the walk.

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Md. Abid Hasan received the M.Sc. degree in Mechatronic from the University of Siegen, Germany in 2016, and B.Sc. degree from the American International University Bangladesh (AIUB) in 2013. Since August 2017 to January 2019 he had been a lecturer of EEE department in City University Bangladesh. Currently he holds lecturer position of CoE department of AIUB. His research focuses on indoor localization, sensor fusion, wireless sensor networks, filtering technique and Signal processing.

Md. Hafizur Rahman received the B.Sc. degree in Electrical and Electronic Engineering from the Pabna University of Science and Technology, Bangladesh in 2016. Since April 2017 he has been working as a lecturer at Department of Electrical and Electronic Engineering in City University Bangladesh. His research focuses on sensor fusion, indoor and outdoor mapping, path planning, tracking, pattern recognition, robotics, and machine learning.