

Evaluation and Comparison of Performance Analysis of Indoor Inertial Navigation system Based on Foot Mounted IMU

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Abstract—This paper proposes to verify the performance & error analysis of pedestrian indoor navigation system using commercially available low-cost inertial sensors. This self-contained approach employs Euler for attitude representation, where the estimation problem is formulated as an Extended Kalman filter (EKF) for INS strap down mechanization equations. The algorithm outputs are the foot kinematic parameters, which include foot orientation, position, velocity, acceleration, and stance phase. The approach is based on a zero-velocity update (ZUPT), Zero angular rate update (ZARU), Heuristic heading drift reduction (HDR) algorithms. The main contribution of the paper is to compare and analyse the heading drift reduction algorithms on Kalman-based IEZ platform and estimating the return position error. Orientation is then determined from the foot's initialized from accelerometer sensor information. Finally, we evaluated using experiments, including both short distance walking with different patterns and long distance walking performed in indoor.

Keywords—Inertial Navigation, zero velocity update, Heading Drift Reduction, sensor fusion, Extended Kalman Filter

I. INTRODUCTION

The application of a pedestrian navigation system have attracted many researchers attention for the last two decades. Improving the performance of the system is an important issue and still an open research challenge. From indoor positioning point of view, during the last decade several methodologies have been proposed for accurate person's position estimation indoors. Indoor positioning system is used in place where GPS signals are degraded such as warehouse, tunnels and hospitals. Inertial navigation systems use dead-reckoning to estimate the pedestrian's position. There are two types of PDR, the strap down algorithm method that uses double integration of three orthogonal accelerometer reading and the step-and-heading approach estimates sequentially the pedestrian's position based on the previous position for each detected step, the step length and the heading, but the later lack the vertical

displacement estimation. The main problem for the low cost IMUs is the accumulation of error over time. To overcome this error accumulation, the Zero velocity update (ZUPT) is applied. However, the yaw (heading) cannot be observed in ZUPT alone unless coupled with the Heuristic heading drift update. Zero angular update (ZARU) enhances the accuracy of heading estimation of the system when the object is static, and further improves the whole attitude estimation.

The major advantage of inertial and motion sensors are that do not require any setup of measurement devices or supporting sensors located at the site. IMU's are very accurate over short distances, but require some external calibration such as from a GPS unit to remain accurate over long periods. Pedestrian Dead Reckoning (PDR) systems are becoming feasible options for indoor and outdoor. They use inertial and other sensors, often combined with other domain to improve the performance of the pedestrian navigation system, and evaluated using indoor and outdoor field tests. The implementation compares different method such as heuristic heading HDR, zero velocity update, zero angular update, and concatenating each together to minimize the error accumulated in the INS by giving measurement error to the extended Kalman filter to estimate position, velocity, and heading of the pedestrian in multi-story building.

This paper organized as follows. Section 2 describes, related work, section 3 ground information, section 4 coordinate transformation, section 5 Heading drifts Error correction, section 6 required hardware, section 7 final return position error estimation, section 8 implementation and evaluation and section 9 conclusion and future work .

II. RELATED WORK

A variety of systems has been proposed to address the location of users in indoor environment [1], [2]. Research on the topic of indoor navigation can be broadly classified into two main categories of beacon free and beacon based approaches [8]. The foot-mounted IMU-based PDR algorithm proposed first by Foxlin [1]. The implementation in [3] proposed the performance of HDE-based method for improved heading error elimination. The most common methods for reducing the effects of gyro drift are by

integrating INS and GPS information [9, 10]. The implementation in [11] integrate data from a magnetic compass as well. The work in [12] propose a method that makes use of available maps and uses map matching techniques for further enhancement. The main drawback of these approaches is that either they use external references or information ahead of time, which may not be available all the time. For example, GPS only works outdoors and magnetic fields are often disturbed and unreliable in indoor.

III. BACK GROUND INFORMATION

A. Inertial navigation system (INS)

Inertial sensors have long been used in many disciplines for different application such as fire fighter, lands, air, space and autonomous vehicles. However, in some applications require high-grade IMUs, which are costly and bulky, to navigate reliably for extended periods, even though no aiding signal is available for INS. The basic principles of inertial navigation system consists of calculating the IMU's position and attitude in gyro and acceleration measurements in the body b coordinate system attached to IMU.

B. Foot-mounted INS Mechanization

All Inertial navigation system mechanization equations are a set of equations which form the basis of inertial navigation in a given navigation frame. Depending on the application, these equations take slightly different form in different navigation frames. It is well known that IMU output is related to the navigation information (i.e. position, velocity and attitude) through kinematic equations, known as 'INS Mechanization' given by [4]. The velocity of the agent in navigation frame is expressed as follows:

$$\dot{v}^n = c_b^n f^b - (2\omega_{ie}^n + \omega_{en}^n) \times v^n + g^n \quad (1)$$

The first term is the specific force (SF) experienced by accelerometer transformed in navigation frame by transformation matrix (C_b^n), which in turn is formed by angular rates sensed by gyroscopic. The second term is the Coriolis acceleration due to the rotation of the Earth itself and last term is the effective gravity expressed in local navigation frame. The terms ω_{ie}^n , and ω_{en}^n are the Earth rotation vector and navigation frame transport rate vector respectively, which are ignored for Pedestrian navigation system. Hence, the effective acceleration for PNS application in Earth fixed, locally tangent frame is expressed as

$$\dot{v}^n = c_b^n f^b + g^n \quad (2)$$

C. Extended kalman filter

Due to the drift characteristics of IMU sensors and integrations error of INS mechanization, the Extended Kalman Filter (EKF) is usually used to fuse solutions such as the position and velocity. The EKF estimates the optimal state of a process by satisfying the criterion, which minimizes the mean of the square errors (MMSE). When the EKF is used to fuse INS, the error state vector is determined first as follows:

$$\delta x_{k/k} = [\delta \psi_k \ \delta \omega_k \ \delta r_k \ \delta v_k \ \delta a_k] \quad (3)$$

Where $\delta \psi_k$ are attitude errors, $\delta \omega_k$ are the bias vector of gyroscopes δr_k are position errors; δv_k are velocity errors, and δa_k are the bias vector for accelerometers. In the prediction stage, the linearized state transition model is:

$$\delta x_{k/k-1} = F_k \delta x_{k-1/k-1} + w_{k-1} \quad (4)$$

where $\delta x_{k/k-1}$ is the predicted error states vector, $\delta x_{k-1/k-1}$ is the filtered error states vector at time k-1, w_{k-1} is the process noise with covariance matrix Q, and F_k is the 15×15 error states transition matrix:

$$F_k = \begin{bmatrix} I_{3 \times 3} & \Delta t C_{bk-1}^n & O_{3 \times 3} & O_{3 \times 3} & O_{3 \times 3} \\ O_{3 \times 3} & I_{3 \times 3} & O_{3 \times 3} & O_{3 \times 3} & O_{3 \times 3} \\ O_{3 \times 3} & O_{3 \times 3} & I_{3 \times 3} & \Delta t I_{3 \times 3} & O_{3 \times 3} \\ -\Delta t S(a_k^n) & O_{3 \times 3} & O_{3 \times 3} & I_{3 \times 3} & \Delta t C_{bk-1}^n \\ O_{3 \times 3} & O_{3 \times 3} & O_{3 \times 3} & O_{3 \times 3} & I_{3 \times 3} \end{bmatrix} \quad (5)$$

where Δt is the time step measurement, a_k^n is the bias-corrected acceleration in navigation frame transformed from a_k^b in body frame, $S(a_k^n)$ is the skew symmetric matrix using accelerations in the navigation coordinates to estimate the attitude of the sensor:

$$S(a_k^n) = \begin{bmatrix} 0 & -a_{zk}^n & a_{yk}^n \\ a_{zk}^n & 0 & -a_{xk}^n \\ -a_{yk}^n & a_{xk}^n & 0 \end{bmatrix} \quad (6)$$

In the update stage, the EKF fed by discretised dynamic error measurement and the observation model. The discrete-time system model and observation model can be expressed as:

$$Z_k = H \delta x_{k/k} + v_k \quad (7)$$

Where Z_k is the observation vector, H is the design matrix at, and v_k is the additive white zero-mean Gaussian noise with covariance matrix R_k . When Zero Angular rate update (ZARU) and zero-velocity updates (ZUPT) concatenated, Z_k and H are given as follows:

$$Z_k = [\delta \omega_k^b \ \delta v_k^b] = [\omega_k^b \ v_k^b] \quad (8)$$

$$H = \begin{bmatrix} 0_{3 \times 3} & I_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} \\ 0_{3 \times 3} & 0_{3 \times 3} & 0_{3 \times 3} & I_{3 \times 3} & 0_{3 \times 3} \end{bmatrix} \quad (9)$$

The H matrix selects the velocity error component and the angular rate components from the error state vector $\delta x_{k/k}$. The estimated error states vector $\delta x_{k/k}$ is updated as follows:

$$\delta x_{k/k} = \delta x_{k/k-1} + K_k \cdot [Z_k - H \delta x_{k/k-1}] \quad (10)$$

Where $\delta x_{k/k-1}$ is the predicted error state vector.

K_k is the Kalman gain given by

$$K_k = P_{k/k-1} H^T (H P_{k/k-1} H^T + R_k)^{-1} \quad (11)$$

Where $P_{k/k-1}$ is the estimation error covariance matrix based on measurements received at time k-1. The covariance matrix $P_{k/k}$ at time k is computed using the Kalman gain in the Joseph form equation is given as

$$P_{k/k} = (I_{15 \times 15} - K_k H) P_{k-1/k-1} (I_{15 \times 15} - K_k H)^T + R_k \quad (12)$$

D. Stance phase detection

When a person walks, their feet alternate between a stationary stance phase and a moving stride phase. Stance phase represents about 60% of the gait cycle, and starts from initial contact with the ground. Swing phase is the phase of the normal gait cycle during which the foot is off the ground. The stance phase detection employed a gyroscope and accelerometer to measure the angular velocity of the foot and three forces exerted by the foot on the shoe during walking respectively. At the stance phase, zero-velocity updates (ZUPT) and Zero angular update (ZARU) are pseudo measurements provided to the Extended Kalman Filter (EKF) error corrector. This allows the EKF to correct the velocity error after each stride, breaking the cubic-in-time error growth and replacing it with an error accumulation that is linear in the number of steps.

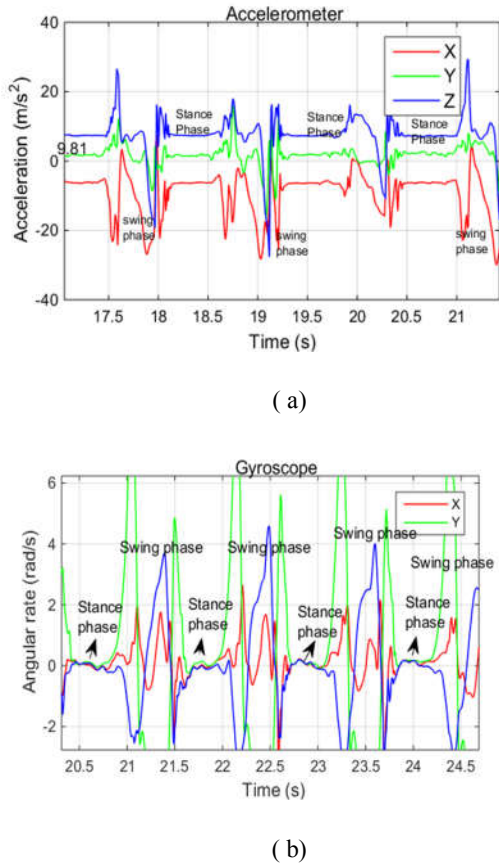


Fig. 1. IMU measurements stance and swing phase. (a) Accelerometer & (b) Gyroscope measurement

IV. COORDINATE TRANSFORMATION

The transformation from the body frame to the navigation frame requires the rotation about three axes. A convenient way of describing these rotations is using a direction-cosine matrix (DCM). If one defines three angles, and as the yaw, pitch, and roll of the body, respectively, with referenced to

the navigation frame, one can define a DCM to rotate from the body to the navigation frame.

Hence, once the three separate rotation matrices have been multiplied out, the final DCM is given as:

$$C_k^n \begin{bmatrix} \cos\theta\cos\psi & -\cos\theta\sin\psi & \sin\theta\sin\psi & \sin\theta\cos\psi \\ \cos\theta\sin\psi & \cos\theta\cos\psi & \sin\theta\cos\psi & \sin\theta\sin\psi \\ -\sin\theta & \sin\phi\cos\theta & \sin\phi\sin\theta & \cos\phi\cos\theta \end{bmatrix} \quad (13)$$

The Direction cosine matrix (DCM) in equation (13) represents orientation transforms accelerations from the body to the navigation frame.

$$a_k^n = c_k^n a_k^b \quad (14)$$

where a_k^b is the noiseless acceleration in the body (b), a_k^n is the noiseless acceleration in the navigation (n) coordinates and C_b^n is the rotation matrix which transforms vectors from the body coordinates to the navigation coordinates.

The INS algorithm integrates the compensated IMU measurements to estimate the raw INS states by solving the discrete-time navigation equations

$$c_{bk}^n = \begin{bmatrix} 2I_{3 \times 3} + \Omega_k \Delta t \\ 2I_{3 \times 3} - \Omega_k \Delta t \end{bmatrix} c_{bk-1}^n \quad (15)$$

$$v_k^n = v_{k-1}^n + (c_{bk}^n a_k^b - g) \Delta t \quad (16)$$

$$p_k^n = p_{k-1}^n + (v_{k-1}^n + v_k^n) \Delta t / 2 \quad (17)$$

V. HEADING DRIFTS ERROR CORRECTION

1) Zero Velocity Detection (ZUPT)

The ZUPT method treats the raw velocity as pseudo measurement of the velocity error and feeds it into the Extended Kalman filter via the measurement model.

$$z_{k+1} = H_{k+1} x_{k+1} + v_{k+1} \quad (18)$$

Where z_{k+1} is the aiding measurement derived from v_{k+1} at epoch $k + 1$. For explaining the test statistics of zero velocity detection, we first define two conditions for judging stationary state.

(a) In stationary state, no external force except gravity acts on the MEMS, so the specific force $\|f_k\|$ at the time instant k should equal to the local gravity value theoretically.

$$\|f_k\| = \sqrt{f_x^2 + f_y^2 + f_z^2} \quad (19)$$

Where f_x , f_y and f_z are the components of the specific force in x-axis y-axis and z-axis directions at the time thus constraint is determined that the specific force $\|f_k\|$ at stationary instant should be in a certain range around gravity. (b) Angular rate is also considered in detecting stationary state. Similar to Equation (19), angular rate ω_k at the time instant k is defined as

$$\|\omega_k\| = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2} \quad (20)$$

Where ω_x , ω_y and ω_z are the components of the angular rate in x-axis, y-axis and z-axis directions at the time k . In stationary state, angular rate ω_k is theoretically equal to zero. In our paper, we considered the two logical conditions in equation (19) & (20) should be satisfied simultaneously for foot stationary detection, so a logical "AND" is applied as shown in Figure 2.

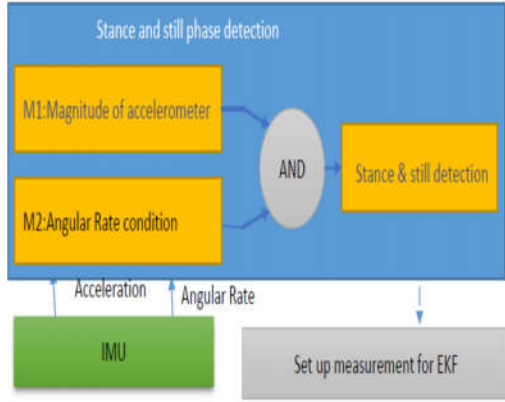


Figure. 2. Stance and Still detection.

2) Zero angular rate update (ZARU)

Zero Angular rate update (ZARU) is the measurement that helps estimating the bias of gyroscope, with the assumption of a fixed orientation when the sensor is in a still phase. Zero angular rate update (ZARU) reduce the heading drift but in situation where there is no initialization or where the stance is too short (unstable) or fast walking for ZARU a complimentary bias estimation method is required.

3) Heuristic drift Reduction (HDR)

Heuristic drift reduction work with the assumption that most of the time human walks in straight paths inside building along corridor. With this assumption, it corrects computed heading rate of turn. If the likelihood that the pedestrian walks straight along a corridor is high, HDR applies a correction method to the gyro output, which contains the bias error to reduce the heading error. To distinguish the near straight path from the curved path, we can use two different method analysing the orientation change among successive steps in yaw space as shown in equation (21).

$$\Delta\psi_k = \psi_k - \frac{1}{n} \sum_{m=1}^n \psi_{k-m} \quad (21)$$

If $|\Delta\psi_k| < th_{\Delta\psi}$, then the likelihood that the pedestrian walking in straight line is considered to be high. Where $th_{\Delta\psi}$ is threshold value. We assumed $th_{\Delta\psi}$ between (0.5~2.5). However, $th_{\Delta\psi}$ varies based on the type of scenarios. For example for the **figure 3**, the likelihood for the walker is walking straight in a corridor is very low for $th_{\Delta\psi}$ above 2.5

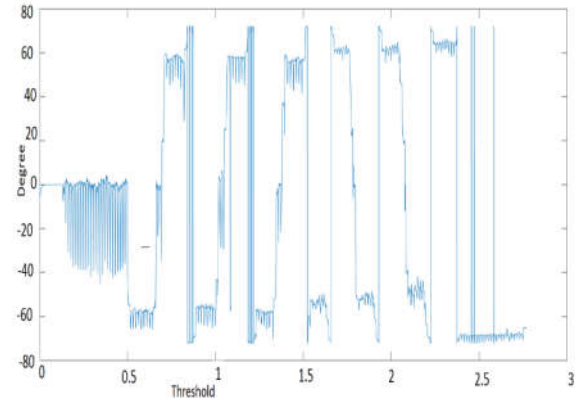


Figure 3. Yaw (degree) vs threshold

The second hypothesis that we used are computing change in heading from two consecutive x-y position of footfall of the walker's momentary heading (orientation). with regard to heading, there is no good method for estimating or totally reducing the effect of drift.

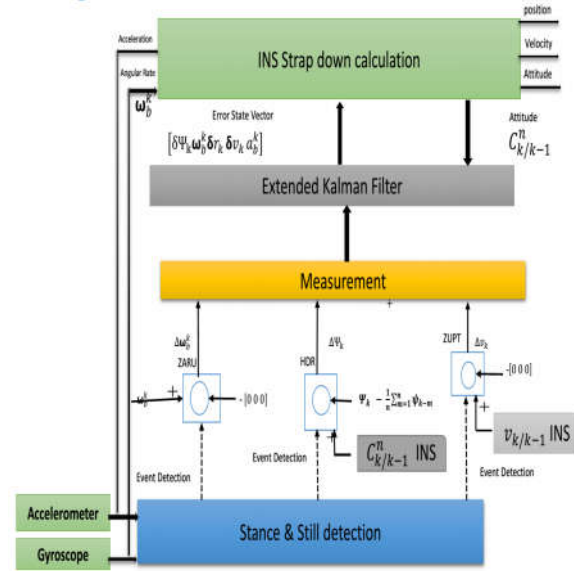


Figure 4. A diagram of EKF-based PDR

The error corrector utilizes the error estimates to refine the raw INS states by

$$c_{bk}^n = \begin{bmatrix} 2I_{3 \times 3} + \Omega_k \Delta t \\ 2I_{3 \times 3} - \Omega_k \Delta t \end{bmatrix} c_{bk-1}^n \quad (22)$$

$$\dot{v}_k^n = v_k^n - \delta v_k^n \quad (23)$$

$$\dot{p}_k^n = p_k^n - \delta p_k^n \quad (24)$$

Where c_{bk-1}^n is the corrected attitude matrix, Ω_k is the skew symmetric matrix used to refine the attitude matrix, v_k^n is the corrected velocity, and p_k^n is the corrected position. As given (22), a first order Pad'e approximation is used to update and correct the attitude matrix.

VI. REQUIRED HARDWARE

We use a commercially available IMU; model MTx from Xsens Technologies). Its size is $58 \times 58 \times 22$ mm (length $\times$ width $\times$ height), and it weighs 50 g. It is configured to provide inertial data at 120 Hz. The MEMS is mounted on the right foot, with x-axis pointing forward, y-axis pointing to the left (the inside of the right foot), z-axis is perpendicular to the x-y plane to complete a right hand coordinate system as shown in Figure 5.

Table 1. Technical parameters of the MTx sensor

	Accelerometers	Gyroscopes
Full Range	$\pm 50 \text{ m/s}^2$	$\pm 1200^\circ/\text{s}$
Non-linearity	0.02%FS	0.01%FS
Noise density	$80 \mu\text{g}/\sqrt{\text{Hz}}$	$0.01^\circ/\text{s}/\sqrt{\text{Hz}}$
Bias repeatability	0.02 m/s ²	$1^\circ/\text{s}$
Bandwidth	30 Hz	50 Hz
Max update rate	512 Hz	512 Hz



Figure 5: IMU attached the to user's right shoe

VII. FINAL RETURN POSITION ESTIMATION

For a closed-loop walk, the absolute return position error E_a is estimated for the position error in the x and y direction. The return position error is quantified by the difference between the initial and final positions of the estimated trajectory, and smaller values indicate less drift, which can be computed as:

$$E_a = \sqrt{E_x^2 + E_y^2} \quad (21)$$

Where E_x is the position error in the x-direction, and E_y is the position error in the y-direction.

VIII. IMPLEMENTATION AND EVALUATION

First, our system was initialized with pitch and roll angles (Euler equivalent) from acceleration and gyroscope obtained from 10 second standing before starting the movement in order to generate a ZARU measurement and estimate the gyroscope biases. The accelerometer noise was set to $\sigma_a = 0.01 \text{ m/s}^2$ and for gyroscope noise $\sigma_\omega = 0.01 \text{ rad/s}$. Our evaluation criterion based on the altitude error, the yaw error (the accumulation of the heading change error ψ_k) and the return position error. We evaluated the 15 full state representations, algorithms ZUPT, HDR & ZARU. The heading estimation test

trajectories with IMU on shoe was in ETRI in our building corridor layout and walking route are as in Fig. 6, 8 and 9. The trajectory in Figure 6, 7 starts from first floor to the 4th floor and coming back to the initial position. The second scenario is walking in a rectangular path and coming to the initial position in our lab as in Figure 9.

In our Test scenario, we tested the IEZ based PDR by tuning the EKF to get stable operation by selecting appropriate matrix values of R_k , Q_k and $P_{k/k-1}$. We can observe that the ZUPT+HDR reduce the heading errors in the estimation of the position compared to the ZUPT+ZARU. The result reported herein are being confirmed by further testing.

Our experimental findings have confirmed that addition of ZARU was rather minor which contribute the stability of gyro bias during stand still and in which correction is not observable in pedestrian walking.

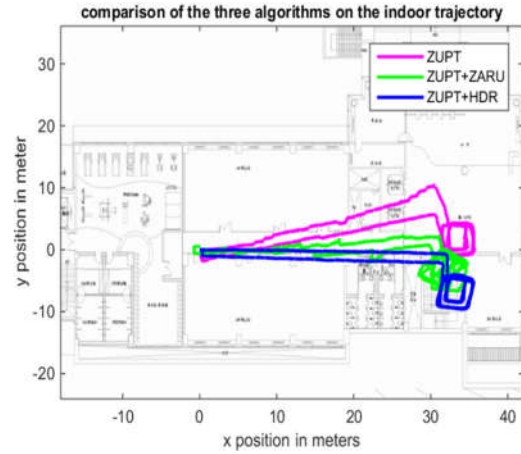


Figure 6. ZUPT+HDR method 2D estimated Trajectory

This test result shows the estimated 2D altitude trajectories for a path 160 meters long, completed in 150 seconds.

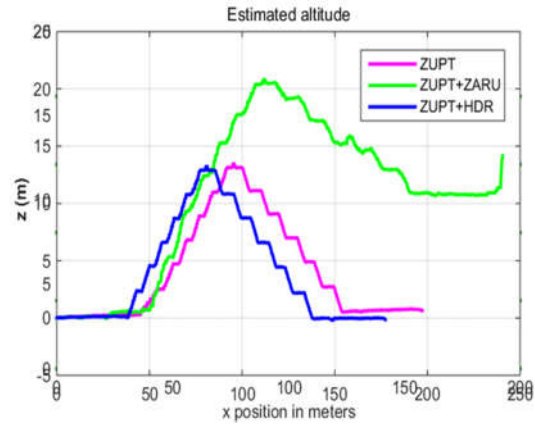


Figure 7. Height Estimation results for multi-Floor

This Figure shows the vertical displacement (estimated altitude). In this figure, we observe that there is drift in

altitude in ZUPT + ZARU method. In Applying algorithm ZUPT+HDR,the position drift in Z-component significantly decreased.

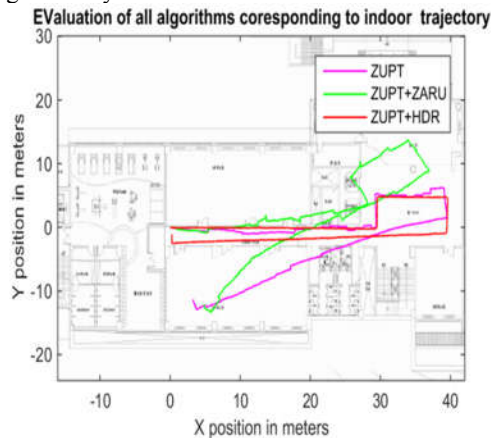


Figure 8.Performance of each algorithm using pure ZUPT, ZUPT+ZARU,ZUPT+HDR

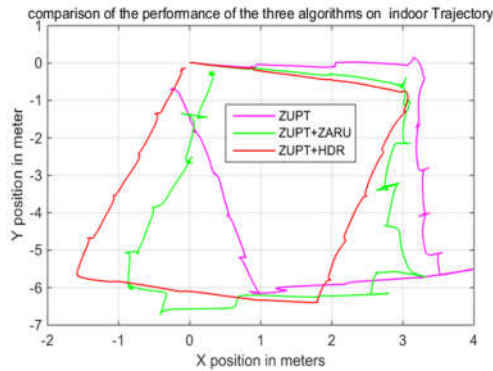


Figure 9.Performance of each algorithm using ZUPT, ZUPT+ZARU,ZUPT+HDR in square closed trajectory.

Figure 8- 9 presents similar return position error statics in our repeatedly taken test result in INS +ZUPT+HDR as shown in summary in table2. Therefore,one can conclude that by applying some method related with heading drift reduction,gyro bias wich can contribute the accumulation of heading drift can be reduced.

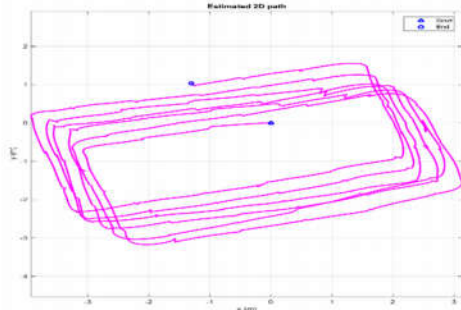


Figure 10. ZUPT+ZARU estimated 2D Trajectory

This figure shows the estimated closed loop rectangular path in our office. One of the main source of error in this test result is increment of yaw error due to the fact that yaw is not observable. In ZARU +ZUPT, there is the loss of

heading (Unobserved state yaw), that after sometime can generate significant errors in positioning.

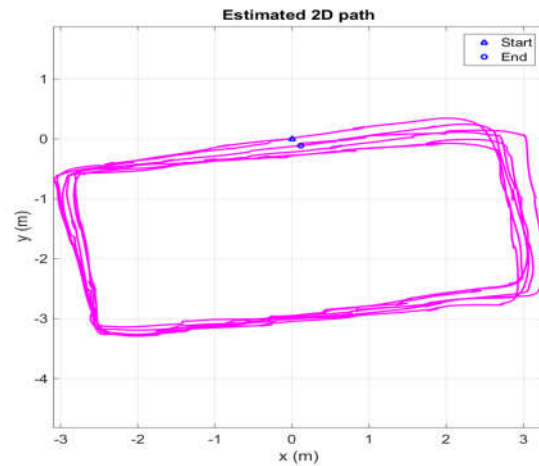


Figure 11. ZUPT+ HDR method estimated 2D Trajectory

As compared with the previous Figure 10, Fig 11. shows improvement drift in heading. So that HDR compensates for gyro drift when pedestrians walk along approximately in straight line.

Table 2. Return Position Errors of each method

Algorithm	Return position error in (TTD in %)
INS+ZUPT	> [6]
INS+ZUPT+ZARU	< [6~8]
INS+ZUPT+HDR	< [1~3]

IX. CONCLUSION AND FUTURE WORK

Within this work we have evaluated and presented pedestrian navigation system using foot mounted IMU using different heading error reducing technique algorithm. The ZUPT +HDR showed very good result on the test result. We observed that the uncorrected heading drift is proportional to travelled distance. In future works, we will extend our method to include the usage of quaternion angles in the angle propagation to avoid gimbal lock and other pedestrian locomotion such as running, sidestepping to evaluate the system performance as fully as possible. It is clear that a Dead-Reckoning will always have an increasing error due to integration.

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