IMU/GPS Based Pedestrian Localization

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***Abstract*—The low cost Inertial Measurement Unit(IMU) can be used to provide accurate position information of a pedestrian when it is combined with Global Positioning System(GPS). This paper investigates how the integration of IMU anf GPS can be effectively used in pedestrian localization. The position calculation is achieved in sequence by three different strategies, namely basic double integration of IMU data, Zero-velocity Update (ZUPT) and Extended Kalman Filter(EKF) based fusion of IMU and GPS data. Experiments that are conducted in two fields show that EKF based localization outperform the double integration and ZUPT methods in terms of both positioning accuracy and robustness.**

***Keywords*-IMU;GPS;Localization;ZUPT;EKF**

I. INTRODUCTION

It is highly demanded that a navigation system is able to keep tracking the location of a person, such as in search and rescue operations, as well as training exercises, location-aware computing and augmented reality [1]. To realize the pedestrian localization, Global Positioning System(GPS) is considered as the main tool. However, since GPS signals can be blocked and influenced by high buildings, human bodies, mountains, a GPS normally has errors between 1 to 10 meters, which is unacceptable for some applications.

An Inertial Navigation System(INS) could be deployed to locate a pedestrian based on accelerometers, gyroscopes and magnetometers. The unit integrating these sensors together is called Inertial Measurement Unit(IMU). As opposed to GPS, IMU will not be affected by the environment where the pedestrian is located. Integral calculations of accelerations from accelerometers and angular rates from gyroscopes produce the position, velocity as well as the orientation information of the pedestrian. However, the mean-squared navigation errors of an IMU increase with time quadratically or cubically without a boundary.

As for the pedestrian localization, some methods are based on step counters and the estimation of step length [2], [3], multiplying the counters by a step length yields the distance that the pedestrian has walked. Other methods apply double integration of the accelerations when the pedestrian is walking [4], [5]. Jimenez *et. al* [6]and Isaac Skog *et. al* [7] combine Zero-Velocity Update(ZUPT) with Extended Kalman Filter(EKF) which is used to correct the IMU errors. However, high accuracy of positioning is only achieved in a short distance since IMU errors can not be eliminated completely. In this paper, instead of using IMU alone, we integrate ZUPT strategy of IMU with GPS by designing an EKF algorithm to optimally estimate the position and attitude of a person while walking.

(a) Foot Mounted IMU (b) GPS Receiver

Fig. 1. Placement of IMU and GPS receiver module. (a) Foot-Mounted IMU; (b) GPS Module

The rest of the paper is organized as follows. Section II briefly presents the system configuration. Section III introduces the basic position calculation equation using Xsens Mti IMU. Then error correction by stop detection(ZUPT) is discussed in Section IV to improve the position calculation accuracy. In section V, an EKF algorithm is applied to the IMU/GPS based pedestrian localization, where GPS signals are fused with IMU to provide more accurate trajectory information than ZUPT. Section VI presents some experimental results to validate the proposed IMU/GPS localization algorithm. Finally, a brief conclusion and future work are presented in Section VII.

II. SYSTEM CONFIGURATION

The purpose of this study is to track the position of a pedestrian walking outside. One foot of the pedestrian is mounted with an IMU (MTi from Xsens), which is used to measure the acceleration and angular rate of the walking foot(see Figure 1a). The GPS module (from Phidgets) is attached to a straight pole with the GPS antenna on the top of it so that the GPS position signal can be obtained more easily. The pedestrian localization is achieved by integrating the inertial and GPS information.

As shown in Figure 2, there are two coordinate systems involved in the pedestrian tracking: 1) Inertial sensor body frame (B); 2) The global reference frame (W) whose X-Y plane is parallel with the earth surface with X axis pointing to the East, Y axis pointing to the North and Z axis pointing to

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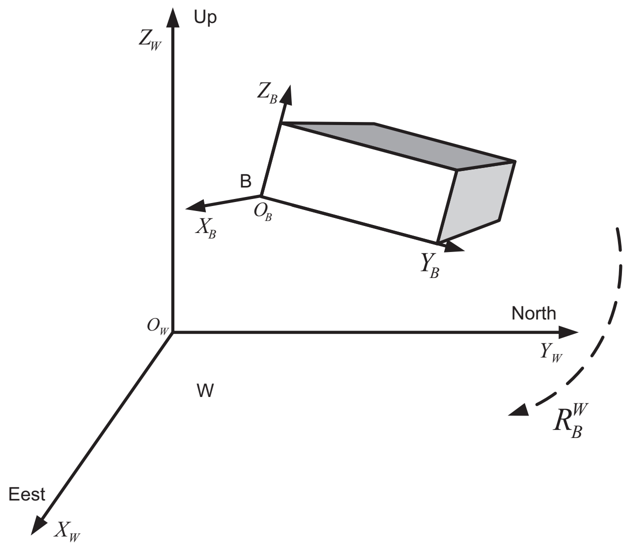

Fig. 2. Body frame B, global frame W and their coordinate transformation R_B^W

the Up direction according to the right-hand rule. $\mathbf{R}_B^W$ is the rotation transformation between the inertial sensor frame B and global frame W. Obviously, the position of a pedestrian should be based on the global frame W. In order to yield pedestrian position by integrating accelerations and angular rate in W, the accelerations and angular rates measured in the body frame B need to be projected onto the global frame W using rotation transformation $\mathbf{R}_B^W$.

III. Basic Position Calculation

The basic position calculation principle is based on the Strapdown IMU navigation algorithm [8]. The first step of the conventional IMU navigation algorithm is to integrate the angular rate information with respect to time to yield orientation. However, with Xsens Mti IMU, the accurate orientation information can be directly obtained thanks to the built-in micro processor running a kalman filter to fuse multi-sensor data from accelerometer, gyros and magnetometer. This is one of the advantages of using the Mti IMU. We will directly use the orientation data from the inertial sensor and use unit quaternion $\mathbf{Q} = (q_w, q_1, q_2, q_3)$ to represent $\mathbf{R}_B^W$. Quaternion representation does not have a Gimbal lock problem and facilitates transformation and calculation in a simple form.

Using state space representation, the system's state vector can be given as follows:

$$\begin{aligned} X_k &= (\mathbf{P}_k \ \mathbf{V}_k \ \mathbf{O}_k)^T \\ &= (x_k \ y_k \ z_k \ \dot{x}_k \ \dot{y}_k \ \dot{z}_k \ \phi_k \ \theta_k \ \psi_k \ )^T \end{aligned} \tag{1}$$

where $\mathbf{P}_k = (x_k, y_k, z_k)^T$ is the position of the pedestrian in frame W, $\mathbf{V}_k = (\dot{x}_k, \dot{y}_k, \dot{z}_k)^T$ is the velocity of the foot of the pedestrian, $\mathbf{O}_k = (\phi_k, \theta_k, \psi_k)$ is the orientation-Euler Angle of the IMU.

As analyzed above, the useful acceleration data is the foot accelerations in reference frame W, which are represented as a_k^W. It is calculated from the inertial measurements using

$$a_k^W = \mathbf{Q}_k * a_k^B * \mathbf{Q}_k^{'} - G \tag{2}$$

where $*$ is the quaternion multiplication. $\mathbf{G} = (0, 0, g)^T$ represents the earth gravity. $\mathbf{Q}_k = (q_{w,k}, q_{1,k}, q_{2,k}, q_{3,k})$ is a quaternion representation of the rotation transformation between the inertial sensor frame B and the global reference frame W. The acceleration measured by the inertial sensor a_k^B includes the acceleration caused by a specific force and gravity. After transforming the acceleration into frame W and subtracting the gravity, the a_k^W represents the acceleration caused by the specific force only imposed on the target.

There is a transformation formula between quaternion and Euler Angle, which is represented as follows:

$$\begin{aligned} X_k(7:9) = \mathbf{O}_k &= \begin{pmatrix} \phi_k \\ \theta_k \\ \psi_k \end{pmatrix} \\ &= Q2Euler(\mathbf{Q}) \\ &= \begin{pmatrix} atan2(2(q_w q_1 + q_2 q_3), 1 - 2(q_1^2 + q_2^2)) \\ arcsin(2(q_w q_2 - q_3 q_1)) \\ atan2(2(q_w q_3 + q_1 q_2), 1 - 2(q_2^2 + q_3^2)) \end{pmatrix} \end{aligned} \tag{3}$$

where $\mathbf{Q}_k = (q_w, q_1, q_2, q_3)$, $Q2Euler(\mathbf{Q})$ represents the function of Q to convert quaternion value to Euler angle.

The rest elements of X_k can be written as $X_k(1:6)$, which then can be obtained after double integration of the acceleration, the discrete form of which is

$$\begin{aligned} X_k(1:6) = \begin{pmatrix} \mathbf{P}_k \\ \mathbf{V}_k \end{pmatrix} &= \begin{pmatrix} \mathbf{I} & \mathbf{I} * T_S \\ \mathbf{0} & \mathbf{I} \end{pmatrix} X_{k-1}(1:6) \\ &+ \begin{pmatrix} T_S^2/2 * \mathbf{I} \\ T_S * \mathbf{I} \end{pmatrix} a_{k-1}^W \end{aligned} \tag{4}$$

where T_s is the sensor sampling time interval, $\mathbf{I}$ is a 3×3 identity matrix, a_{k-1}^W is calculated with equation (2). By iteratively implementing equation (4) with the initial state, the position and velocity of the pedestrian can be calculated real-timely.

However, the position values obtained by this method are reliable for only a short period of time. This is due to the accelerometer's inherent drift error as well as the gyro rate drift error, which means that when double integration of the acceleration measurements, the drift error is also accumulated over time and increases dramatically with time. So the estimated position will be far away from the actual position. This can be seen from the experiment described as follows: The IMU data is collected when the pedestrian, whose right foot is mounted with the IMU, is walking around a square of 30m×30m (see Figure 3). The collected IMU data is then substituted into equation (2) and (4) without considering any error compensation methods, the calculated trajectory of the pedestrian can be seen in Figure 4. It is clear from the figure that the calculated trajectory is tremendously away from

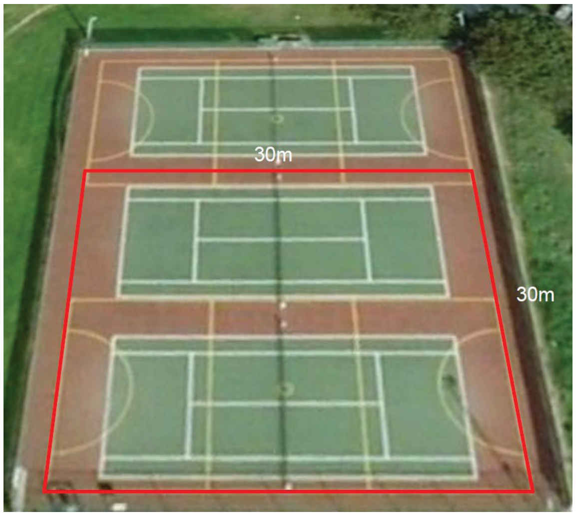

Fig. 3. The square of 30m×30m where pedestrian walks and IMU data is collected

the true one, which is quite unacceptable. Therefore, efforts should be taken to correct the accumulated error, which will be discussed in the following part of this paper.

IV. Error Correction by Stop Detection

It is noted that when a person walks, their feet alternately undergo a stationary stance phase and a moving stride phase. During the stationary stance phase, the velocity of the feet should be zeros. As long as the stationary stance phase is detected, setting the velocity of the feet of this phase as zeros is likely to correct some drift errors, and thus the accuracy of pedestrian localization should be improved compared with the basic position calculation algorithm described in the previous section. This method of correcting the position error is known as zero-velocity updates (ZUPTs).

There are several stop detection algorithms that have been applied by researchers in the literature. For instance, Feliz $et\,al.$ [9] consider current state as stop phase only when the total angular velocity value is lower than a given threshold, otherwise, the state is considered as moving stride phase. This method is not robust because it can not eliminate the small fluctuations, although the fluctuation can be eliminated by filtering, the filtering has the disadvantage of phrase lag which affects the real-time performance of the system. Jimenez $et\,al.$ [6] implemented a multi-condition stance detection algorithm using both sources of information (accelerometers and gyroscopes) and an order low pass filter. This algorithm makes the detection process robust so that it is able to adapt to both slow and quick walk. Therefore, we will adopt this algorithm to detect stop phase, the detail of which is described as follows:

1) Condition 1:

$$C1 = \begin{cases} 1 & \text{thrhd}_{a_{min}} < \|\mathbf{a}_k\| < \text{thrhd}_{a_{max}} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

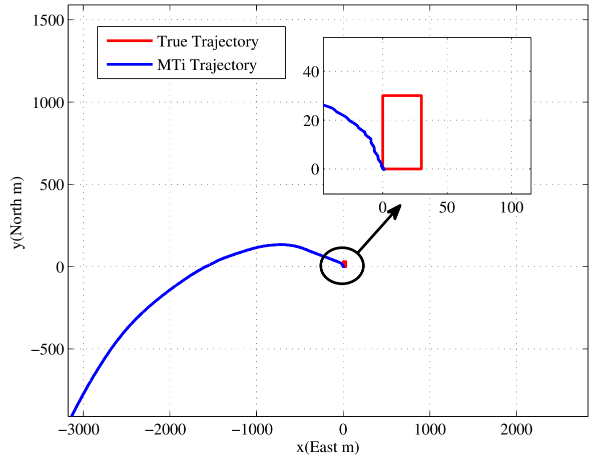

Fig. 4. The true trajectory and the calculated pedestrian trajectory.

where $\|\mathbf{a}_k\| = [a_k^b(1)^2 + a_k^b(2)^2 + a_k^b(3)^2]^{0.5}$, $\text{thrhd}_{a_{min}}$ and $\text{thrhd}_{a_{max}}$ are the minimum and maximum threshold respectively.

2) Condition 2:

$$C2 = \begin{cases} 1 & \sigma^2_{a_k^b} > \text{thrhd}_{\sigma_a} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where

$$\sigma^2_{a_k^b} = \frac{1}{2s+1} \sum_{j=k-s}^{k+s} (a_k^b - \overline{a_k^b}^2) \tag{7}$$

is the local variance of the accelerations, $\overline{a_k^b}$ is the local mean acceleration value, s is the size of the averaging window and thrhd_{σ_a} is the threshold.

3) Condition 3:

$$C3 = \begin{cases} 1 & \|\omega_k\| < \text{thrhd}_{\omega_{max}} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where $\|\omega_k\| = [\omega_k^b(1)^2 + \omega_k^b(2)^2 + \omega_k^b(3)^2]^{0.5}$ is the magnitude of the gyroscope, $\text{thrhd}_{\omega_{max}}$ is the threshold.

These three conditions are combined together with logical "AND" which means they must be satisfied simultaneously, a median filter is used to get rid of the abnormal states. The combined logical values "1" and "0" represents the stationary stance phase and the moving stride phase respectively. Figure 5 shows the result of the stop detection.

Taking the stop detection into account, the equation (4) is modified as follows:

$$X_k(1:6) = \begin{pmatrix} \mathbf{P}_k \\ \mathbf{V}_k \end{pmatrix} = \begin{pmatrix} \mathbf{I} & \mathbf{I} * T_S \\ \mathbf{0} & \mathbf{I} * C_{stop} \end{pmatrix} X_{k-1}(1:6) + \begin{pmatrix} T_S^2/2 * \mathbf{I} \\ T_S * \mathbf{I} \end{pmatrix} a_{k-1}^W \tag{9}$$

where C_{stop} is the logical value of the stop detection and $C_{stop} = C1 \,\&\, C2 \,\&\, C3$.

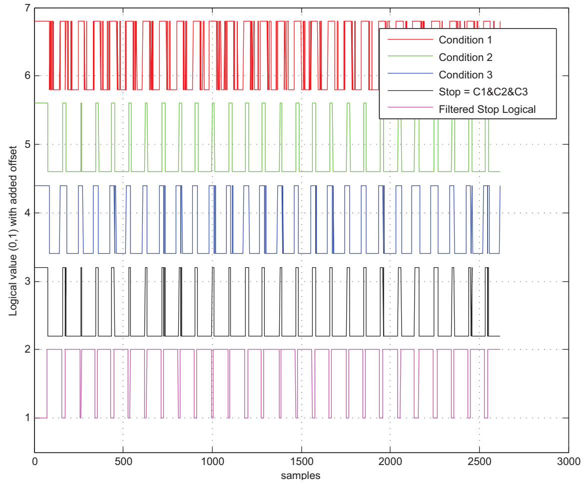

Fig. 5. The results of stop detection.

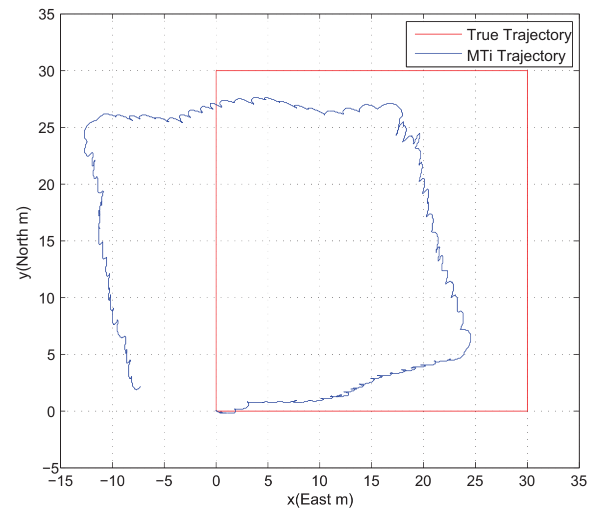

Fig. 6. The true trajectory and the IMU calculated trajectory using stop detection.

Multiplying C_{stop} resets the velocity of the foot as zeros when the stop is detected, which reduces the accumulated velocity error and thus further reduces the position error. Figure 6 shows the true trajectory and the pedestrian trajectory with stop detection, it can be seen clearly that the pedestrian trajectory is slightly away from the true trajectory, which is much more acceptable than the situation when stop detection is not considered. However, it can also be concluded that the error correction by stop detection still needs to be improved since the pedestrian trajectory is away from the true trajectory in terms of both orientation and distance. This phenomenon can also be explained by the fact that drift errors from both accelerometers and gyroscopes are accumulated over time, which can not be eliminated only by stop detection.

V. Error Correction by GPS

The major disadvantage of IMU navigation is that the drift error will accumulate over time causing the errors to be unbounded. In contrast, GPS errors are relatively noisy from second to second, but exhibit no long-term drift [10]. Therefore, GPS is typically used for aiding IMU navigation making the GPS-aided IMU navigation superior to either of them alone. Hence, GPS is also used in this study for correcting the error of foot-mounted IMU localization. An Extended Kalman Filter (EKF) algorithm is designed to implement the error correction with GPS signal, which is presented as follows.

As described above, the system state vector at time k is equation (1). Considering the logical value of stop detection, the system transition model is:

$$\hat{\mathbf{X}}_k = \begin{pmatrix} \hat{\mathbf{P}}_k \\ \hat{\mathbf{V}}_k \\ \hat{\mathbf{O}}_k \end{pmatrix} = \underbrace{\begin{pmatrix} \mathbf{I} & \mathbf{I}*Ts & \mathbf{0} \\ \mathbf{0} & \mathbf{I}*C_{stop} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix}}_{\mathbf{A}} \mathbf{X}_{k-1} + \underbrace{\begin{pmatrix} T_s^2/2*\mathbf{I} \\ T_s*\mathbf{I} \\ \mathbf{0} \end{pmatrix}}_{B} \mathbf{a}_k^w + \begin{pmatrix} \mathbf{0} \\ \mathbf{0} \\ Q2Euler(\mathbf{Q}_k) \end{pmatrix} + \mathbf{w}_k \tag{10}$$

where A is the 9×9 state transition matrix, B is the control matrix, $\mathbf{w}$ is the process noise with covariance matrix $\mathbf{N}_k = E(\mathbf{w}_k \mathbf{w}_k^T)$.

The measurement model is

$$\mathbf{z}_k = \mathbf{H}\hat{\mathbf{X}}_k + \mathbf{n}_k \tag{11}$$

where $\mathbf{z}_k$ is the predicted measurement, $\mathbf{H}_k$ is the measurement matrix, and $\mathbf{n}_k$ is the measurement noise with covariance matrix $R_k = E(n_k n_k^T)$.

The signals from GPS are longitude, latitude, altitude, heading and velocity, only longitude, latitude and heading are used as the actual measurement in this study, as altitude and velocity is too unreliable to use. The longitude and latitude must be converted to coordinate in the global frame before they are fed into the EKF algorithm. The conversion formula presented by Dupree in [11] is

$$x_{gps} = cos(\phi)\sqrt{\frac{1}{(\frac{sin(\phi)}{a})^2 + (\frac{cos(\phi)}{c})^2}}[(lon1 - lon0) * \frac{\pi}{180}]$$
$$y_{gps} = \sqrt{\frac{1}{(\frac{sin(\phi)}{a})^2 + (\frac{cos(\phi)}{c})^2}}[(lat1 - lat0) * \frac{\pi}{180}] \tag{12}$$

where $\phi = \frac{\pi}{2} - \frac{lat0+lat1}{2} * \frac{\pi}{180}$, $(lon0, lat0)$ is the geographic coordinates of the original point, $(lon1, lat1)$ is the geographic coordinates of the specific point, a = 6378136.6 meters, the equatorial radius of the earth, and c = 6356751.9 meters , the polar radius of the earth. The actual measurement is therefore:

$$\mathbf{m}_k = (x_{gps}, y_{gps}, \psi_{gps})^T \tag{13}$$

According to $\mathbf{m}_k$, the measurement matrix must be:

$$\mathbf{H} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{14}$$

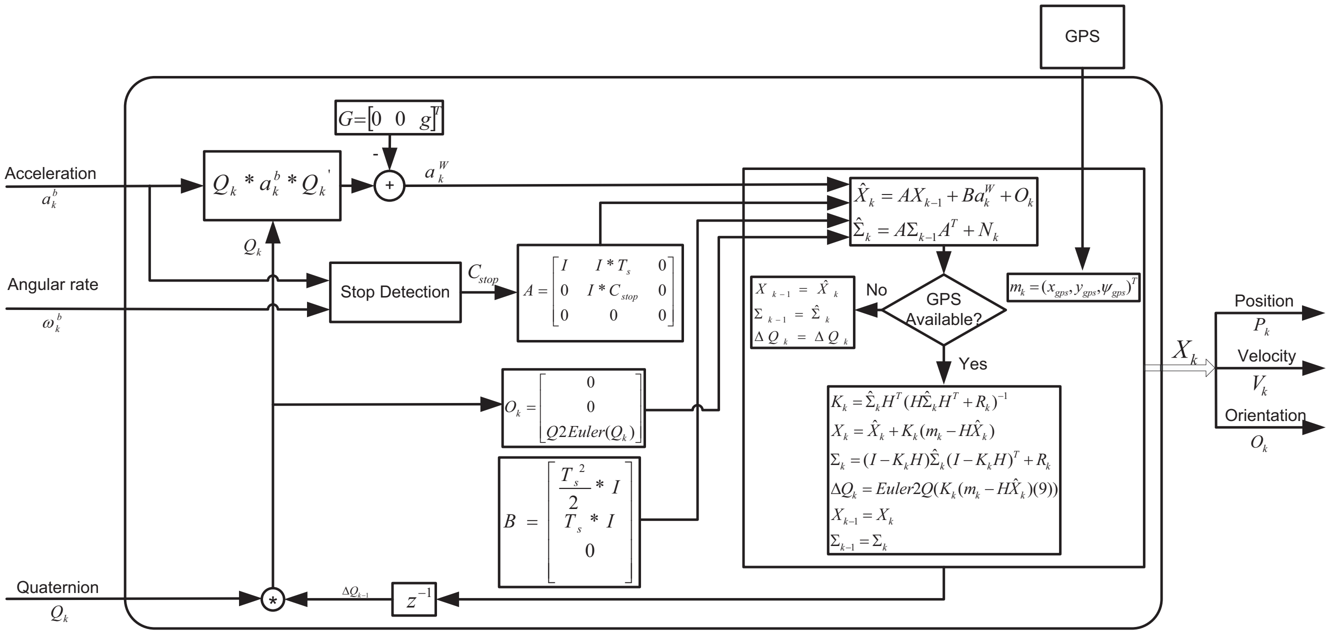

Fig. 7. The IMU/GPS based pedestrian localization algorithm.

Then the Kalman update equation

$$\mathbf{X}_k = \hat{\mathbf{X}}_k + \mathbf{K}_k * (\mathbf{m}_k - \mathbf{H}\hat{\mathbf{X}}_k) \tag{15}$$

where K_k is the Kalman gain, m_k is the actual measurement which are GPS signals, $\hat{\mathbf{X}}_k$ is the predicted system state described as equation (10).

The Kalman gain is calculated with the usual formula:

$$\mathbf{K}_k = \hat{\mathbf{\Sigma}}_k \mathbf{H}^T (\mathbf{H}\hat{\mathbf{\Sigma}}_k \mathbf{H}^T + \mathbf{R}_k)^{-1} \tag{16}$$

where $\hat{\mathbf{\Sigma}}_k$ is the state estimation covariance matrix, calculated with the classical form:

$$\hat{\mathbf{\Sigma}}_k = \mathbf{A}\mathbf{\Sigma}_{k-1}\mathbf{A}^T + \mathbf{N}_k. \tag{17}$$

The covariance matrix $\mathbf{\Sigma}_k$ at time k is then calculated with the Kalman gain in the Joseph form equation $\mathbf{\Sigma}_k = (\mathbf{I}_{9\times 9} - \mathbf{K}_k\mathbf{H})\hat{\mathbf{\Sigma}}_k(\mathbf{I}_{9\times 9} - \mathbf{K}_k\mathbf{H})^T + \mathbf{R}_k$.

From equation (2), we can see that any error of quaternion will cause the drift error of acceleration in global frame. However, it should be noted that although the heading part of the error correction term $\mathbf{K}_k(\psi_k - \psi_{gps})$ can be used to correct the heading error of the pedestrian position, the correction value has not been embodied on the control input term-quaternion. In order to make the heading error correction take effect on the quaternion, the quaternion can be modified as:

$$\mathbf{Q}_k = \Delta\mathbf{Q}_{k-1} * \mathbf{Q}_k \tag{18}$$

where $\Delta\mathbf{Q}_{k-1}$ can be calculated with following formula:

$$\mathbf{Q} = (w\ x\ y\ z)^T = Euler2Q(\phi, \theta, \psi) \tag{19}$$

Then $\Delta\mathbf{Q}_{k-1} = Euler2Q(0, 0, \mathbf{K}_k * (\mathbf{m}_k - \mathbf{H}\hat{\mathbf{X}}_k)(9))$, where $\mathbf{K}_k * (\mathbf{m}_k - \mathbf{H}\hat{\mathbf{X}}_k)(9)$ is the heading part of the error correction term, $Euler2Q()$ is the function converting Euler angle to quaternion.

GPS signals are not always available because they can be blocked by high buildings, canyons or forests among others. When GPS is in outage, the predicted system state $\hat{X}_k$ will not be updated by EKF, instead it is directly used for next iteration of state calculation.

Figure 7 shows the diagram of the IMU/GPS based pedestrian localization algorithm.

VI. Experiments

The IMU/GPS based pedestrian localization algorithm is firstly implemented when a pedestrian is walking along a 30×30 square which is shown in Figure 3. The result of the implementation is shown in Figure 8 which presents the pedestrian trajectory represented by different methodologies. It can be seen that the IMU/GPS based localization algorithm using EKF outperforms the ZUPT algorithm alone in two respects: First, the EKF corrected trajectory is closer to the true trajectory than stop detection corrected trajectory to the true trajectory, in other words, the former is more accurate than the latter; Second, even though there is GPS outage during the walking, EKF corrected trajectory is only affected slightly thanks to the advantage of data fusion algorithm.

In order to further validate the accuracy of the IMU/GPS based pedestrian localization algorithm, another test was conducted in an environment shown in Figure 9, and the corresponding trajectory represented by different methodologies is presented in Figure 10. It is obvious that EKF corrected trajectory is more accurate than the trajectory calculated by stop detection based algorithm. There are two spots of GPS outage, where EKF corrected trajectory keeps the same accuracy with places where GPS signals are available. Therefore, the result

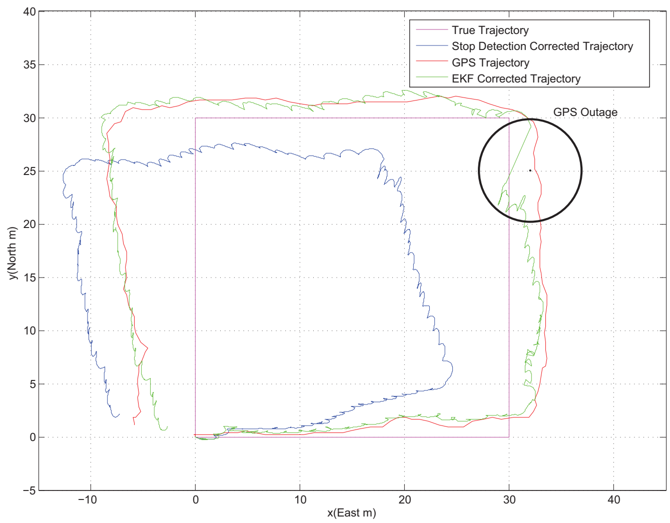

Fig. 8. The pedestrian trajectory represented by different methodologies, (0,0) is the starting point. The environment for this test is a 30×30 square.

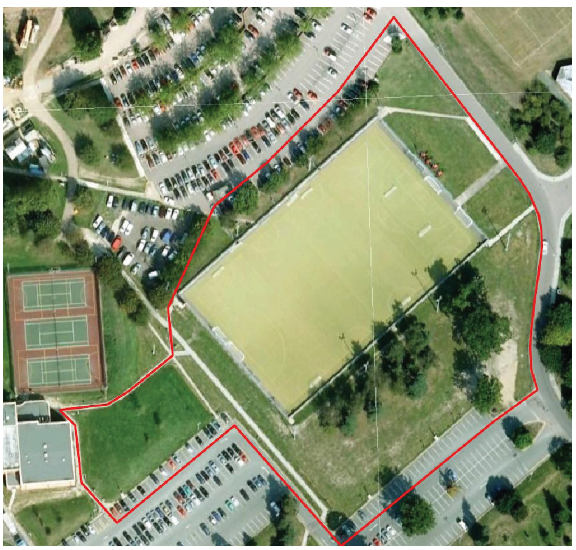

Fig. 9. A larger testing environment compared to the 30×30 square

shows the superiority of the IMU/GPS integrated pedestrian localization algorithm over the ZUPT algorithm alone.

VII. Conclusion

This study presents a new IMU/GPS based pedestrian localization algorithm, in the order of basic position calculation principle, error correction by stop detection (ZUPT) and error correction by GPS data and EKF algorithm. By analyzing theoretically and practical experiment, it is known that ZUPT based position calculation method works better than basic position calculation principle in terms of accuracy since the accumulated integration error can be compensated by setting the velocity as zero when the stance phase of the foot is detected. However, even adopting ZUPT can not completely eliminate the accumulated integration error, thus EKF based IMU/GPS fusion algorithm is applied. The tests for two

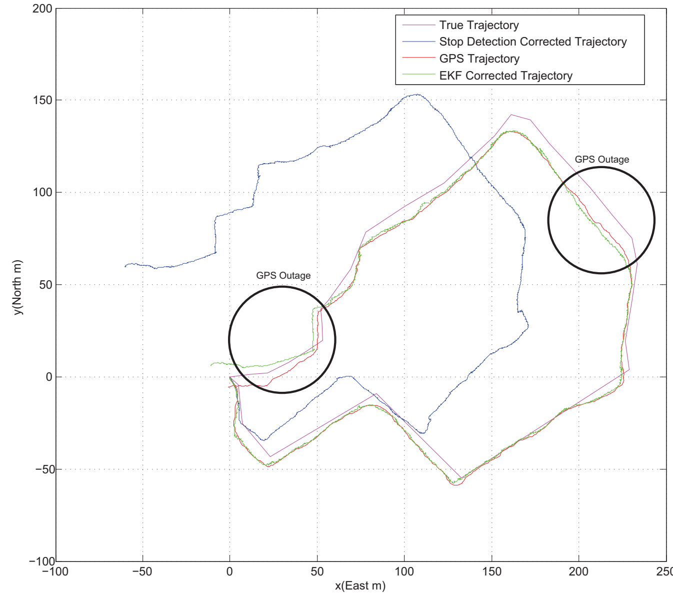

Fig. 10. The pedestrian trajectory represented by different methodologies, (0,0) is the starting point.The environment for this test is the one shown in Figure 9

different environments show that the error correction by GPS data and EKF algorithm is accurate and robust. However, the situation of long-term GPS outage is not considered in this paper. Our future work will focus on the improvement of the localization accuracy in long-term operations.

References

[1] S. Wan and E. Foxlin, “Improved pedestrian navigation based on drift-reduced mems imu chip,” in *Proceedings of the 2010 International Technical Meeting of The Institute of Navigation*, 2001, pp. 220–229.

[2] S. Cho and C. Park, “Mems based pedestrian navigation system,” *Journal of Navigation*, vol. 59, no. 01, pp. 135–153, 2006.

[3] P. Schneider, S. Crouter, O. Lukajic, and D. Bassett Jr, “Accuracy and reliability of 10 pedometers for measuring steps over a 400-m walk,” *Medicine & Science in Sports & Exercise*, vol. 35, no. 10, p. 1779, 2003.

[4] L. Ojeda and J. Borenstein, “Non-gps navigation for emergency responders,” in *2006 International Joint Topical Meeting: Sharing Solutions for Emergencies and Hazardous Environments*. Citeseer, 2006, pp. 12–15.

[5] X. Yun, E. Bachmann, H. Moore, and J. Calusdian, “Self-contained position tracking of human movement using small inertial/magnetic sensor modules,” in *2007 IEEE International Conference on Robotics and Automation*. IEEE, 2007, pp. 2526–2533.

[6] A. Jiménez, F. Seco, J. Prieto, and J. Guevara, “Indoor pedestrian navigation using an ins/ekf framework for yaw drift reduction and a foot-mounted imu,” in *2010 7th Workshop on Positioning Navigation and Communication (WPNC)*. IEEE, 2010, pp. 135–143.

[7] I. Skog, J. Nilsson, and P. Handel, “Evaluation of zero-velocity detectors for foot-mounted inertial navigation systems,” in *2010 International Conference onIndoor Positioning and Indoor Navigation (IPIN)*. IEEE, 2010, pp. 1–6.

[8] O. Woodman, “An introduction to inertial navigation,” *University of Cambridge, Computer Laboratory, Tech. Rep. UCAMCL-TR-696*, 2007.

[9] R. Feliz, E. Zalama, and J. Gómez, “Pedestrian tracking using inertial sensors,” *Journal of Physical Agents*, vol. 3, no. 1, pp. 35–42, 2009.

[10] G. Schmidt and R. Phillips, “Ins/gps integration architectures,” *NATO-OTAN*, 2011.

[11] P. Dupree, “Autonomization of a mobile hexapedal robot using a gps,” *SUN*, 2009.