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Indoor positioning based on foot-mounted IMU

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Abstract. The paper presents the results of the project which examines the level of accuracy that can be achieved in precision indoor positioning by using a pedestrian dead reckoning (PDR) method. This project is focused on estimating the position using step detection technique based on foot-mounted IMU.

The approach is sensor-fusion by using accelerometers, gyroscopes and magnetometers after initial alignment is completed. By estimating and compensating the drift errors in each step, the proposed method can reduce errors during the footsteps. There is an advantage of the step detection combined with ZUPT and ZARU for calculating the actual position, distance travelled and estimating the IMU sensors' inherent accumulated error by EKF. Based on the above discussion, all algorithms are derived in detail in the paper. Several tests with an Xsens IMU device have been performed in order to evaluate the performance of the proposed method.

The final results show that the dead reckoning positioning average position error did not exceed 0.88 m (0.2% to 1.73% of the total traveled distance – normally ranges from 0.3% to 10%), what is very promising for future handheld indoor navigation systems that can be used in large office buildings, malls, museums, hospitals, etc.

Key words: indoor positioning, foot-mounted, pedestrian dead reckoning, IMU, ZARU, ZUPT.

1. Introduction

Positioning and navigation systems have achieved great success in personal navigation applications or location-based services (LBS) and are now becoming standard features in today's intelligent mobile devices [1–10]. As GPS is essential for outdoor navigation, locating a mobile user anytime and anywhere it is still a challenging task, especially in GPS degraded and denied environments such as urban canyons and indoor environments Lately, some other positioning techniques have been developed such as wearable dead reckoning (DR) sensors, pseudolites, Wi-Fi, ZigBee, Ultra Wideband (UWB), and RFID to obtain a seamless indoor/outdoor positioning solution. However, the characteristics of wireless signal (Time of Arrival (TOA), Angle of Arrival (AOA), and Received Signal Strength (RSS)) are uncertainty and effected easily by multi-path, random moving of people and so on. The positioning accuracy and application of these techniques is limited.

Recently, some new techniques using camera control [2] or multichannel ultrasonic range finder [9] have supported indoor positioning and put them to practical use, especially for blind people.

During the last decade, some methodologies have been also proposed based on inertial sensors for person's location [7], which is often called Pedestrian Dead Reckoning (PDR) The conventional PDR solutions measure the acceleration from accelerometers to take the step count and to estimate the step length and propagate the position with the heading from angular sensors such as magnetometers or gyroscopes. However, these signals are sensitive to the alignment of sensor units, the inherent instrumental errors and disturbances from the ambient environment. PDR has a large range of applications, such as emergency rescue workers, finding goods in a shopping mall, guiding blind pedestrians or even navigating firefighters in a burning house

The sensors (normally three accelerometers and three gyroscopes and even other sensors, such as magnetometers, thermometers and pressure sensors) are small, low power, and inexpensive due to the advances in Micro-electromechanical Sensors (MEMS) technology.

However, the MEMS sensors suffer from a significant bias that varies greatly over time So PDR algorithms have the challenge of decreasing error In this paper, a PDR indoor positioning method with step detection based on foot-mounted IMU is designed, tested, and analyzed. Firstly, initial alignment is completed with accelerometers and magnetometers. Then, step detection method with the foot on the ground determines when the person is at rest (static) with the zero velocity and angular rate. And an Extended Kalman Filter (EKF) is applied to estimate the errors accumulated due to the IMU sensor biases. Several tests with Xsens IMU device have been performed in order to evaluate the performance of the proposed method. The results show that the dead reckoning positioning system has a high performance for indoor positioning applications.

2. PDR indoor positioning method

In inertial pedestrian navigation, IMU was used successfully by strapping the IMU on foot/shoe. The PDR indoor positioning method has been implemented in a Kalman-based

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framework [3]. The basic idea is to use an EKF to estimate the errors accumulated by the IMU sensor biases. The EKF is updated with velocity and angular rate measurements by the Zero-Velocity-Update (ZUPT) and Zero-Angular-Rate Update (ZARU) separately detected the foot is on the floor. Then the sensor biases are compensated with the estimated errors. Therefore the frequent use of ZUPT/ZARU measurements consistently bounds many of the errors and as a result, even relatively low cost sensors can provide useful navigation performance.

Figure 1 shows the framework. It contains five blocks. 1) an initial alignment that calculates the initial attitude with the static data of accelerometers and magnetometers during the first few minutes; 2) an IMU mechanization algorithm to compute the navigation parameters (position, velocity and attitude); 3) a step detection algorithm to determine when the foot is on the ground and velocity and angular rate of IMU are zero; 4) ZUPT and ZARU feed the EKF with the measured errors when step detected; and 5) a EFK that estimates the errors and feedback to IMU mechanization algorithm.

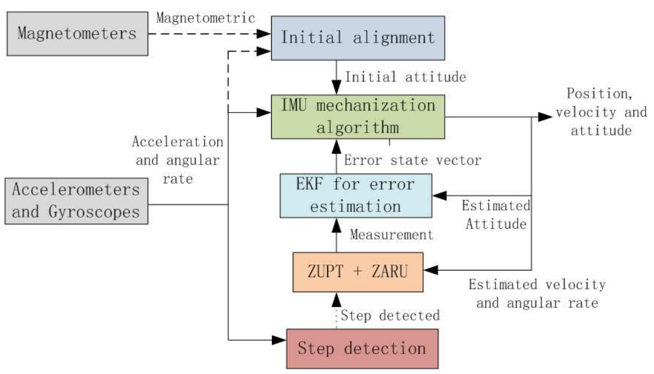

Fig. 1. The framework of pedestrian dead reckoning indoor positioning with step detection based on foot-mounted IMU

2.1. Initial alignment. The initial alignment of an IMU is accomplished by two steps, leveling and gyro compassing. Leveling refers to getting the roll and pitch using the acceleration and gyro compassing refers to obtaining the heading using the angular rate. However, the bias and noise of gyroscopes are larger than the value of the Earth's rotation rate for the MEMS IMU, so the heading has a big error. In this paper, initial alignment of MEMS IMU is completed using the static data of accelerometers and magnetometers during the first few minutes, and a method for heading is presented using the magnetometers

In static base, the roll (φ) and pitch (θ) angles are:

$$\theta = -arc\sin(a^b_{ibx}/g), \tag{1}$$

$$\varphi = arc\sin(a^b_{iby}/(g \cdot \cos\theta)), \tag{2}$$

where a^b_{ibx} and a^b_{iby} denote the x and y-axis output of accelerometers separately in body frame – body fixed to the device (b, defined to be Front-Left-Up) in the right handed Cartesian coordinate system as Fig. 2 below from Xsens Technologies [10], and g represents the acceleration of gravity.

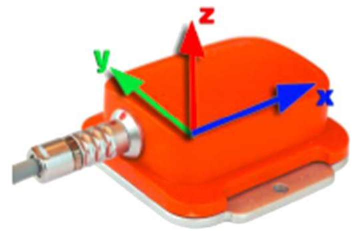

Fig. 2. MTi sensor coordinate frame

In order to use the magnetometers to obtain the heading, we first compute the intensity of magnetic field in navigation frame (n, defined to be North-West-Up) with magnetometers' outputs:

$$M_{nx} = M_{bx}\cos\theta + M_{by}\sin\varphi + M_{bz}\cos\varphi, \tag{3}$$

$$M_{ny} = M_{by}\cos\phi - M_{bz}, \tag{4}$$

where M_{bx}, M_{by} and M_{bz} denote the x, y and z-axis output of magnetometers separately, M_{nx} and M_{ny} represent the x and y-axis of magnetic field intensity in navigation frame.

So the heading angle is:

$$\psi = \tan^{-1}(M_{ny}/M_{nx}) - M_d, \tag{5}$$

where M_d is the earth magnetic declination at a given position of IMU.

2.2. IMU mechanization algorithm. The IMU mechanization algorithm uses the outputs of accelerometers and gyroscopes in the body frame (b), (a^b_k and ω^b_k, respectively) which are sampled at discrete times k at every sample interval Δt.

As the bias of MEMS sensors, firstly subtracting the errors estimated by the EKF from the raw acceleration and angular rate.

$$\overline{a^b_k} = a^b_k - \delta a^b_{k-1}, \tag{6}$$

$$\overline{\omega^b_k} = \omega^b_k - \delta\omega^b_{k-1}, \tag{7}$$

where $\overline{a^b_k}$ and $\overline{\omega^b_k}$ denote the bias-compensated acceleration and angular rate respectively at discrete times k, δa^b_{k-1} and $\delta\omega^b_{k-1}$ represent the error estimated by EFK separately at discrete times $k-1$.

Then, we update the direction cosine matrix (DCM) with respect to the navigation frame:

$$C^n_b(k,k-1) = C^n_b(k-1,k-1) \cdot \frac{2 \cdot I_3 + \delta\Omega_k \cdot \Delta t}{2 \cdot I_3 - \delta\Omega_k \cdot \Delta t}, \tag{8}$$

where $C^n_b(k,k-1)$ denotes the DCM from body frame to navigation frame at time k but not corrected by EKF. And $C^n_b(k-1,k-1)$ is the DCM from body frame to navigation frame at time $k-1$ that was already corrected. And $\delta\Omega_k$ is the skew symmetric of the bias-compensated angular rate.

$$\delta\Omega_k = \begin{bmatrix} 0 & \overline{\omega^b_k}(3) & \overline{\omega^b_k}(2) \\ \overline{\omega^b_k}(3) & 0 & -\overline{\omega^b_k}(1) \\ -\overline{\omega^b_k}(2) & \overline{\omega^b_k}(1) & 0 \end{bmatrix}. \tag{9}$$

We update the velocity and position but not yet compensated by EKF in navigation frame:

$$v(k,k-1) = v(k-1,k-1) + (C_b^n(k,k-1)\cdot \overline{a}_k^b - [0\,0\,g]^T)\cdot \Delta t, \tag{10}$$

$$r(k,k-1) = r(k-1,k-1) + v(k,k-1)\cdot \Delta t, \tag{11}$$

where $v(k,k-1)$ and $r(k,k-1)$ denote the velocity and position in navigation frame at time k but not corrected by EKF, and $v(k-1,k-1)$ and $r(k-1,k-1)$ are the bias-compensated velocity and position in navigation frame at time $k-1$.

Lastly, we correct the DCM, velocity and position with the estimated errors of EKF:

$$r(k,k) = r(k,k-1) - \delta r_k, \tag{12}$$

$$v(k,k) = v(k,k-1) - \delta v_k, \tag{13}$$

$$C_b^n(k,k) = \frac{2\cdot I_3 + \delta\Theta_k}{2\cdot I_3 - \delta\Theta_k}\cdot C_b^n(k,k-1), \tag{14}$$

where $C_b^n(k,k)$, $v(k,k)$ and $r(k,k)$ denote the DCM, velocity and position at time k, and $\delta\phi_k$, δv_k and δr_k are the estimated errors by EKF accordingly. And $\delta\Theta_k$ is the skew symmetric matrix of $\delta\phi_k$.

$$\delta\Theta_k = \begin{bmatrix} 0 & -\delta\phi_k(3) & \delta\phi_k(2) \\ \delta\phi_k(3) & 0 & -\delta\phi_k(1) \\ -\delta\phi_k(2) & \delta\phi_k(1) & 0 \end{bmatrix}. \tag{15}$$

It is mentioned that the estimated errors of angle, velocity and position are reset to zero after IMU mechanization algorithm uses them to correct. This is because they are already compensated.

2.3. Step detection. The movement of foot-mounted IMU can be divided into two phases when a person walks. The first one is the swing phase that means the foot-mounted IMU in moving. The other is the stance phase that means the foot-mounted IMU on the ground. Angular and linear velocity of the foot-mounted IMU must be very close to zero in theory in the stance phase. So the angular and linear velocity of the foot-mounted IMU can be as the measurements of EKF. This is the main idea of ZUPT and ZARU.

There are a few algorithms in the literature for step detection based on acceleration [6] and angular rate [7]. We use a multi-condition algorithm to complete the step detection by using the outputs of accelerometers and gyroscopes.

1. As the acceleration of gravity, the magnitude of the acceleration ($|a_k|$) must be between two thresholds.

$$|a_k| = \sqrt{a_k^b(1)^2 + a_k^b(2)^2 + a_k^b(3)^2}, \tag{16}$$

$$C1 = \begin{cases} 1 & 9 < |a_k| < 11 \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

2. The acceleration variance must be above a given threshold.

$$\overline{a_k^b} = \frac{1}{2s+1}\sum_{q=k-s}^{k+s} |a_q|, \tag{18}$$

where $\overline{a_k^b}$ is a mean acceleration value at time k, and s is the size of the averaging window ($s = 15$). The variance is computed by this expression:

$$\sigma(a_k^b)^2 = \frac{1}{2s+1}\sum_{j=k-s}^{k+s} (|a_j| - \overline{a_k^b})^2. \tag{19}$$

The second condition is computed by this way:

$$C2 = \begin{cases} 1 & \sigma(a_k^b) < 0.5 \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

3. The magnitude of the angular rate ($|\omega_k|$) must be below a given threshold.

$$|\omega_k| = \sqrt{\omega_k^b(1)^2 + \omega_k^b(2)^2 + \omega_k^b(3)^2}, \tag{21}$$

$$C3 = \begin{cases} 1 & |\omega_k| < 1 \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

The three logical conditions must be satisfied at the same time, which means a logical "AND" is used:

$$C = C_1 \& C_2 \& C_3. \tag{23}$$

Finally, the logical result is filtered out by a median filter with a neighboring window of 11 samples. The logical "1" denotes the stance phase that means the foot-mounted is on the ground. Figure 3 shows the results of this multi-condition step detection.

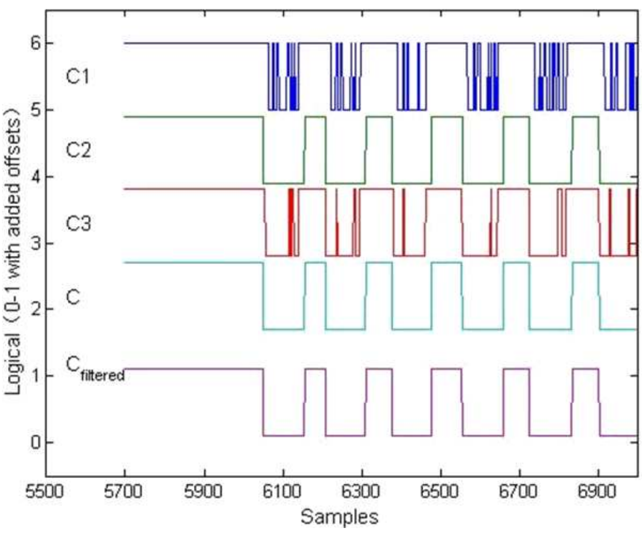

Fig. 3. The logical value of multi-condition step detection

2.4. EKF. The Kalman filter is widely used in inertial navigation systems. However, a Kalman filter is based on linear operations, and the navigation algorithms consist of non-linear systems. One way to solve this problem is to linearize the non-linear system, which is known as the Extended Kalman Filter (EKF).

In the proposed PDR indoor positioning method, the 15-element error state vector at time k is used [3]:

$$\delta X(k,k) = [\delta\phi_k, \delta\omega_k^b, \delta r_k, \delta v_k, \delta a_k^b], \tag{24}$$

where $\delta X(k,k)$ denotes the three angle errors for roll, pitch and yaw, the angular errors in body frame, position errors and velocity errors in navigation frame, and acceleration errors in body frame. Then, the linear state transition model is:

$$\delta X(k,k-1) = \Phi_k \delta X(k-1,k-1) + w_{k-1}, \tag{25}$$

where $\delta X(k,k-1)$ is the predicted error state vector at time k, $\delta X(k-1,k-1)$ is the estimated error state vector at time $k-1$, and w_{k-1} is the system noise at time $k-1$ with covariance matrix $Q_{k-1} = E\left(w_{k-1}w_{k-1}^T\right)$, and Φ_k is the state transition matrix:

$$\Phi_k = \begin{bmatrix} I_3 & \Delta t \cdot C_b^n(k,k-1) & 0 & 0 & 0 \\ 0 & I_3 & 0 & 0 & 0 \\ 0 & 0 & I_3 & \Delta t \cdot I_3 & 0 \\ -\Delta t \cdot S(\overline{a_k^n}) & 0 & 0 & I_3 & \Delta t \cdot C_b^n(k,k-1) \\ 0 & 0 & 0 & 0 & I_3 \end{bmatrix}, \tag{26}$$

where $S(\overline{a_k^n})$ is the skew symmetric matrix of predicted acceleration in navigation frame $(\overline{a_k^n})$:

$$\overline{a_k^n} = C_b^n(k,k-1) \cdot \overline{a_k^b}, \tag{27}$$

$$S(\overline{a_k^n}) = \begin{bmatrix} 0 & -\overline{a_k^n}(3) & \overline{a_k^n}(2) \\ \overline{a_k^n}(3) & 0 & -\overline{a_k^n}(1) \\ -\overline{a_k^n}(2) & \overline{a_k^n}(1) & 0 \end{bmatrix}. \tag{28}$$

The measurement model is:

$$Z_k = H\delta X(k,k) + n_k, \tag{29}$$

where Z_k is the measurement value, H is the measurement matrix, and n_k is the measurement noise with covariance matrix $R_k = E\left(n_k n_k^T\right)$.

So the estimated error state vector at time k by EKF is computed:

$$\delta X(k,k) = \delta X(k,k-1) + K_k[Z_k - H\delta X(k,k-1)], \tag{30}$$

where K_k is the Kalman gain:

$$K_k = P_{k|k-1}H_k^T(H_k P_{k|k-1}H_k^T + R_k)^{-1}, \tag{31}$$

where $P_{k|k-1}$ is the estimation error covariance matrix:

$$P_{k|k-1} = \Phi_{k-1}P_{k-1|k-1}\Phi_{k-1}^T + Q_{k-1}, \tag{32}$$

where $P_{k|k}$ is the error covariance matrix:

$$P_{k|k} = (I_{15} - K_k H)P_{k|k-1}(I_{15} - K_k H)^T + K_k R_k K_k^T. \tag{33}$$

2.5. ZUPT and ZARU. In this project an IMU/EKF with Zero Velocity Update (ZUPT) and Zero Angular Rate Update (ZARU) is tested. The ground truth allowed the detection of an implementation error and these two methods to correct it are proposed. We focus on reducing the drift without using any external infrastructure such as GPS and LPS, nor map matching techniques After evaluating the effect of the IMU errors in the positioning, the reduction in the positioning standard deviation is shown.

The measurement vector is represented for ZUPT and ZARU [1]:

$$Z_k = [\omega_k^b, v(k,k-1)]. \tag{34}$$

The measurement matrix must be:

$$H = \begin{bmatrix} 0_{3\times3} & I_3 & 0_{3\times3} & 0_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & 0_{3\times3} & 0_{3\times3} & I_3 & 0_{3\times3} \end{bmatrix}. \tag{35}$$

2.6. EKF Tuning. EKF had to be fine-tuned for getting a stable performance, and the values of matrixes $\boldsymbol{Q}$ and $\boldsymbol{R}$ have to be selected carefully [1]. The process noise covariance matrix $\boldsymbol{Q}$ of state equation is set as a diagonal 15×15 matrix with these 15 in-diagonal elements of $[1 \times 10^{-4}_{1\times3}$ rad, $0_{1\times3}$, $0_{1\times3}$, $1 \times 10^{-4}_{1\times3}$ m/s, $0_{1\times3}]$. The measurement noise covariance matrix $\boldsymbol{R}$ of observation equation is a square diagonal matrix with rows and columns equal to the number n, of measurements available ($n = 6$ for ZUPT and ZARU), and this matrix is set as these in-diagonal elements with values of 0.01 m/s for ZUPT, 0.1 rad/s for ZARU. And the state estimation covariance matrix $\boldsymbol{P}$ is initialized as a diagonal 15×15 matrix with these in-diagonal elements of $[0_{1\times3}$, $1 \times 10^{-2}_{1\times3}$ rad/s, $0_{1\times3}$, $0_{1\times3}$, $1 \times 10^{-2}_{1\times3}$ m/s$^2]$.

During IMU data processing, we have to tune EKF again for trying to get the best PDR algorithm results.

3. Test results

The proposed method for PDR indoor positioning was tested in an indoor environment. Two tests (slow and fast walking) with MTi attached to the right foot of person were implemented in the corridor of a building at campus of Nanchang University, China. IMU has been configured to output data at the rate of 100 Hz (Fig. 4).

Fig. 4. Device setup, route and implementation of tests

In addition, we designed the noise covariance matrixes of state and observation equations, $\boldsymbol{Q}$ and $\boldsymbol{R}$, according to the discussion of Subsec. 2.6 and the technical specifications from Xsen Technologies [10]. And then matrixes $\boldsymbol{Q}$ and $\boldsymbol{R}$ have to be finely modified during the tests for fitting into our EKF.

In this research, we tested it twice. Figure 5 shows the first of estimated trajectories for a path 9048 meters long (the same for both tests), which is slow walking in the hallway in Counter-Clock-Wise directions. Initial alignments in both cases took one minute. The start position is marked with a green square.

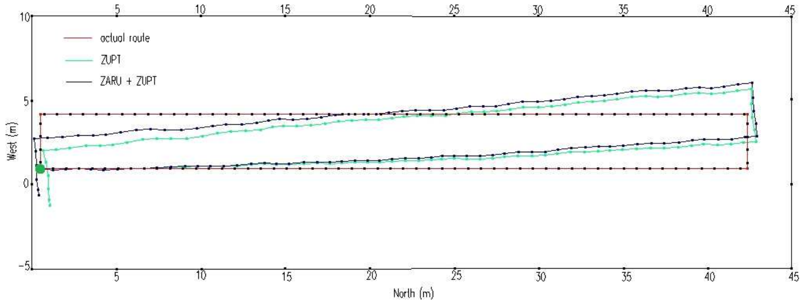

Fig. 5. The positioning result (slow walking) using ZUPT and ZARU corrections

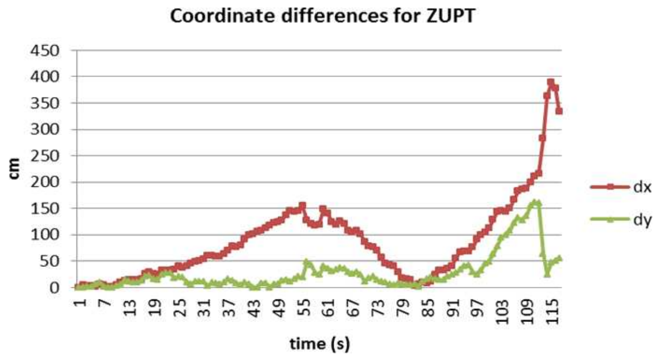

Fig. 6. Coordinate differences (slow walking) for ZUPT correction

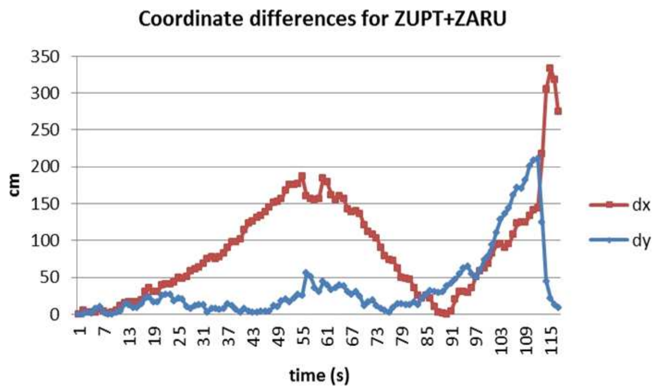

Fig. 7. Coordinate differences (slow walking) for ZUPT and ZARU corrections

Table 1 and Table 2 show summary of position errors using ZUPT only and ZUPT and ZARU corrections.

The second experiment was carried out on the same test route used previously. This time, the walking speed was faster to check the performance of MTi unit. Figure 8 shows the obtained trajectories.

Table 1
Coordinate differences (slow walking) for ZUPT correction

	dx	dy
MIN (cm)	0	0
MAX (cm)	390	161
AVERAGE (cm)	87	28
STDEV (cm)	78	35

Table 2
Coordinate differences (slow walking) for ZUPT and ZARU corrections

	dx	dy
MIN (cm)	0	0
MAX (cm)	333	211
AVERAGE (cm)	88	36
STDEV (cm)	70	48

Figures 9 and 10 show the comparison of the MTi IMU position results to real positions.

After comparing the results to the reference positions, in spite of long and narrow hallway, the average differences were still at the centimeter level (Table 3 and Table 4).

As the real trajectories closed, we additionally computed the distance errors (difference between initial and final position) with respect to the total traveled distance. Table 5 shows the differences in distances. The results show that the dead reckoning positioning system has higher performance for a pedestrian indoor, and the position error ranges from 0.9% to 1.73% (slow walking) and from 0.2% to 0.5% (fast walking) of the total traveled distance This is definitely better than existing PDR positioning accuracy which normally ranges from 0.3% to 10% of the total traveled distance.

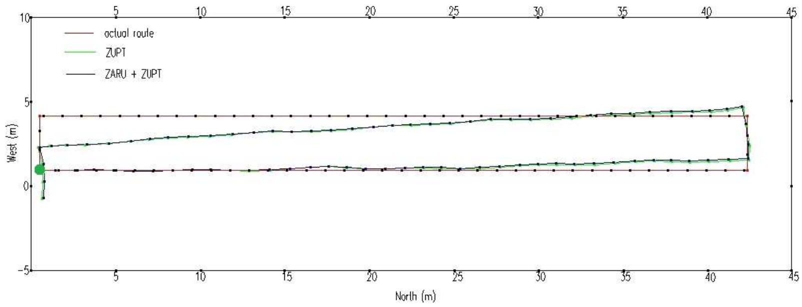

Fig. 8. The positioning result (fast walking) using ZUPT and ZARU corrections

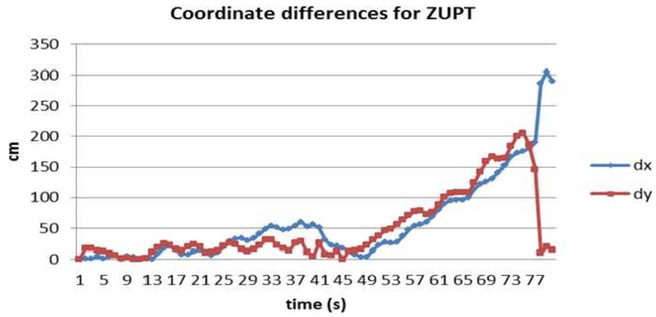

Fig. 9. Coordinate differences (fast walking) for ZUPT correction

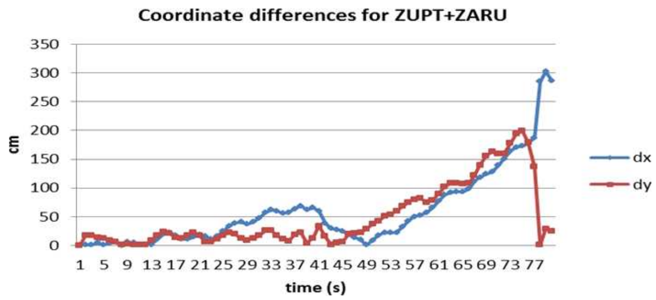

Fig. 10. Coordinate differences (fast walking) for ZUPT and ZARU corrections

Table 3
Coordinate differences (fast walking) for ZUPT correction

	dx	dy
MIN (cm)	0	0
MAX (cm)	305	206
AVERAGE (cm)	57	49
STDEV (cm)	68	56

Table 4
Coordinate differences (fast walking) for ZUPT and ZARU corrections

	dx	dy
MIN (cm)	0	0
MAX (cm)	302	199
AVERAGE (cm)	59	48
STDEV (cm)	67	55

Table 5
Distance differences

Reference distance (cm)	slow	slow	fast	fast
	ZUPT	ZUPT and ZARU	ZUPT	ZUPT and ZARU
9048	9130	9205	9030	9003
Error %	0.9%	1.73%	0.2%	0.5%

4. Conclusions

We proposed a PDR indoor positioning with step detection based on foot-mounted IMU. The research contains initial alignment with accelerometers and magnetometers, step detection using accelerometers and gyroscopes, and EKF with ZUPT and ZARU.

Several tests with an Xsens IMU device have been performed in order to evaluate the performance of the proposed method.

The final results show that the dead reckoning positioning average position error did not exceed 0.88 m (0.2% to 1.73% of the total traveled distance, what is very promising for future handheld indoor navigation systems that can be used in large office buildings, malls, museums, hospitals, etc.

Due to the inherent drift errors of accelerometers and gyroscopes, the velocity and position obtained by IMU are only reliable for just a short period of time, and so other methods have to be added to overcome the IMU drawback. Based on this discussion, future work will focus on the following plan:

1. Using magnetometer sensors as an orientation aid to and initializing IMU indoors;
2. Obtaining absolute positioning update indoors with other position method, such as Map Matching, ZigBee [8], RFID [5], WiFi [4], for the purpose of improving the accuracy of the trajectory calculation.

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