IEIE Transactions on Smart Processing and Computing, vol. 6, no. 1, February 2017
https://doi.org/10.5573/IEIESPC.2017.6.1.001

IEIE Transactions on Smart Processing and Computing

Performance Improvement of an INS by using a Magnetometer with Pedestrian Dynamic Constraints

Feyissa Woyano[1], Aangjoon Park[2], and Soyeon Lee[3]

[1] Department of Computer Software, Korean University of Science and Technology / Daejeon, Korea
{feyissa, Sangjoon}@etri.re.kr
[2] Positioning/Navigation Technology Research Section, Electronic and Telecommunication Research Institute (ETRI)
{feyissa, Sangjoon, sylee}@etri.re.kr

***** Corresponding Author: Feyissa Woyano Gobana

Received October 24, 2016; Revised December 28, 2016; Accepted January 11, 2017; Published February 28, 2017

** Regular Paper*

***Abstract*:** This paper proposes to improve the performance of a strap down inertial navigation system using a foot-mounted low-cost inertial measurement unit/magnetometer by configuring an attitude and heading reference system. To track position accurately and for attitude estimations, considering different dynamic constraints, magnetic measurement and a zero velocity update technique is used. A conventional strap down method based on integrating angular rate to determine attitude will inevitably induce long-term drift, while magnetometers are subject to short-term orientation errors. To eliminate this accumulative error, and thus, use the navigation system for a long-duration mission, a hybrid configuration by integrating a miniature micro electromechanical system (MEMS)-based attitude and heading detector with the conventional navigation system is proposed in this paper. The attitude and heading detector is composed of three-axis MEMS accelerometers and three-axis MEMS magnetometers. With an absolute algorithm based on gravity and Earth's magnetic field, rather than an integral algorithm, the attitude detector can obtain an absolute attitude and heading estimation without drift errors, so it can be used to adjust the attitude and orientation of the strap down system. Finally, we verify (by both formula analysis and from test results) that the accumulative errors are effectively eliminated via this hybrid scheme.

***Keywords*:** Zero velocity update, ZUPT, Zero altitude update, Pedestrian navigation, Kalman filter, Dynamic constraint

1. Introduction

A navigation system that tracks the position and heading of pedestrians in indoor/outdoor environments using a foot-mounted inertial sensor has numerous applications [1]. These systems do not require any infrastructure other than the inertial measurement unit (IMU) itself, which makes them the preferred option for navigation in many scenarios, e.g., position tracking, search-and-rescue operations, and pedestrian guidance. With the development of miniature micro electromechanical systems (MEMS), the inertial navigation system's algorithm can estimate the orientation result from an accelerometer reading (yaw, pitch, and roll) for attitude initialization and update. However, because of sensor noise and bias in the low-cost inertial sensors, such orientation suffers from drift errors that degrade the long-term performance requirement. The main concern of a researcher in this area is to achieve a long-term, stable navigation solution. To do so, it is suitable to integrate measurements from an IMU carried by the pedestrian. These long-term drift problems can be mitigated by configuring the attitude and heading reference system (AHRS). We mechanize the value measured by the accelerometer and magnetometer to get the attitude and position changes of the foot. A strap down inertial navigation system (SINS) algorithm using a low-cost MEMS is not enough to satisfy attitude and heading performance requirements.

Filtering techniques with pedestrian dynamic constraints are used to build an AHRS based on a system-and-measurement model. For the nonlinear state, an extended Kalman filter is used. Zero velocity update (ZUPT) reduces the IMU velocity drift. In addition, a zero height constraint is used to reduce position drift by clamping the mechanization result to ground at the end of each step, except on stairs. Zero velocity update detection implementation is a threshold value of the total acceleration vector magnitude. A pitch change magnitude threshold was used on stairs.

2. Related Work

In personal navigation, the foot alternates between stance and swing phases [1], and zero velocity update is applied as a navigation error corrector. ZUPT is applied as a pseudo measurement update inside the extended Kalman filter (EKF). However, as emphasized by both Ojeda et al. [3] and Bebek et al. [4], reset this pseudo-measurement ZUPT to zero during zero velocity. In this way, updating the zero velocity during the stance phase itself does not improve the entire movement of the pedestrian-movement foot-mounted inertial navigation. For instance, Jun's pedestrian dead reckoning (PDR) system considers the heel-strike and toe-off phases when using a foot-mounted IMU [11]. Extensive research has been performed on how to use ZUPT for accurate position estimation. However, simply resetting the integrated velocity to zero during zero velocity phases does not only improve the performance of PDR. Yun et al. [5] further improved the idea of ZUPT and applied a time-variant acceleration bias error to revise the acceleration in the swing phases. Similarly, Schepers et al. [23] proposed using high-pass filters to remove bias error. The integrated velocity and the integrated position were high-pass filtered by first-order recursive Butterworth filters to alleviate the integration drift, but it is quite challenging to determine the cutoff frequencies of the filters, which makes this method not straightforward enough to use in practice. However, all the aforementioned acceleration double-integration methods assumed that the gravitational acceleration could be removed from the accelerometer signal to obtain the motion acceleration, but such procedures are extremely difficult due to sensor bias and noise.

This paper presents a methodology for the technique, performs an analysis, and gives the testing results of the system based on the extended Kalman filter. Our approach in this paper uses a zero height constraint, magnetometer, and EKF.

3. Basic Navigation Equation

Inertial measurements are used to compute basic navigation solutions. In addition to this, magnetic field measurement improves heading accuracy. In this section, a navigation equation is introduced for both the inertial sensor and magnetometer.

3.1 Inertial Navigation System (INS)

The combination of an inertial measurement unit and a navigation processor to do the computation can be collectively known as an inertial navigation system (INS). The INS estimates position, velocity, and attitude by using accelerometer and gyroscope readings. The sensor data are related to the coordinate frame of the IMU, which is called the IMU frame. In the first step, the bias-compensated accelerations of the IMU frame, which are taken at discrete time k, are first transformed into building the local navigation frame in order to remove gravity from the sensor data. The discrete navigation equation is as follows:

$$\begin{bmatrix} p^n(k+1) \\ v^n(k+1) \\ \psi^n(k+1) \end{bmatrix} = \begin{bmatrix} p^n(k)+v^n(k)\Delta k \\ v^n(k)+\left[C_b^n(k)f^b(k)+g^n\right]\Delta k \\ \psi^n(k)+E_b^n(k)\omega^b(k)\Delta k+w(k) \end{bmatrix} \tag{1}$$

where p^n is the position, v^n is the velocity, ψ^n is the attitude, C_b^n is the direction cosine matrix, E_b^n is the rotation rate transformation matrix from the body frame to the navigation frame, f^b is the specific force in the body frame, g^n is gravity, ω^b is the angular rate in the body frame, Δk is the time interval, and w is the process noise of the INS.

3.2 Zero Height Constraint

An inertial navigation system has inherent drift error in its navigation solutions unless correction information is provided by an external system. There are several techniques to reduce this error, such as zero velocity update, zero angular rate update, and heading update. This paper focuses on pedestrian kinematic constraints, called zero height constraint (ZHC).

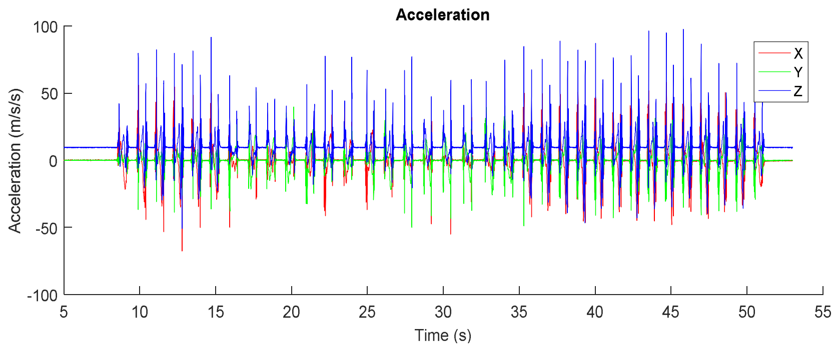
In ZHC, the basic assumption is that height can be estimated from the floor level. In reality, these constraints are acceptable for a person who walks on the same zero floor, so we set the altitude equal to zero in every stance phase, as shown below:

$$p_z^b \simeq 0 \tag{2}$$

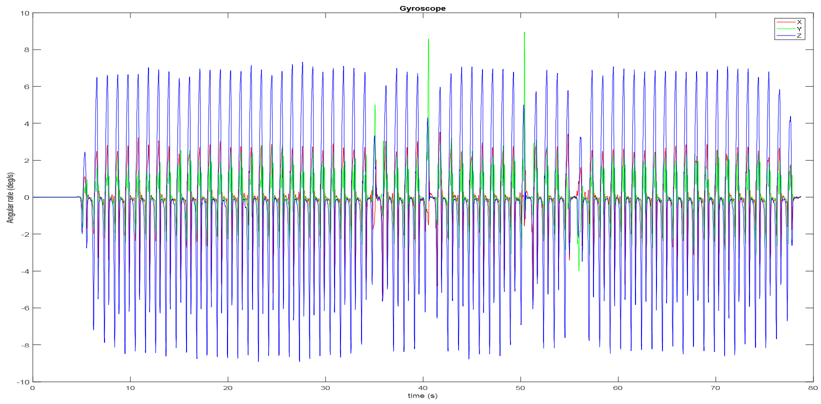
3.3 Zero Velocity Update

The other most widespread PDR constraint is provided by zero velocity update. The constraints can be regarded as a ZUPT for the velocity of the pedestrian in the plane perpendicular to the forward direction (*x*-axis), the velocities (y-axis), and vertical (z-axis) are always assumed to be zero in the stance phase, as shown below:

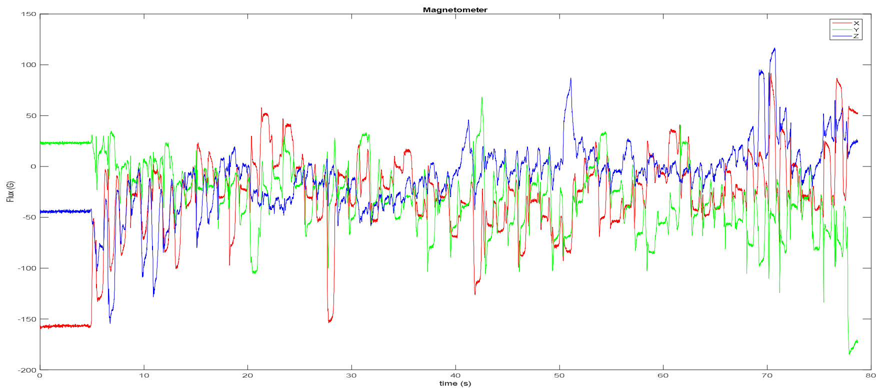
$$\begin{aligned} v_y^b &\simeq 0 \\ v_x^b &\simeq 0 \\ v_z^b &\simeq 0 \end{aligned} \tag{3}$$



(a)



(b)



(c)

Fig. 1. Raw (a) accelerometer; (b) gyroscope, (c) magnetometer data.

A coordinate transformation matrix (C_n^b) is used to convert the position and velocity from the navigation frame to the body frame, and it is expressed as follows:

$$\tilde{v}^b = C_n^b \tilde{v}^n \tag{4}$$

$$p^b = C_n^b \tilde{p}^n \tag{5}$$

The x-, *y*-, and z-axis velocities computed using (3) should be zero, because the foot is at a standstill in (2). However, they are not exactly zero because of the velocity and attitude estimation errors of the INS. These errors can be estimated and corrected by using a Kalman filter. Three velocity residuals from the ZUPT are considered as measurements for the navigation filter. The equation for the residuals (*r*) is expressed as follows:

$$r = \begin{bmatrix} \delta v_x^b \\ \delta v_y^b \\ \delta v_z^b \end{bmatrix} = \begin{bmatrix} \hat{v}_x^b - v_x^b \\ \hat{v}_y^b - v_y^b \\ \hat{v}_z^b - v_z^b \end{bmatrix} = \begin{bmatrix} \hat{v}_x^b \\ \hat{v}_y^b \\ \hat{v}_z^b \end{bmatrix} \tag{6}$$

Similarly, for zero height constraint, the z-axis component position that could be estimated from the floor level, computed using (1), should be zero because of the ZHC in (5).

$$r = \left[\delta p_z^b \right] = \left[\hat{p}_z^b - p_z^b \right] = \hat{p}_z^b \tag{7}$$

Table 1. MTw sensor specifications.

Tracker Placement	Easy fastening with velcro straps		
Orientation	1000 Hz		
Static Accuracy (Roll/Pitch)			
(Heading)	0.5 deg RMS accuracy		
(Roll/Pitch)	1 deg RMS accuracy		
(Heading)	0.75 deg RMS accuracy		
Tracker components			
Dimensions	3 AXES	3 AXES	3 AXES
Full scale	± 2000 deg/s	± 160 m/s2	± 1.9 Gauss

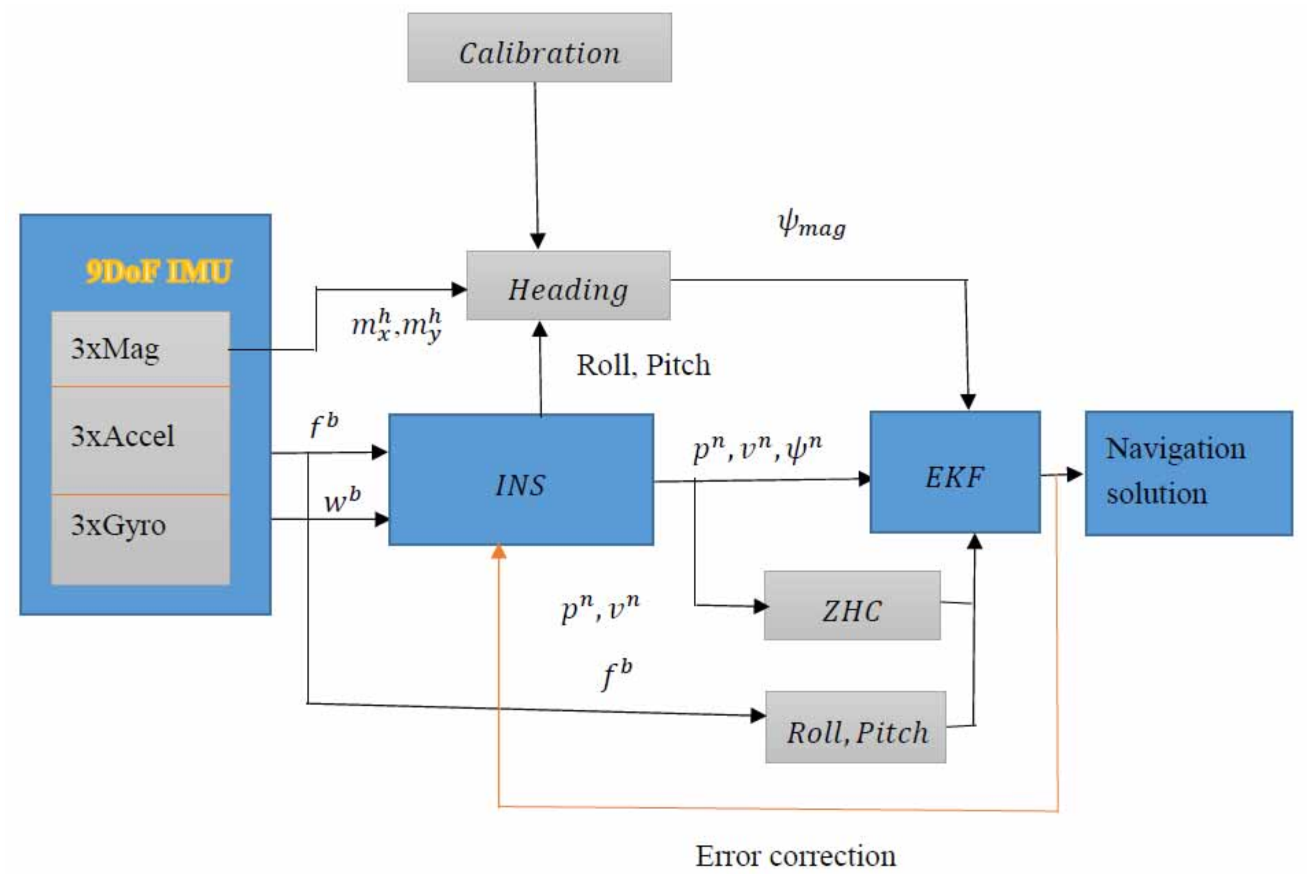


Fig. 2. Pedestrian Navigation system (PNS) aided with dynamic constraint and magnetic field data.

3.4 Heading Estimation

This residuals are given as input to the EKF to improve the position drift.

The Eq. (2) for ZHC were presented in the previous section. However, this technique is not vulnerable to error in heading estimation. Therefore, the heading–attitude angle is computed from the corrected magnetic readings and acceleration angle. The magnetometer-based heading estimation is relatively stable in tests over longer hours. Prior to applying the heading estimation, calibration is needed. Magnetometer measurement provides the horizontal component of the magnetic field component, which is used for computing magnetic north, which differs from true north. First, the magnetometer attached to the foot is not always horizontal to Eearth's local plane (see Fig. 3). The accelerometer is used to measure the tilt angle roll and pitch with respect to the horizontal plane, which makes heading estimation difficult. When the foot is stationary, the transformed acceleration of the sensor body reading b into the navigation frame of reference is given below:

$$f^b = C_n^b f^n = C_n^b \begin{bmatrix} 0 \\ 0 \\ -g \end{bmatrix} = \begin{bmatrix} g\sin\theta \\ -g\sin\phi\cos\theta \\ -g\cos\phi\cos\theta \end{bmatrix} \qquad (8)$$

where f^b is the three accelerometer measurements in x, y,

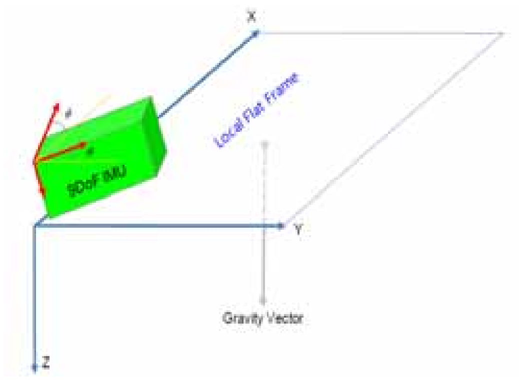


Fig. 3. Compass frame (red) orientation with respect to Earth's surface. Local flat frame (blue) is parallel to Earth's surface, and ϕ, θ represent the roll and pitch angles, respectively.

and z axis directions in the b frame. C_n^b is the direction cosine matrix based on (8), and the pitch and roll can be calculated as

$$\phi = \tan^{-1}\left(\frac{-f_y^b}{-f_z^b}\right) \tag{9}$$

$$\theta = \tan^{-1}\left(\frac{f_x^b}{\sqrt{(f_y^b)^2 + (f_z^b)^2}}\right)$$

With measured attitude angles, the relationship between the geomagnetic field vector measured by the magnetometer in the b frame, H^b, and the geomagnetic field vector in the frame H^n could be expressed as:

$$H^n = C_n^b H^b \tag{10}$$

where H^b and H^n are defined as

$$H^b = \begin{bmatrix} H_x^b & H_y^b & H_z^b \end{bmatrix}, \quad H^n = \begin{bmatrix} H_x^b & H_y^b & H_z^b \end{bmatrix}$$

After compensating for the magnetic readings by using the tilt angle, declination, and distortions, then the magnetic heading can be computed by using an arctangent function as follows:

$$\psi_{mag} = -\arctan\left(H_y^n / H_y^n\right) \tag{11}$$

3.5 Attitude Propagation based on Gyroscope Measurements

After the heading estimation for attitude initialization from the three-axis magnetic compass, and given the gyroscope measurement, the attitude is update by quaternion attitude estimation as a strap down inertial navigation system. Quaternion-based attitude update was chosen because of computational efficiency and having no singularity problem when the pitch angle is equal to $\pm\pi/2$.

Given the ggyroscope measurement angular rate is $\omega_{ib}^b = [p,\ q\ \ r]^T$ where p, q, and r are the three angular rates in the body frame, the process model of the quaternion is a discrete integration of the input angular rate:

$$\dot{q} = \frac{1}{2}\begin{bmatrix} 0 & r & -q & p \\ -r & 0 & p & q \\ q & -p & 0 & -r \\ -p & -q & -r & 0 \end{bmatrix} q = \begin{bmatrix} q4 & -q3 & q2 \\ q3 & q4 & -q1 \\ -q2 & q1 & q4 \\ -q1 & -q2 & -q3 \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{12}$$

The rotation matrix from the body frame to the tangent frame can be calculated as

$$C_T^b = \left(q_4^2 - R^T R\right) I_{3x3} + RR^T - 2q_4 [RX] \tag{13}$$

where R $= [q_1\ \ q_3\ \ \ q_3\ \ ]^T$, I_{3x3} is the identity matrix, and

$$[RX] = \begin{bmatrix} 0 & -q_3 & q_2 \\ -q_3 & 0 & q_1 \\ -q_2 & q_1 & 0 \end{bmatrix} \tag{14}$$

And the quaternion can be calculated from

$$q_4 = \pm\frac{1}{2}\left(1 + C_T^b(1,1) + C_T^b(2,2) + C_T^b(3,3)\right)^{0.5} \tag{15}$$

$$q_1 = \frac{1}{4q_4}\left(C_T^b(2,3) - C_T^b(3,2)\right) \tag{16}$$

$$q_2 = \frac{1}{4q_4}\left(C_T^b(3,1) - C_T^b(1,3)\right) \tag{17}$$

$$q_3 = \frac{1}{4q_4}\left(C_T^b(1,2) - C_T^b(2,1)\right) \tag{18}$$

4. Extended Kalman Filter

We presented the ZUPT, ZHC, and magnetic heading in the section above. In this section, we will address the details of the estimation filter, i.e. the extended Kalman filter, used to implement the navigation algorithm with an IMU and a magnetometer. The EKF has two distinct steps: predict and update. In the predict step, the state vector is propagated from the current epoch into the next epoch by using a system dynamic model. The zero velocity measurements during the stance phase, the zero height constraint when the person walks on the same zero height floor, and the magnetic heading estimation are used to update the error state vector estimated after the predicted state vector.

4.1 Process Model

The process model employed by the EKF governs the dynamic relationship between the states of two successive time steps. First, the state vector is defined on the navigation frame using position, velocity, and attitude. The state vector at time step k, denoted by x_k, consists of position p_k, velocity v_k, and motion acceleration ψ_k. It is expressed as follows:

$$x_k = \left[\psi_k^n \quad p_k^n \quad v_k^n \quad q_k^n\right] \tag{19}$$

The system model for the EKF should be linear because of the EKF constraints. Eq. (1) can be linearized and expressed with respect to the error of the state vector in (11). The final system model with the error state vector (δx) can be written as follows:

$$x_{k+1} = F_k x_{k-1} + \omega_k \tag{20}$$

$$F_k = \begin{bmatrix} I_{3x3} & 0_{3x3} & 0_{3x3} & 0_{3x4} \\ 0_{3x3} & I_{3x3} & I_{3x3} * dk & 0_{3x4} \\ -dk * s & I_{3x3} & I_{3x3} & 0_{3x4} \\ 0_{4x3} & 0_{4x3} & 0_{4x3} & q_{4x4} \end{bmatrix} \tag{21}$$

where I is the identity matrix, 0 is a zero matrix, [f^n] is the skew-symmetric matrix of f^n, the subscript □ denotes the time stamp, and the subscript $a\ x\ b$ shows the number of matrix rows (a) and columns (b). The process noise (ω_k) is assumed to be white noise. Eq. (10) propagates the state vector into the next time step ($k+1$), and q_{4x4} denotes quaternion propagation.

4.2 Observation Model

In addition to the five observation equations for the magnetic heading, zero height constraint and zero velocity in the stance phase, the acceleration reading of the accelerometer is used as a measurement to predict the roll and pitch angle during rotation of the pedestrian in different directions, i.e. turning or taking stairs up or down. The relationship between the accelerometer reading and attitude is written as follows:

$$f^b = C_n^b f^n = \begin{bmatrix} g\sin\theta \\ -g\sin\phi\cos\theta \\ -g\cos\phi\cos\theta \end{bmatrix} \tag{22}$$

$$\phi = \tan^{-1}\left(\frac{-f_y^b}{-f_z^b}\right) \tag{23}$$

$$\theta = \tan^{-1}\left(\frac{f_x^b}{\sqrt{(f_y^b)^2 + (f_z^b)^2}}\right)$$

The error state vector is updated by the Kalman filter, when a measurement comes from an external sensor. Possible measurements are attitude, position, or velocity. In our approach, we use zero velocity, altitude measurements (z component of the position), and roll and pitch based on angles measured by the accelerometer ($pitch_{acc}, roll_{acc}$).

The observation model can be expressed as follows:

$$Z = \left[p_z^b \quad v_x^b \quad v_y^b \quad v_z^b \quad q_k^b \quad pitch_{acc}, roll_{acc} \quad \psi_{mag}\right]^T \tag{18}$$

$$Z_k = H_k \delta x_k + v_k \tag{19}$$

$$H_k = \begin{bmatrix} O_{3x3} & O_{3x3} & O_{3x4} \\ [0\,0\,1; I_{5x3}] & [0\,0\,0; I_{5x3}] & I_{6x4} \end{bmatrix} \tag{24}$$

where the measurement noise (v_k) is assumed to be white noise. This model is only reliable at low accelerations. Therefore, we need an additional observation model for high accelerations. The roll and pitch measurements are no longer reliable at high accelerations. Thus, the observation model should be changed as follows:

$$Z = \left[p_z^b \quad v_x^b \quad v_y^b \quad v_z^b \quad , q_k^b \quad \psi_{mag}\right]^T \tag{25}$$

$$H_k = \begin{bmatrix} O_{3x3} & O_{3x3} & O_{3x4} \\ [0\,0\,1; I_{5x3}] & [0\,0\,0; I_{5x3}] & I_{5x4} \end{bmatrix} \tag{26}$$

Thus, the ZUPT implemented in the Kalman filter, not only corrects the velocity, but also the position and the attitude errors.

4.3 Filter Structure

We obtained the system model and observation model to implement the EKF. Fig. 2 shows a block diagram of the proposed method for estimating the navigation solution using a magnetometer and an IMU. Basically, the navigation solution is computed using the INS block, and the output is not compensated for until the EKF result is feed back.

5. Performance Evaluation

The following sub-sections describe preliminary experimental results demonstrating the accuracy of position estimation using the PDR system.

5.1 Hardware Description

We evaluated our pedestrian tracking method in the institute building by using an IMU equipped with a magnetometer and IMU, which are attached to the shoe of the right foot (see Fig. 4)

We used an Xsens MTw sensor. An MTw is a highly accurate wireless motion tracker that measures acceleration, rotation, and Earth's magnetic field, all in three directions. Measurements of the MTw were transmitted to a wireless receiver connected to a computer. In our trials, we used a laptop computer to record and store all measurement data. The transmission rate of the sensor

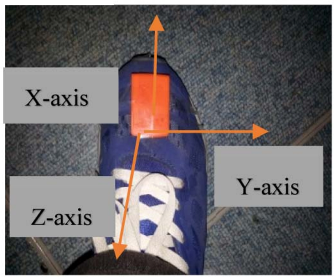


Fig. 4. IMU attached to the right foot.

Fig. 5. MTw sensor.

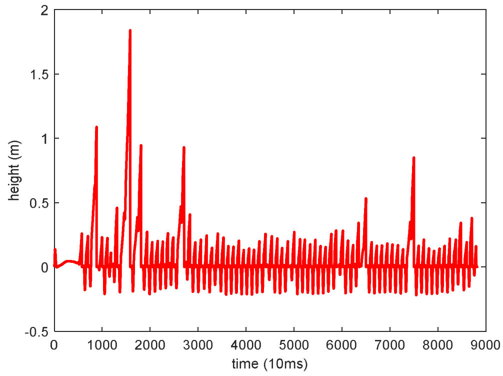


Fig. 6. Estimated altitude (ZUPT+ZHC).

was set to 100 Hz.

We performed several types of recording trial where users walked known patterns. The trials included walking in a straight line, walking a large rectangle, and walking for 10 minutes throughout the building (starting and ending at exactly the same location). During the trials, measurements were recorded on the laptop so they could be played back and analyzed afterwards. Based on the recorded trials, all algorithms were run to provide an estimation of position. These estimated positions were plotted on a visual two-dimensional map, so they could be visually inspected and compared.

5.2 Test Setting

An experimental test with a pedestrian was conducted to verify the proposed method. Data were recorded while the user was at a standstill for 10 seconds for gyro bias compensation, and then the subject moved to the desired scenario. The sensor specifications are shown in Table 1.

5.3 Test Result

The estimated position results are presented in Figs. 6-9. Without ZHCs, as shown in Fig. 9, vertical position

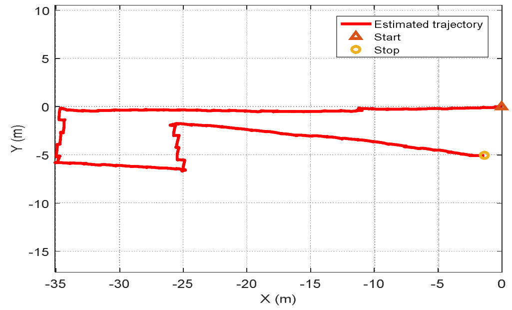


Fig. 7. Estimated 2D trajectory (ZUPT+ZHC).

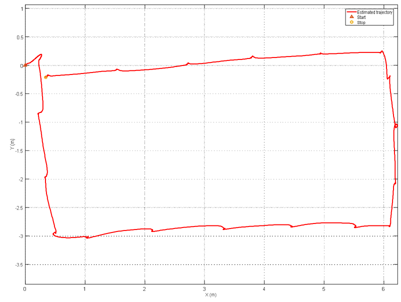


Fig. 8. Estimated trajectory on a horizontal plane (ZUPT+ZHC+ψ_{mag}).

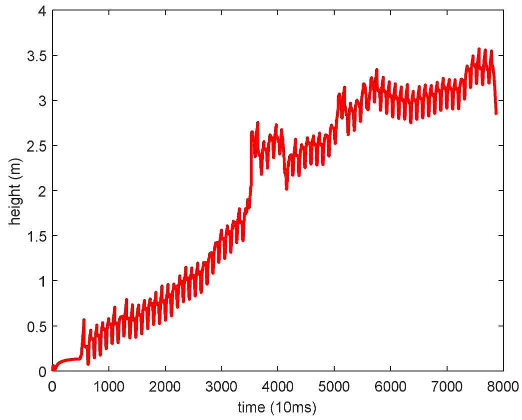


Fig. 9. Estimated altitude of a walk along a corridor (ZUPT).

results drift at each stance phase when the foot touches the ground for a short time. Fig. 8 shows the results of walk-tracking whereby the estimated trajectory in the horizontal plane is closer to rectangular. The estimated travelled distance was 30 m, which differs slightly from the true distance. However, as depicted in Fig. 9, the error of the estimated z component grows slowly with time.

Using ZHC, the estimated z component drift is reduced (as shown in Fig. 6), and the total distance traveled is also straight in the direction the user moved. When the magnetometer is integrated with a traditional zero velocity update, i.e. resetting the velocity to zero when the foot is on the ground, the drift rate was slightly smaller, compared with zero velocity update only

6. Conclusion

In this paper, we have proposed a new scheme for attitude estimation using an accelerometer and an electric compass for magnetic heading estimation to improve inertial navigation for a foot-mounted inertial sensor. From the test results, we observed that if the system is not stationary, dynamic acceleration will influence the gravity field measurement in the b frame. So the attitude results willbe not accurate, and eventually, these errors will be propagated in the magnetic heading result. If high dynamic acceleration occurs, orientation results will be significantly biased. Algorithm performance was examined in a real-world experiment, and the experimental results indicate less vertical position error of the total distance traveled. The proposed method could improve estimation performances for position, velocity, and attitude without additional hardware, except for an inertial sensor and a magnetometer. Additionally, the method increased accuracy, compared with a conventional INS, and provided accurate information for a longer time.

Acknowledgement

This work was supported by the ICT R&D program of MSIP/IITP (R0101-15-0168, Development of ODM Interactive Software Technology Supporting Live-Virtual Soldier Exercises).

This research was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MEST) (No. 2011-0009454)

References

[1] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," IEEE Comput. Graph. vol. 25, no. 6, pp. 38–46, Dec. 2005. Article (CrossRef Link)

[2] S. Godha and G. Lachapelle, "Foot mounted inertial system for pedestrian navigation," *Meas. Sci. Technol.*, vol. 19, no. 7, pp. 075 202:1–9, 2008. Article (CrossRef Link)

[3] L. Ojeda and J. Borenstein, "Non-GPS navigation for security personnel and first responders," J. Navigation, vol. 60, no. 3, pp. 391–407, 2007. Article (CrossRef Link)

[4] O. Bebek, M. Suster, S. Rajgopal, M. Fu, X. Huang, M. Cavusoglu, D. Young, M. Mehregany, A. van den Bogert, and C. Mastrangelo, "Personal navigation via high-resolution gait-corrected inertial measurement units," *IEEE T. Instrum. Meas.*, vol. 59, no. 11, pp. 3018–3027, 2010. Article (CrossRef Link)

[5] X. Yun, J. Calusdian, E. R. Bachmann, and R. B. McGhee, "Estimation of human foot motion during normal walking using inertial and magnetic sensor measurements," IEEE Trans. Instrum. Meas., vol. 61, no. 7,pp. 2059–2072, Jul. 2012. Article (CrossRef Link)

[6] Dollar, C. Wojek, B. Schiele, and P. Perona. Pedestrian detection: an evaluation of the state of the art. IEEE Trans.Pattern AnaL Mach. IntelL, 34(4): 74761, 2012. Article (CrossRef Link)

[7] Chien-Hsun Chu The performance of a tight INS/GNSS/photogrammetric integration scheme for land based mms applications in GNSS denied environments.

[8] H. N. Fallah, I. Apostolopoulos, K. Bekris, and E. Folmer, "Indoor human navigation systems: A survey," Interact. Comput. vol. 25, no. 1, pp. 21–33, 2013. Article (CrossRef Link)

[9] I. Skog, P. Handel, J. Nilsson, and J. Rantakokko, "Zero-velocity Detection—An algorithm evaluation," IEEE Trans. Biomed. Eng., vol. 57, no. 11, pp. 2657–2666, Nov. 2010. Article (CrossRef Link)

[10] Godha and G. Lachapelle, "Foot mounted inertial system for pedestrian navigation," Meas. Sci. Technol., vol. 19, no. 7, pp. 075 202-1–075 202-9, 2008.Coming.

[11] Zhang Xinxi "The performance impact evaluation on bias of gyro and accelerometer for foot-mounted INS" Article (CrossRef Link)

[12] H. Skog, P. Handel, J. Nilsson, and J. Rantakokko, "Zero-velocity Detection—An algorithm evaluation," IEEE Trans. Biomed. Eng., vol. 57, no. 11, pp. 2657–2666, Nov. 2010. Article (CrossRef Link)

[13] Evaluation and comparison of performance analysis of indoor inertial navigation system based on foot mounted IMU Feyissa Woyano; Soyeon Lee; Sangjoon Park 2016 18th International Conference on Advanced Communication Technology (ICACT) Article (CrossRef Link)

[14] Hojin Ju, A pedestrian dead-reckoning system that considers the heel-strike and toe-off phases when using a foot-mounted IMU Article (CrossRef Link).

[15] Integrated Online Localization and Navigation for People with Visual Impairments using Smart Phones Article (CrossRef Link)

[16] Xiaoping Yun, Eric R. Bachmann "Estimation of Human Foot Motion During Normal Walking Using Inertial and Magnetic Sensor Measurements". Article (CrossRef Link)

[17] L. Ojeda and J. Borenstein, "Non-GPS navigation for security personnel and first responders," J. Navigat., vol. 60, no. 3, pp. 391–407, Sep. 2007. Article (CrossRef Link)

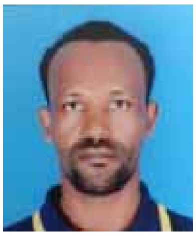
[18] A. M. Sabatini, C. Martelloni, S. Scapellato, and F. Cavallo, "Assessment of walking features from foot inertial sensing," IEEE Trans. Biomed. Eng., vol. 52, no. 3, pp. 486–494, Mar. 2005. Article (CrossRef Link)

[19] K. Sagawa, Y. Satoh, and H. Inooka, "Non-restricted measurement of walking distance," in Proc. IEEE Int. Conf. Syst., Man, Cybern., Nashville, TN, Oct. 2000, vol. 3, pp. 1847–1852. Article (CrossRef Link)

[20] A. M. Sabatini, "Quaternion-based extended Kalman filter for determining orientation by inertial and magnetic sensing," IEEE Trans. Biomed. Eng., vol. 53, no. 7, pp. 1346–1356, Jul. 2006. Article (CrossRef Link)

[21] C. Randell, C. Djiallis, and H. Muller, "Personal position measurement using dead reckoning," in Proc.

7th IEEE Int. Symp. Wearable Comput.,Oct. 18–21, 2003, pp. 166–173. Article (CrossRef Link)
[22] S. W. Lee and K. Mase, "Activity and location recognition using wearable sensors," IEEE Pervasive Comput., vol. 1, no. 3, pp. 24–32, Jul.–Sep. 2002. Article (CrossRef Link)
[23] H. M. Schepers, H. F. J. M. Koopman, and P. H. Veltink, "Ambulatory assessment of ankle and foot dynamics," IEEE Trans. Biomed. Eng., vol. 54, no. 5, pp. 895–902, May 2007. Article (CrossRef Link)
[24] I. P. I. Pappas, M. R. Popovic, T. Keller, V. Dietz, and M. Morari, "A reliable gait phase detection system," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 9, no. 2, pp. 113–125, Jun. 2001. Article (CrossRef Link)
[25] X. Yun, E. R. Bachmann, and R. B. McGhee, "A simplified quaternionbased algorithm for orientation estimation from earth gravity and magnetic field measurements," IEEE Trans. Instrum. Meas., vol. 57, no. 3, pp. 638–650, Mar. 2008. Article (CrossRef Link)
[26] D. Roetenberg, P. J. Slycke, and P. H. Veltink, "Ambulatory position and orientation tracking fusing magnetic and inertial sensing," IEEE Trans. Biomed. Eng., vol. 54, no. 5, pp. 883–890, May 2007. Article (CrossRef Link)
[27] C. Randell, C. Djiallis, and H. Muller, "Personal position measurement using dead reckoning," in Proc. 7th IEEE Int. Symp. Wearable Comput., Oct. 18–21, 2003, pp. 166–173. Article (CrossRef Link)
[28] C. Toth, D. A. Grejner-Brzezinska, and S.Moafipoor, "Pedestrian tracking and navigation using neural networks and fuzzy logic," in Proc. Int. Symp. Intell. Signal Process. WISP, Oct. 3–5, 2007, pp. 1–. Article (CrossRef Link)
[29] Multi-sensor personal navigator supported by adaptive knowledge based system: Performance assessment Article (CrossRef Link)



Feyissa Woyano Gobana received a BSc in Electrical Engineering from Adama University in Adama, Ethiopia, in 2011. He is an assistant lecturer at Adama Science & Technology University, Adama, Ethiopia, and is currently a PhD student in the Computer Software and Engineering Department of the University of Science and Technology (UST) on the Electronics and Telecommunication Research Institute (ETRI) campus, Daejeon, South Korea. His research interests include pedestrian navigation, indoor localization, inertial navigation and gait analysis.

Sangjoon Park received his BSc and MSc in Electronics Engineering from the Kyung-Pook National University in 1988 and 1990, respectively. He received his PhD from the Computer Science Department at North Carolina State University in 2006. He is currently Director of the Positioning and Navigation Technology Research Section in the Electronics and Telecommunications Research Institute (ETRI), Korea. His current research interests are in positioning, wireless sensor networks, next-generation embedded sensor networks, multi-sensor data fusion, and target tracking. He also worked as a senior researcher

Soyeon Lee received her PhD in Computer and Information Science from Korea University in 2015. She received her BSc from Ewha Woman's University in 1992, and an MSc from Seoul National University in 1994. Since 1994, she has been with ETRI, Daejeon, Korea, where she has been working on communications and information technologies, ICT convergence technologies and standardization, and positioning technologies. Her current interests include motion (or inertial) sensor-based human pose tracking and indoor positioning technologies.