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Multi-IMU Data Fusion for Indoor Navigation

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ABSTRACT

Due to the drift of measurement, it is difficult to get the accuracy trajectory for pedestrian indoor navigation. In this paper, we proposed an algorithm to improve the accuracy of pedestrian trajectory by fusing the information from 3 inertial sensors based on the zero-velocity detection approach. Experiments showed that the accuracy of the trajectory was able to significantly improved using the proposed algorithm.

1. Introduction

Pedestrian navigation, considering outside and indoor conditions, mainly involves two technologies, i.e., the global position system (GPS) and self-contained sensors. Since GPS signal attenuation is severe in buildings and tunnels, it is not applicable for accurate indoor pedestrian position estimation (e.g. Chen, L. and Hu, H, 2012). Therefore, indoor positioning technology is mainly based on self-contained sensors, such as the inertial measurement unit (IMU) (e.g. Luan, V. N. et al., 2016). Recently, more and more family service robots have come into people's life, for example, Bellarbi, Abir, et al. use the tour-guide robot in human environment (e.g. Bellarbi, A. et al., 2017), and Boujelben M, et al.also provide an improved robot navigation way (e.g. Boujelben, M., 2017).

Thanks to miniaturization technologies, such as micro-electro-mechanical systems or nano-electro-mechanical systems, being smaller and low-cost, IMU consumes less power, and could be fixed to the feet of pedestrians. Foot-mounted IMUs have many indoor applications, such as in anti-terrorism, and assessing fire scenes and other dangerous areas (e.g. Rüppel, U. et al. 2010). For instance, in anti-terrorism applications, the IMU system can provide the location of each policeman, which can improve the cooperation ability for police groups indoor.

Using the information from the IMU, including acceleration and orientation measurements, the current position of a pedestrian can be obtained based on a previously determined position. However, the measurement of the IMU has unknown drift, which reduces the performance of indoor navigation greatly. One way to correct drift is to use other information. For example, Li et al (e.g. Li, Y. et al. 2017) used Wi-Fi and magnetic information together with acceleration and orientation measurements to cut down the navigation error. Nevertheless, this kind of method has a great demand for a priori information about the environment and the system. Another approach to correct the drift of position is to use the feature of target motion. At each step when a pedestrian is moving, the foot touches the ground, at which time the speed with respect to the ground is zero. This is so-called "zero-velocity updates (ZUPT)" (e.g., Norrdine, A. et al., 2016; Skog, I. et al., 2010), an effective technique to reduce error.

Nilsson et al. had given an open-source, real-time, embedded implementation of a foot-mounted, zero-velocity-update-aided inertial navigation system (e.g. Nilsson, J. O. et al., 2012), which only used ZUPT information in stance phases, and ignored accumulated errors in non-stance phases of gait cycles. Furthermore, an adaptive zero-velocity interval (ZVI) detection algorithm was proposed based on a smoothed pseudo Wigner Ville distribution to remove multiple frequencies intelligently, which utilizes an adaptive threshold method to improve positioning accuracy (e.g. Nilsson, J. O. et al., 2016); but the error of this method gradually grows larger and larger as time goes on. Therefore, in practice, it is still difficult to detect the ZVI and the position error due to the unknown drift of the IMU.

We here present a method to obtain accurate pedestrian navigation using a foot-mounted inertial sensor based on the data fusion method, which does not require any installation in the environment and any prior knowledge of the environment (such as a map). The data fusion method uses the multi-sensor measurement,

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and can produce more consistent, accurate, and useful information than that provided by any individual data source, especially when the measurements have noise and drift (e.g. Grigorie, L. T. et al., 2014; Paola, A. D. et al., 2017). Therefore, here we used 3 low-cost IMUs and the effective fusion method to reduce the error of navigation.

Three inertial sensors were used to obtain the measurements when the pedestrian is walking, which were then fused by the weights based on the data synchronization method. Experimental results showed that the fusion method greatly improved the performance of indoor navigation.

This paper is organized as follows. Section 2 introduces zero-velocity detection, which is the important method used to synchronize data and label the state of steps. The data fusion algorithm is discussed in Section 3, including the methods for calculating the weight, and fusing measurement data, and presents the out-of-sequence problem of the practical measurement data. Section 4 shows the evaluation results for several navigation tests. In Section 5, we give the main conclusions drawn from this work.

2. Zero-velocity Detection

Zero-velocity detection examines whether the pedestrian's foot is on the ground. The detected zero-velocity state reduces speed errors of the external measurement information for the system, and the error of navigation system can be corrected to improve positioning accuracy. One of the 2 different states, i.e., moving and static, is output by zero-velocity detection based on the signal source.

The output of the IMU can be expressed as follows:

$$x_k = [x_k^a, x_k^w]$$

where $x_k^a \in \Omega^3$ is the specific acceleration measurement vector, and $x_k^w \in \Omega^3$ is the angular velocity measurements vector. By the Neyman-Pearson rules, we assumed a series of values $z_n = \{x_k\}_{k=n}^{n+W-1}$, where n represents the sampling time, W represents the number of samples, and 2 states H_0 and H_1 are set respectively, where H_1 describes the object being moving and H_0 describes it being static. Here, the detection probability $P_d = P\{H_0 | H_0\}$ determines whether the target is in the static state, and the false alarm probability is expressed as follows:

$$P_f = P\{H_0 | H_1\} = \alpha \tag{1}$$

In other words, we should ensure the maximum correct probability of judgment P_d due to P_f constraints.

Two hypothesis observation data probability density functions are defined as $P(z_n;H_0)$, $P(z_n;H_1)$. The sensor model used can be represented by the following model:

$$x_k = d_k(\Phi) + v_k \tag{2}$$

where $d_k(\Phi) = [d_k^a(\Phi), d_k^w(\Phi)]^T$, $d_k^a(\Phi)$ represents the acceleration of the IMU, and the angular velocity is expressed as $d_k^w(\Phi)$. The symbol Φ denotes the vector of unknown elements, and $v_k = [v_k^a, v_k^w]^T$, $v_k^a \in \Omega^3$ denotes accelerometers noise and $v_k^w \in \Omega^3$ indicated gyroscopes noise respectively. We assumed the noises follows a zero mean Gaussian distribution, with noise covariance matrix $E\{v_k v_k^T\} = \begin{bmatrix} \delta_a^2 I_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & \delta_w^2 I_{3\times3} \end{bmatrix}$, where δ_a^2 and δ_w^2 represent accelerometers and gyroscopes noise variance, respectively.

Then we constructed a likelihood ratio function,

$$p(z_n;\Phi,H_i) = \prod_{k\in\Omega_n} p(x_k^a;\Phi,H_i)\, p(x_k^w;\Phi,H_i) \tag{3}$$

where $i = 0,1$ and

$$p(x_k^a;\Phi,H_i) = \left(\frac{1}{\sqrt{2\pi\delta_a^2}}\right)^3 \exp\left\{-\frac{1}{2\delta_a^2} \| (x_k^a - d_k^a(\Phi)) \|^2\right\} \tag{4}$$

$$p(x_k^w;\Phi,H_i) = \left(\frac{1}{\sqrt{2\pi\delta_w^2}}\right)^3 \exp\left\{-\frac{1}{2\delta_w^2} \|(x_k^w - d_k^w(\Phi))\|^2\right\} \tag{5}$$

Zero-velocity detection's status value is determined by the hypothesis H_0 if $T(z_n) < \eta$, where η is set 0.3×10^{-5}.

$$T(z_n) = -\frac{2}{W}\ln L(z_n) \tag{6}$$

$$L(z_n) = \frac{p(z_n;\hat{\Phi}_0,H_0)}{p(z_n;\hat{\Phi}_1,H_1)} \tag{7}$$

Here, $\hat{\Phi}_0$ and $\hat{\Phi}_1$ represent the maximum likelihood estimate of the unknown element under the assumptions H_0 and H_1, respectively. Finally, we can get $T(z_n)$ by combining equations (3), (4), (5), and (6) as follows:

$$T(z_n) = \frac{1}{W}\sum_{k=n}^{n+W-1} \frac{1}{\delta_a^{\ 2}} \| (x_k^a - g\frac{\bar{x}_k^a}{\| \bar{x}_k^a \|}) \|^2 + \frac{1}{\delta_w^{\ 2}} \| \bar{x}_k^w \|^2 \tag{8}$$

where g represents gravitational acceleration, and $\bar{x}_k^a$, $\bar{x}_k^w$ represent the means of the samples, respectively.

In Fig.1, the red line represents the calculated the value of T by equation (8), and the bold blue line represents the set threshold. If the value of T is higher than the set threshold η, the pedestrian will be considered as moving, while it will be determined to be in the static state if the value of T is below the set threshold η.

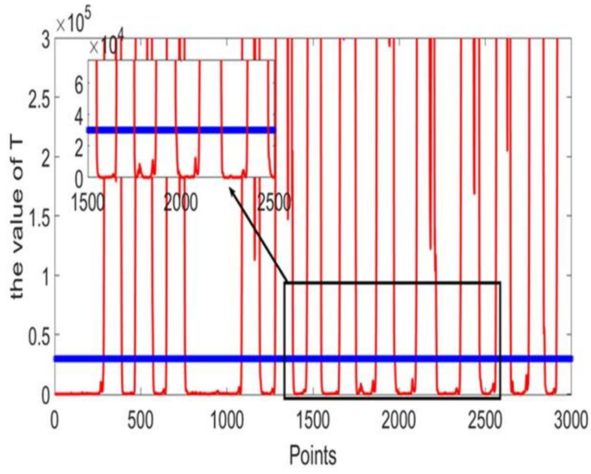
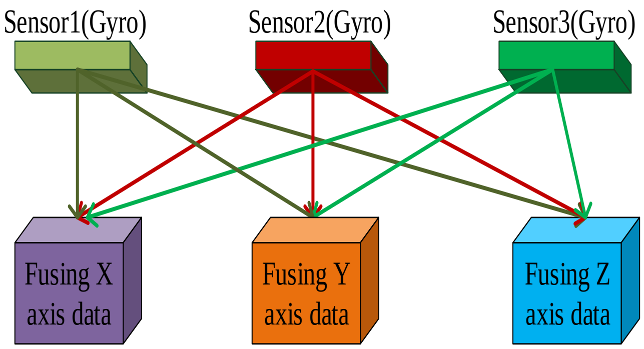


Fig.1. The value of T

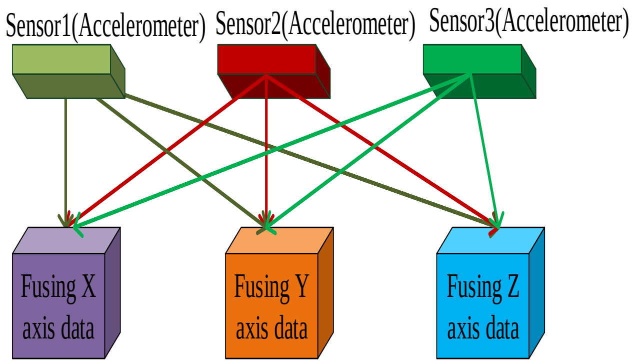
3. Data Fusion Algorithms

3.1 Information Fusion Based on the IMU

In this paper, we used 3 inertial sensors to track the position of the target. Therefore, we needed to fuse the data collected by these 3 inertial sensors. As we know, there are 3 kinds of sensors in the inertial sensors, i.e., the gyro, accelerometer, and magnetometer. In this paper, we considered the measurement data from the gyroscope and accelerometer. For each sensor, measurement data from 3 axes, x, y, and z, were obtained. The fusion process for multi-inertial sensors is shown in Fig. 2.



(a) fusion process by gyro sensor data



(b) fusion process by accelerometer data

Fig.2. Fusion process for multi-inertial sensors

Considering n sensors from the same measurement data in Fig. 1, the evaluation of the standard deviation of the signal for i th sensor within m samples with the same sampling time is obtained by using the following equation:

$$\sigma_i = \sqrt{\frac{1}{m}\sum_{k=1}^{m}(r_{i,k} - \overline{r}_i)^2} \tag{9}$$

where $r_{i,k}$ denotes the k th sample in the data frame measured by the i th sensor in the cluster, and $\overline{r}$ is the mean of the m consecutive samples measured by the same sensor.

$$\overline{r}_i = \left(\sum_{k=1}^{m} r_{i,k}\right) / m \tag{10}$$

Applying the inverse proportionality between weights and standard deviations, and considering the sum of the weights equaling the unity, we have

$$\omega_i = \frac{1}{\sigma_i} \cdot \left(1 / \sum_{k=1}^{n} \frac{1}{\sigma_k}\right),\ i = 1,2,3,\cdots,n \tag{11}$$

where $\sum_{i=1}^{n}\omega_i = \omega_1 + \omega_2 + \cdots + \omega_n = 1$.

Here is a group of data fusion methods, and its fusion formulae is as follows:

$$\omega = \sum_{i=1}^{n}\omega_i \times w_{ri}, i = 1,2,3,\cdots,n \tag{12}$$

$$accR = \sum_{i=1}^{n}\omega_i \times accR_i,\ i = 1,2,3,\cdots,n \tag{13}$$

where w_{ri} represent the angular velocity (w_{xi}, w_{yi}, w_{zi}) of all measurement sensors, and $accR_i$ represents the acceleration $(accX_i, accY_i, accZ_i)$ of all measurement sensors. $w = [w_x, w_y, w_z]$ and $accR = [accX\ \ accY\ \ accZ]$ are the fused measurement data in the body coordinate system.

3.2 Data Synchronization

We found that the data from different sensors cannot be sent simultaneously, although they are caught at the same time. Even worse, the recorded sample time is a pseudo time, which means the sensor system cannot give us the right sample time because of the response time of the hardware; thus, the recorded sampling time is not the actual time when the measurement was obtained. Therefore, in the practical system, the measurement data from different sensors had different sampling times.

We used the x-axis of the gyroscope as an example to show the measurement data and results of fusion. Fig. 3 indicates that measurement data for 3 gyro sensors on the x-axis. We can see the start time of the data was different, which was caused by the delayed response time of the serial data acquisition port in the hardware system. Therefore, formula (12) and (13) could not be used directly, and the data synchronization was both necessary and important.

Data synchronization involved 2 steps. Firstly, each sensor was adjusted to send data with the same baud rate. Then, the data was aligned by zero-velocity detection. In particular, zero-velocity detection was used to find the starting position. and the measurement of the start time was adjusted to the same time. Fig. 4 indicates that the data has been aligned; then, based on the aligned measurement data, the data fused by equation (12) is as shown in Fig. 5.

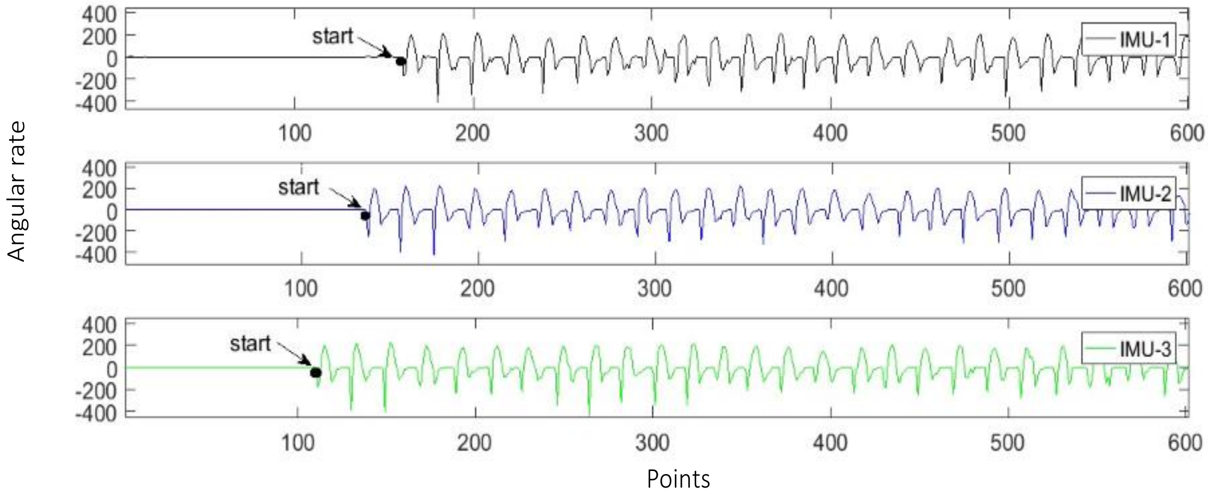


Fig. 3. Data for 3 gyro sensors on the x-axis, unaligned

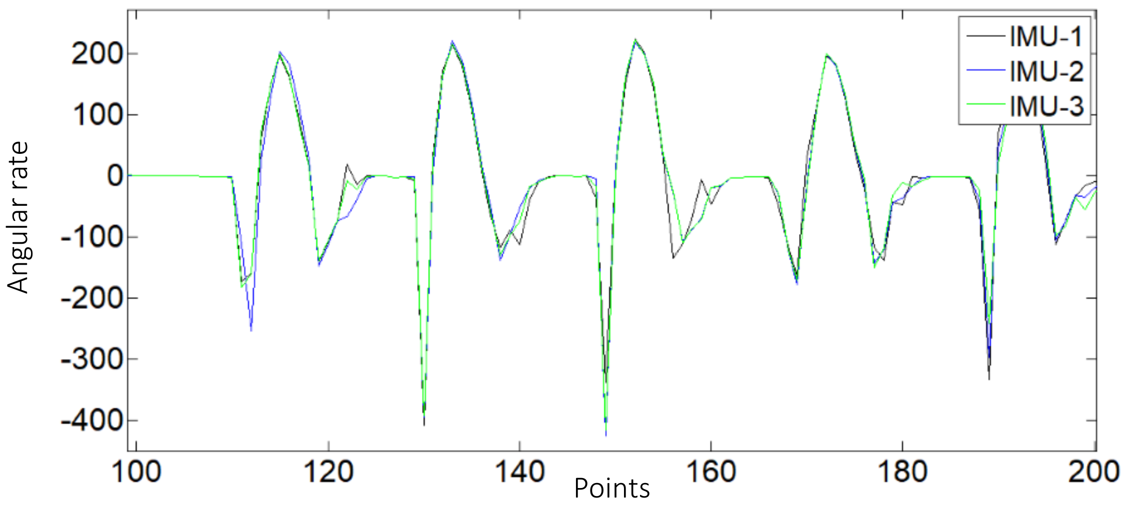


Fig.4. Data for 3 gyro sensors on the x-axis, aligned

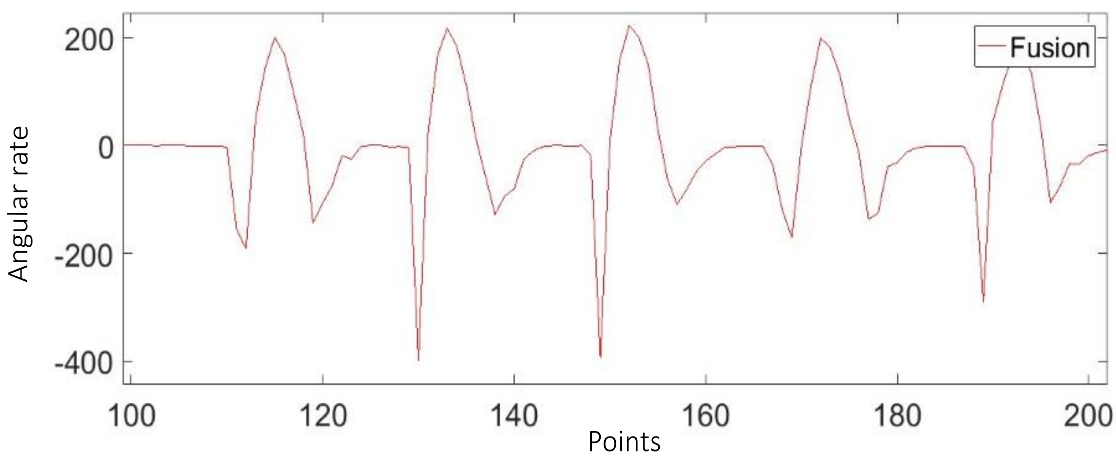


Fig. 5. Gyro x-axis fusion results

4. Results

We conducted an indoor experiment in the corridor of the building (Fig. 5). Fig.7 shows the installation method and location of the sensor。

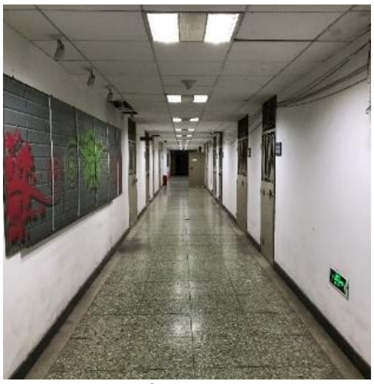
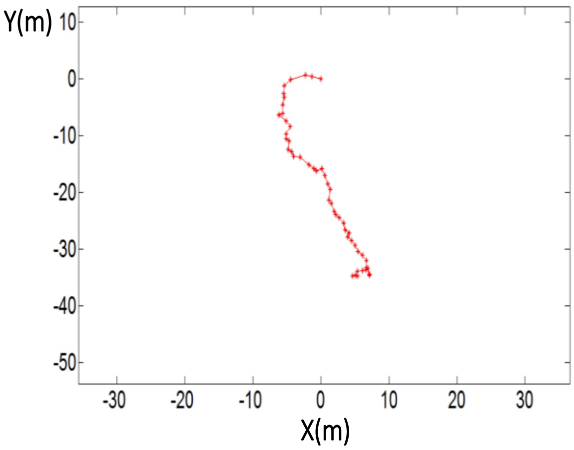


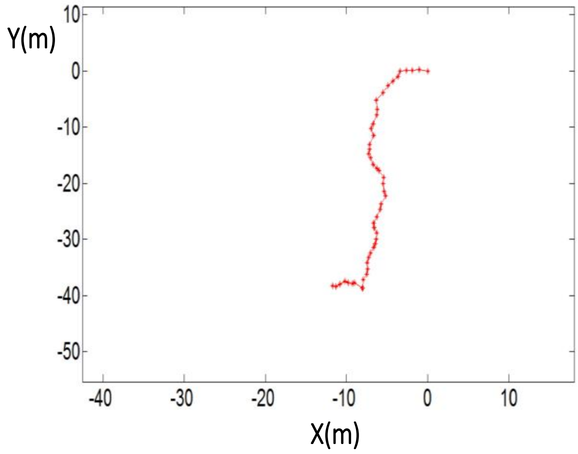
Fig.6. Indoor environment

Fig.7. The installation position of the sensor

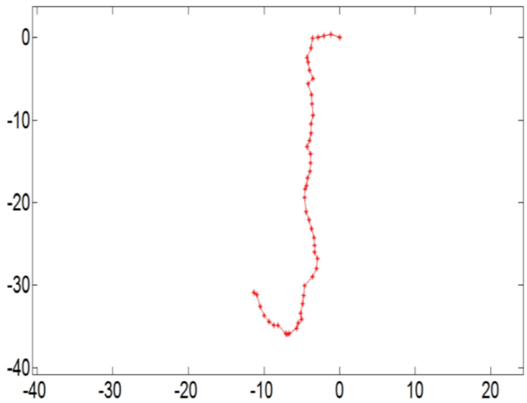
The results of zero-velocity correction by Kalman filter (e.g. Yi, J. et al. 2011) are shown in Fig. 6 (a), (b), and (c). The trajectory following fusion of these 3 sensors, together the zero-velocity correction process, is shown in Fig. 6 (d), in which, all measurement data from the 3 sensors were used to obtain the fused measurement using equations (12) and (13).



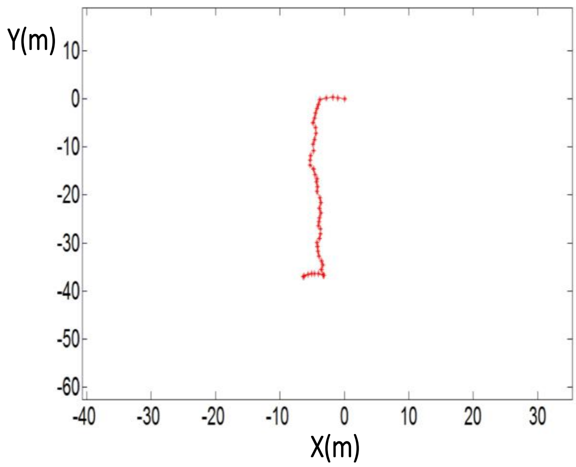
(a) trajectories derived from individual sensor data



(b) trajectories derived from individual sensor data



(c) trajectories derived from individual sensor data



(d) the trajectory derived from the data after fusion

Fig. 8. Comparison of single sensors and fusion processing trajectory obtained by the fusion of 3 sensor: (a), (b), and (c) represent trajectories derived from individual sensor data; (d) represents the trajectory derived from the data after fusion.

Fig. 9 shows the fused trajectory compared with the reference data. Here, the blue line represents the trajectory after fusion, and the red line represents the actual trajectory. We considered the errors of trajectory as

$$error = \sqrt{(X_{truth\ k} - s_{xk})^2} + \sqrt{(Y_{truth\ k} - s_{yk})^2} \tag{14}$$

where $X_{truth\ k}$ and $Y_{truth\ k}$ represent the actual x-axis and y-axis coordinates of the trajectory on the horizontal plane, and s_{xk}, s_{yk} represent the x-axis and y-axis coordinates of the obtained trajectories s_k. It should be noted that we omitted s_{zk}, because we assumed the pedestrian was walking on the horizontal plane.

The errors of trajectory by each sensor and the fused data are shown in Tab. 1, by which we can see that the error of trajectory was reduced greatly by the fusion process.

Tab.1 Error contrast between fusion and no fusion

Sensor	Error (m)	Percentage of error (%)
Sensor1	12.5857	33.5
Sensor2	4.23992	11.3
Sensor3	6.98518	18.6
Fusion sensor	1.35625	3.6

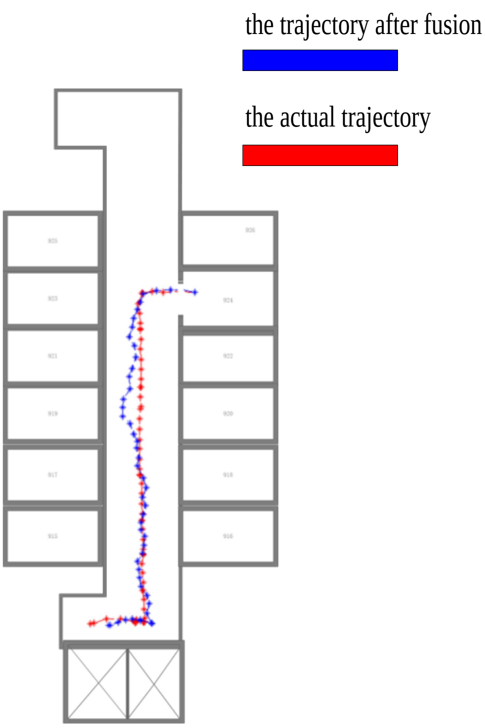


Fig. 9. Comparison of the trajectory obtained by the proposed method with the reference data

Then we conducted outdoor long track experiments, as shown in Fig.10. The outdoor environment map is shown in Fig 11 and the length of the playground is about 320 meters. The trajectory was made by a pedestrian which walk around the playground of our campus, and the green circle represents the both starting point and end of the track.

From Fig.10. we can see the error of fused trajectory is 3 meters and the error of not fused trajectory is 4 meters. Based on the experiments mentioned above, it can be seen that the fusion scheme can reduce the error generation.

5. Summary

Pedestrian indoor navigation based on IMUs tracks the location of a person on foot, and is useful for finding and rescuing firefighters or other emergency first responders, or for location-aware computing, personal navigation assistance, etc. In this paper, we proposed an algorithm to improve the accuracy of determining a pedestrian's trajectory by fusing 3 inertial sensors. The proposed method was then evaluated with walking experiments, and comparisons to a previous method illustrated the effectiveness of the proposed algorithm for information fusion. In a future study, we will study more complicated movement cases, such as walking backwards, sideways walking, and climbing stairs. More complicated walking scenarios will be tested in the near future.

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Shi-yu Peng is currently a postgraduate in Control Theory and Control Engineering in Beijing Technology and Business University. During past four years, he learned several specialized courses including principles of automatic control, process monitoring, computer control system. His research interests involve state estimation, adaptive Kalman filter, indoor-outdoor positioning, and so on.

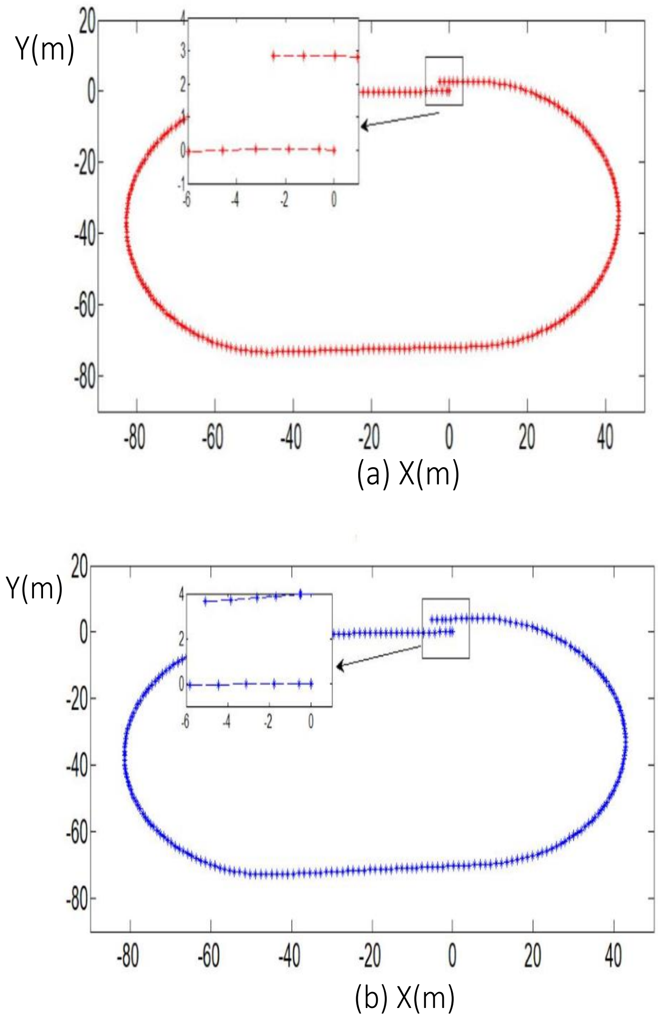

Fig. 10. Comparison of the trajectory obtained by the proposed method with the reference data

Fig. 11. Outdoor environment map