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Ship-board Pedestrian Positioning Method by Integrating Dead Reckoning and Wireless Sensor Networks

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***Abstract*—Aimed at ship-board pedestrian positioning, this paper put forward a low-cost positioning method by integrating Pedestrian Dead Reckoning (PDR) and Wireless Sensor Networks (WSN). In this paper, a stable attitude estimator method has been designed through the calibration of IMU's components -- accelerometer, gyroscopes and magnetometers. Apart from this, a pedestrian dead reckoning system has been achieved through detailed analysis of step detection which estimated the step length. Furthermore, with ship-board Wireless Sensor Networks, an Extended Kalman Filter in this positioning method will be applied to fuse the information if the signal of WSN beacon is available. If the signal of WSN beacon is unavailable, the PDR system will continue working independently and the Extended Kalman Filter is applied as fusion scheme.**

Meanwhile, experiments were carried out in simulative ship environment. When the tester walked with the PDR system receiving correction signals of WSN, the average positioning error was 1.1 meter and the maximum error was 2meter. The experimental results have shown that the proposed scheme can fulfill the demand of pedestrian positioning in nautical situation.

Keywords—Ship-board Indoor Positioning; Extended Kalman Filter; Pedestrian Dead Reckoning,; Wireless Sensor Networks

I. INTRODUCTION

Although the technology of ship-board positioning has developed relatively mature, at present there cannot provide an ideal solution that can be used for positioning inside objects and staffs. In fact, accurate location information of stuffs onboard plays a vital role in elaborate management, emergency rescue and logistics tracking.

Generally speaking, ship environment has been regarded as indoor environment. Currently there are two main positioning technologies for indoor environment: a. wireless positioning system, which is based on established reference substance. This system needs to establish reference points in positioning area in advance. The larger the positioning area is, the more complicated the system is with more considerable costs. In addition, the positioning quality is easily interfered by the outside circumstance[1]. b. Pedestrian Dead-Reckoning System , which is on the basis of inertial navigation. On the base of a given initial point. PDR system is automatic, and it can work independently. Apart from this, it is hard to be interfered. However, there exists the problem of error accumulation in this system. As the distance increases, the error will accumulate considerably.

With to the development of MEMS technology, inertial components become small and low-cost. Since PDR system is based on inertial navigation, more and more studies focus on PDR in the field of indoor positioning. However, an initial point should be signed by external signal; the error accumulation will become larger if PDR system works independently for a long time. As a result, PDR system usually works with other positioning systems in practice to achieve better positioning. Reference [2] integrates GPS locating signal and PDR system together. This new system works as follow: providing a initial point by GPS signal and then using fusion algorithm to calculate the overlapping area. Thus the stability of PDR system increases because it can work in the area in which GPS signal is disconnected. Reference [3] refers to an indoor method on the basis of PDR system, helping RFID signal to correct PDR errors. What's more, it applies Extended Kalman Filter as fusion algorithm. Reference [4] mainly introduces a linear model, which integrates WLAN and PDR system. Generally, the fusion model should be non-linear in this model, but the author has proved that the functions linear model is no less effective than that of non-linear model. Reference [5] suggests a method to integrate data by indoor WIFI signal. It builds spatial location fingerprint of WIFI to get the location marked by WIFI signal, and then applies PDR system to reckon the position by conducting fusion algorithm. Reference [6] goes further than spatial location fingerprint of WIFI. It suggests taking the advantage of particle filter to fuse WIFI and PDR so as to bring in cartographic information for navigation. Compared with Kalman Filter fusion, partial filter fuses location information with support of map-matching.

Currently, the ship environment lacks technology for pedestrian positioning. Thus this paper aims at devising a pedestrian positioning system which can be applied in any complicated environment through careful study on inside pedestrian positioning technology. In the light of complex electromagnetic environment and the structure of cabin, this design adopted two subsystems for integrated positioning, including Wireless Sensor Network and wearable personal PDR based on inertial navigation system.

This paper is organized as follows: in the second part introduces the design of the system; in the third part introduces

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a method to adjust the sensor; in the fourth part suggests the fusion method of attitude angle and the fusion location information based on EKF; in the fifth part introduces the experimental results and analysis; finally comes to a conclusion in the sixth part.

II. SYSTEM DESCRIPTION

In the light of complex electromagnetic environment and the structure of cabin, this design adopted two subsystems for integrated positioning, including Wireless Sensor Network and wearable personal PDR based on inertial navigation system.

On account of enormous size and considerable cost of traditional inertial navigation system, it is inappropriate for personal navigator. Hence, this design applied IMU which is driven by low-cost MEMS technology. And with assistance of MCU, this design established dead reckoning subsystem. After measuring the step numbers, step length and walking azimuth, dead reckoning superimposes the new data onto the previous estimated data so as to reckon the current position of objects. The IMU, comprised of MEMS sensor, contains tri-axial accelerometer, tri-axial gyroscope and tri-axial magnetometer. The performance parameter of this sensor is presented in table I. A 32-bit MCU with the Cortex-M4 of ARM , the STM32F405 MCU, was chosen for its enormous processing capacity and abundant peripheral equipment. The dominant frequency of 168MHZ can meet the requirements of performance.

Dead reckoning system is shown as in Figure 1. In this design, PDR collects the data of sensors by wearing on pedestrians' feet. for accurate estimation on step numbers. The pedestrian gait detection and estimation on step numbers can be achieved firstly by feature analysis on module value of acceleration and angular velocity and local variance of acceleration, and then considering the features of pedestrian stride frequency[7] . When it comes to step length estimation, the step length varies from person to person because it associates with many factors, such as height, weight and mood. Related references have proved that four types of calculating method can be classified according to different calculating models. They are constant model, linear model, non-linear model and artificial neural network model[8] . Most calculation on step length is based on various parameters related to statistical property of walking speed, such as stride frequency and the change of pace. The non-linear compensation model of estimation is adopted in this design.

$$SL = K \times \sqrt[4]{A_{\max} - A_{\min}} \tag{1}$$

SL stands for the step length estimation; A_{max} stands for the maximum acceleration in one gait period while A_{min} stands for the minimum one; K is a constant related to the length of leg and it can be obtained by experiments. In order to obtain pedestrians' walking direction, we firstly fuse the observed value from gyroscope, accelerometer, and magnetometer so as to get a sensor attitude. And then we further extract pedestrians' course angle through gait analysis. Its specific method will be introduced in the following part. Having completed the estimation of step number, step length, and pedestrian's walking direction, the position of pedestrians can be calculated by dead reckoning principle.

In order to tackle the problem of error accumulation in PDR, the signal of wireless sensor network is brought in to correct the error of dead reckoning system. This design selects the WSN which is based on the Zigbee protocol as subsystem to assist positioning. Because there are large amount of staffs on board and every staff needs to wear positioning identification, we apply Zigbee, which can accommodate large number of nodes at one time. Besides, Zigbee meet all the requirements of complex ship environment for its self-organizing ability of network, multiple hops transmission capacity, high adaptability to network, and the reliability of data transmission. Apart from providing pedestrian positioning information, Zigbee network can also monitor the environment. Increasing environmental monitoring sensors (temperature humidity, combustible gas, etc.) in the network of anchor nodes can fulfillment of integration of the environmental information collection and the positioning function. Finally, with low cost but high cost performance, the low-power consumption of Zigbee network suits for long time usage on the ship.

Ship-board staffs wear the Zigbee node and IMU measuring unit as blind nodes. From the neighboring anchor nodes, blind nodes detect the value of RSSI, the wireless signal intensity. Through specific algorithm of blind nod, positioning information can be obtained. Meanwhile, dead reckoning is conducted independently. If the signal of WSN node is available, two positioning information fuse together through Extended Kalman Filter. If the signal of WSN node is unstable or disconnected, the PDR system will continue working independently. The integration of the two positioning technology make it possible for the new navigation system to overcome the interference on WSN positioning. Besides, it solves the problem of growing error along with the increasing distance. Furthermore, it tackles the issue of uploading positioning data. Figure 1 shows the overview of system.

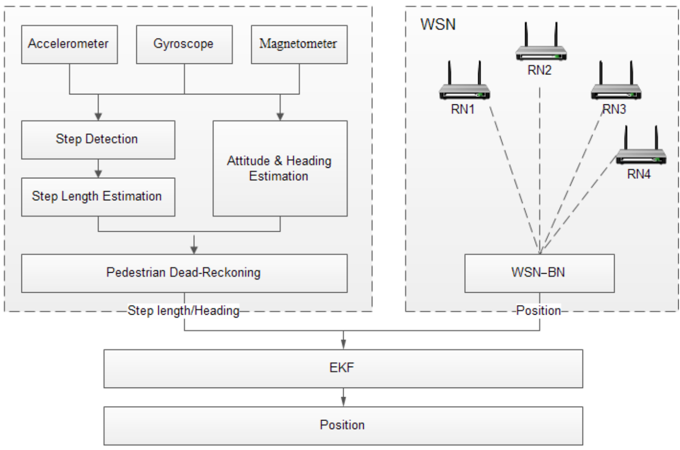

Fig.1. Description of system

TableI. Sensor Parameter

Accelerometer-MPU6050（InvenSense）	
Range	± 16 g(max)
Sensitivity	16384LSB/g
Noise	$400\ \mu g / \sqrt{Hz}$
Gyroscope-MPU6050 (InvenSense)	
Range	± 2000 deg/sec
Sensitivity	131 LSB/(deg/sec)
Noise	0.005(deg/sec)/ $\sqrt{Hz}$
Magnetometer-MPU6050 (Honeywell)	
Range	± 8 gauss
Sensitivity	5 milli-gauss

III. Sensor Calibration

This design mainly utilizes sensors as accelerometer and gyroscope, both of which are based on MEMS. MEMS are characterized by merits of small size and low cost, though with relatively loud noise and great error. Since more precise data is needed for integral operation on the numerical value of accelerometer and gyroscope, thus should calibrate the sensor so as to lower the error. Accelerometer and magnetometer are sensors applied to measure the value of the vector field. The calibration of accelerometer is to be discussed as follow, and the correction of Magnetometer is the same.

There remain two major types of error in MEMS Sensors: static ones and dynamic ones. The former includes the zero-drift error with non-vanishing data in static state, the scale factor error related to sensitivity, and inter-axles coupling error caused by non-orthogonal between sensitive-axis of the sensors. The later includes random error and the temperature drift error[8]. This section mainly discusses the calibration of static error. In consideration of the insignificant inter-axles coupling error, and there is little sense calibrating this error without assistance of professional calibration equipments. Besides, random error will not be covered in this part. Thus, the model of acceleration error can be simplified as follows: As a measuring transducer in vector field, accelerometer measures specific force, which is a kind of non-gravitational external force acting on unit mass. So what the value accelerometer measures is equivalent acceleration of gravity in static state. According to this, we can calibrate tri-axial acceleration. We define measuring error as u, the quadratic difference between the square modulus of observed acceleration and acceleration gravity (G):

$$\begin{pmatrix} A_x \\ A_y \\ A_z \end{pmatrix} = \begin{pmatrix} B_x \\ B_y \\ B_z \end{pmatrix} + \begin{pmatrix} S_x & 0 & 0 \\ 0 & S_y & 0 \\ 0 & 0 & S_z \end{pmatrix} \begin{pmatrix} a_x \\ a_y \\ a_z \end{pmatrix} \tag{2}$$

Among which, a_x, a_y, a_z indicate the outputs of accelerometer on axis of x, y, z respectively; A_x, A_y, A_z indicate the calibrated outputs of accelerometer on axis of x, y, z respectively; B_x, B_y, B_z indicate the zero-drift error of accelerometer on axis of x, y, z respectively; S_x, S_y, S_z indicate the scale factor error of accelerometer.

As a measuring transducer in vector field, accelerometer measures specific force, which is a kind of non-gravitational external force acting on unit mass. So what the value accelerometer measures is equivalent acceleration of gravity in static state. According to this, we can calibrate tri-axial acceleration. We define measuring error as u, the quadratic difference between the square modulus of observed acceleration and acceleration gravity (G):

$$u = A_x^2 + A_y^2 + A_z^2 - G^2 \tag{3}$$

Take the formula (3) into (4) suppose:

$$V = \left[a_x^2\ a_y^2\ a_z^2\ a_x\ a_y\ a_z\ 1 \right]^T \tag{4}$$

$$P = \left[l\ m\ n\ o\ p\ q\ g \right]^T \tag{5}$$

$$\begin{cases} l = S_x^2 \\ m = S_y^2 \\ n = S_z^2 \\ o = 2S_x B_x \\ p = 2S_y B_y \\ q = 2S_z B_z \\ g = B_x^2 + B_y^2 + B_z^2 - G^2 \end{cases} \tag{6}$$

then u can be illustrated as

$$\begin{aligned} u &= la_x^2 + ma_y^2 + na_z^2 + oa_x + pa_y + qa_z + g \\ &= V^T \times P \end{aligned} \tag{7}$$

assume the objective function as U and then use it to measure the global error, which indicates the sum of squares of simple error.

$$U = \sum u^2 \tag{8}$$

The specific correction procedure: to find the parameter in $[l\ m\ n\ o\ p\ q\ g]$ to minimize u value. Sine u is the polynomial function of $[l\ m\ n\ o\ p\ q\ g]$, the minimum of u must be the extreme point and the value of first partial derivatives is 0. Then the first partial derivative of U is as follows:

$$\sum V \times u = \left(\sum V \times V^T \right) \times P = 0 \tag{9}$$

P can be worked out by solving the homogeneous linear equation of (8). By employing Gaussian elimination method, there comes the approximate solution. We assume the solution has a arbitrary constant, marked as C . P_b as fundamental solution

$$\begin{aligned} P &= C\cdot P_b \\ &= [C\cdot l_b \quad C\cdot m_b \quad C\cdot n_b \quad C\cdot o_b \quad C\cdot p_b \quad C\cdot q_b \quad C\cdot g_b]^T \end{aligned} \tag{10}$$

There come six correction parameters from (5), (6), (10):

$$\begin{cases} B_x = \dfrac{o_b}{2l_b}\sqrt{C\cdot l_b} \\ B_y = \dfrac{p_b}{2m_b}\sqrt{C\cdot m_b} \\ B_z = \dfrac{q_b}{2n_b}\sqrt{C\cdot n_b} \\ S_x = \sqrt{C\cdot l_b} \\ S_y = \sqrt{C\cdot m_b} \\ S_z = \sqrt{C\cdot n_b} \\ C = \dfrac{4G^2}{\dfrac{o_b^2}{l_b} + \dfrac{p_b^2}{m_b} + \dfrac{q_b^2}{n_b} - g_b} \end{cases} \tag{11}$$

So the procedure of correcting the accelerometer is as follows: to measure the static data in at least six different locations as a group; to distribute the different positions in the sphere as even as possible; and then to work out the approximate solution P based on this set of parameters; to take P into (11) to get calibration parameter. If l_b, m_b, n_b or C is less than zero, it indicates that the data is not representative and should be recollected. Furthermore, the calibration of gyroscope requires a constant-speed turntable. But with the limited experimental equipments, the design only tackles with zero-bias error for the calibration of gyroscope.

IV. Fusion algorithm

A. Attitude Estimation with EKF

To get the walking directions of pedestrians, this design corrects the error of attitude estimation caused by integral error of gyroscope. The correction is conducted by gyroscope, which fuses the observed values of tri-axial accelerometer and the tri-axial magnetometer sensor. The estimation of attitude angle follows the three steps: (1) fusing the observed value of accelerometer, magnetometer, and gyroscope; (2) updating the quaternion; (3) getting the transition matrix of attitude. This section discusses the design of Extended Kalman Filter with state vector of quaternion.

We assume the observed value from gyroscope as $\omega^b = \left[\omega_x^b \ \omega_y^b \ \omega_z^b\right]^T$; the observed value from accelerometer as $a^b = \left[a_x^b \ a_y^b \ a_z^b\right]^T$; the acceleration of gravity on navigation frame (n) as $g^n = [0\ 0\ g]^T$; the observed value from magnetometer as $m^b = \left[m_x^b \ m_y^b \ m_z^b\right]^T$. In this paper, we take no account of magnetic dip. We assume the magnetic vector value as m, so the magnetic field of navigation frame is : $m^n = [m\ 0\ 0]^T$ .The state vector: $X = [q_0\ q_1\ q_2\ q_3]^T$, W_{k-1} is process noise. So the system state equation is

$$X_{\mathrm{k}} = A_k X_{k-1} + W_{k-1} \tag{12}$$

Based the quaternion equation for attitude and observed value of gyroscope $\omega^b = \left[\omega_x^b \ \omega_y^b \ \omega_z^b\right]^T$, we can obtain the state transition matrix A, as shown in 13, in which Δt indicates the time lag between two updating.

$$A = \begin{bmatrix} 1 & -\dfrac{\omega_x}{2}\Delta t & -\dfrac{\omega_y}{2}\Delta t & -\dfrac{\omega_z}{2}\Delta t \\ \dfrac{\omega_x}{2}\Delta t & 1 & \dfrac{\omega_z}{2}\Delta t & -\dfrac{\omega_y}{2}\Delta t \\ \dfrac{\omega_y}{2}\Delta t & -\dfrac{\omega_z}{2}\Delta t & 1 & \dfrac{\omega_x}{2}\Delta t \\ \dfrac{\omega_z}{2}\Delta t & \dfrac{\omega_y}{2}\Delta t & -\dfrac{\omega_x}{2}\Delta t & 1 \end{bmatrix} \tag{13}$$

The gravity vector measured by accelerating can be used to correct the attitude of pitching and rolling, and the magnetic vector measured by magnetometer can be used to correct heading attitude. Accordingly, the filter selects the observed values from acceleration and magnetometer as observation vectors. Apart from acceleration of gravity, acceleration can measure the acceleration produced by movement. The attitude error in estimation occurs when the carrier moves with great acceleration because he measured value of gravity unit vector will deviate. Therefore, it is necessary to set constraints for correction of acceleration: $|a-g| \le Thr$, Thr is the threshold value, determined by empirical value. When the difference between carrier acceleration and gravity acceleration is less than the threshold value, we use gravity unit vector which is measured by acceleration to correct attitude; when the difference is larger than the threshold value, we disconnect acceleration and correct the loop.

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a. When the unit vector of acceleration of gravidity is used as reference vector, the measurement equation is :

$$Z_1 = h_1(X) + v_1 \tag{14}$$

v_1 is the Gaussian white noise with the mean of zero, and the variance is R_1.

$$h_1(X) = C_n^b g^n = \begin{bmatrix} 2(q_1q_3 - q_0q_2) \\ 2(q_2q_3 + q_0q_1) \\ 1 - 2(q_1^2 + q_2^2) \end{bmatrix} \tag{15}$$

$$H_1 = \begin{bmatrix} \frac{\partial h_{10}}{\partial q_0} & \cdots & \frac{\partial h_{10}}{\partial q_3} \\ \vdots & \ddots & \vdots \\ \frac{\partial h_{13}}{\partial q_0} & \cdots & \frac{\partial h_{13}}{\partial q_0} \end{bmatrix} \tag{16}$$

$$= \begin{bmatrix} -2q_2 & 2q_3 & -2q_0 & 2q_1 \\ 2q_1 & 2q_0 & 2q_3 & 2q_2 \\ 0 & -4q_1 & -4q_2 & 0 \end{bmatrix}$$

b.When the unit vector of magnetic field is used as reference vector, the measurement equation is :

$$Z_2 = h_2(X) + v_2 \tag{17}$$

v_2 is the Gaussian white noise with the mean of zero, and the variance is R_2 .

$$h_2(X) = C_n^b m^n = \begin{bmatrix} 1-2(q_2^2+q_3^2) \\ 2(q_1q_2 - q_0q_3) \\ 2(q_1q_3 + q_0q_2) \end{bmatrix} \tag{18}$$

$$H_2 = \begin{bmatrix} \frac{\partial h_{10}}{\partial q_0} & \cdots & \frac{\partial h_{10}}{\partial q_3} \\ \vdots & \ddots & \vdots \\ \frac{\partial h_{13}}{\partial q_0} & \cdots & \frac{\partial h_{13}}{\partial q_0} \end{bmatrix} \tag{19}$$

$$= \begin{bmatrix} 0 & 0 & -4q_2 & -4q_3 \\ -2q_3 & 2q_2 & 2q_1 & -2q_0 \\ 2q_2 & 2q_3 & 2q_0 & 2q_1 \end{bmatrix}$$

Having obtained the above state equation and observation equation, we can utilize Kalman Filter process to estimate attitude. The program structure is as follows:

- Initializing sensors and equipping accelerometer sensor, gyroscope, output rate of magnetometer and measuring range.
- Initializing matrix and initial parameters related to filter.
- Fetching the data of sensors, and preprocessing the calibration of the sensors.
- Updating the prediction of Kalman filter by the data from gyroscope.
- Updating the observation of Kalman filter by the data from accelerometer and magnetometer to output the estimation of attitude.

B. Fusion of WSN and PDR

In this design, PDR system and WSN positioning system are two subsystems for navigation. Positioning can be conducted only when receiving signals from at least two Blind nodes. However, the quality of WSN positioning signal is easily affected by ship environment. What is worse, it is hard to cover every part of a ship with WSN positioning signal. As a result, this paper adopts dynamic fusion method to encounter these problems. With ship-board Wireless Sensor Networks, an Extended Kalman Filter in this positioning method will be applied to fuse the information if the signal of WSN beacon is available. If the signal of WSN beacon is unavailable, the PDR system will continue working independently to conduct position calculation. The following figure presents the structure of how the position calculation runs.

In the Extended Kalman Filter, which integrated the positioning information of PDR and WSN, the state vector is $X_k = [\delta X_k \; \delta Y_k \; L_e \; H_e]^T$, among which, δX represents the observed error above the X axle of PDR system in the navigation frame , while δY represents the observed error above the Y axle of PDR system in the navigation frame , and $L_{e(t)}$ illustrates the observed error of pedestrians' direction angle. L_t is the estimate step length at t point. The position error equation is:

$$\begin{cases} \delta\dot{X} = nL_{e(t)}\cos\theta_{(t)} - nL_t H_{e(t)}\sin\theta_{(t)} \\ \delta\dot{Y} = nL_{e(t)}\sin\theta_{(t)} - nL_t H_{e(t)}\cos\theta_{(t)} \end{cases} \tag{20}$$

In this system, the step length and the pedestrian's course angle changes as time passes. This suits the first-order Markov process. We illustrate it as

$$\dot{L}_{e(t)} = -\tau_{pe} L_{e(t)} + \omega_{pe} \tag{21}$$

$$\dot{H}_{e(t)} = -\tau_{be} H_{e(t)} + \omega_{be} \tag{22}$$

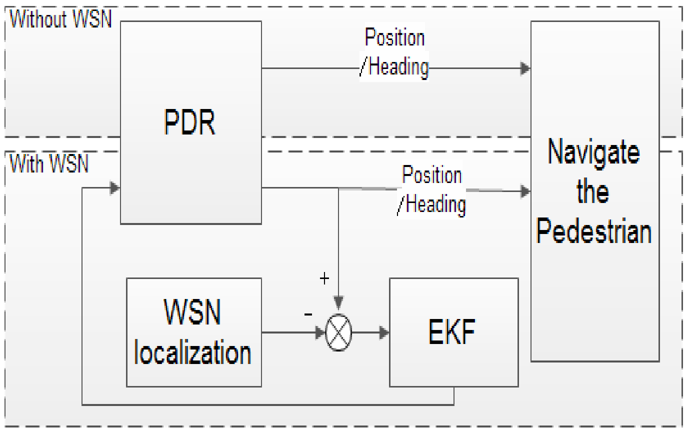

Fig.2. integrated positioning framework

In the above equations, τ_{pe} represents the reciprocal of a constant which is related to timing error for step length, τ_{be} represents the reciprocal of a constant which is related to timing error for pedestrian's walking angle. ω_{pe} ,

ω_{be} are the Gaussian white noise with the mean value of zero, and q_{le}^2, q_{be}^2 are variance.The formula changes into:

$$\dot{X}_{(t)} = \begin{bmatrix} \delta\dot{X} \\ \delta\dot{Y} \\ \dot{L}_e \\ \dot{H}_e \end{bmatrix} = \begin{bmatrix} 0 & 0 & n\cos\theta & -nL\sin\theta \\ 0 & 0 & n\sin\theta & nL\cos\theta \\ 0 & 0 & -\beta_{pe} & 0 \\ 0 & 0 & 0 & -\beta_{be} \end{bmatrix} X_{(t)} + \omega_{(t)} \quad (23)$$

The state equation of Extended Kalman Filter for positioning system is:

$$X_{k+1} = \begin{bmatrix} 1 & 0 & n\cos\theta & -nL\sin\theta \\ 0 & 1 & n\sin\theta & nL\cos\theta \\ 0 & 0 & e^{\frac{-T}{T_p}} & 0 \\ 0 & 0 & 0 & e^{\frac{-T}{T_b}} \end{bmatrix} X_k + Q \quad (24)$$

The measurement vector: $Z_k = \left[X_{PDR} - X_{WSN} \quad Y_{PDR} - Y_{WSN}\right]^T$, $X_{PDR} - X_{WSN}$ stands for the position error between PDR system and WSN positioning system on the x axis while $Y_{PDR} - Y_{WSN}$ stands for the position error between PDR system and WSN positioning system on the x axis. The observation equation is:

$$Z_{k+1} = Z_{PDR(k+1)} - Z_{WSN(k+1)} = \begin{bmatrix} X_{PDR} - X_{WSN} \\ Y_{PDR} - Y_{WSN} \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} X_{k+1} + R \quad (25)$$

Q is the process noise and R is measurement noise. They are gaussian white noise. The result of Extended Kalman Filter is the position error in navigation frame. We can correct the position by putting the error feedback to the PDR. And then we can obtain the corrected position as integrated positioning results.

V. EXPERIMENT

The experiments are designed to verify the effectiveness of the locating method of fusion, in which we select the floor of lab to simulate a ship environment. As shown in figure 3, the laboratory, similar to the internal structure of the ship, includes a corridor, a staircase and six rooms, which space is length 18m and width 12m.

Our experiments are performed within a map consisting of five WSN node with each deployed in one of the $216\,m^2$. By default, the position of the anchor nodes is known, and the researcher walks along a predetermined 38 steps trajectory.

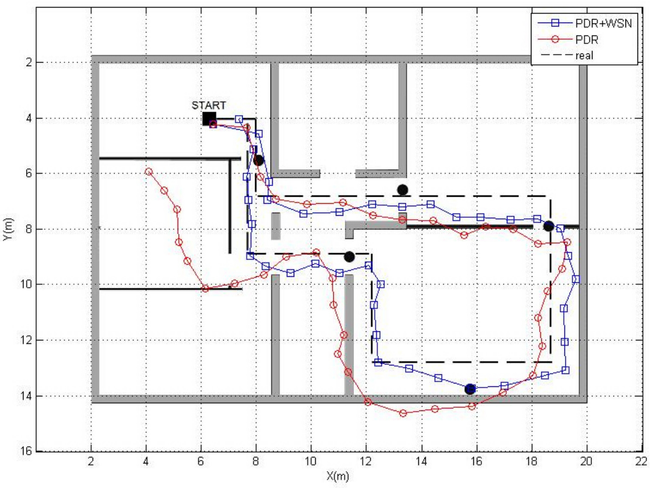

Fig.3. Tests of walking route indoor

In the figure 3: the black solid points denote the anchor nodes, the black dashed line represents the true path and the black rectangular symbols represent the starting point position of the experiment.

In this paper, the results of the PDR method and the locating method of fusion are shown in Figure 3: the black dotted line is the real trajectory and the red is PDR while the blue are the Extended Kalman filtering fusion with PDR. In the process of walking, the basic maintain location error is within 1.5 m in the main.

Figure 4 expresses that the performance of the location system information, compared to the location information without fusion, is obviously improved. In the circumstance of without fusion, the system error is 4m on average, and 90% of location error is about 2.5 m. With the proposed algorithm, the positioning error is 1m on average, and 90% of location error is only about 1.5 m. We can draw conclusions that the position method of fusion is more accurate than the PDR alone, and its performance can meet the requirements of ship-board pedestrian positioning.

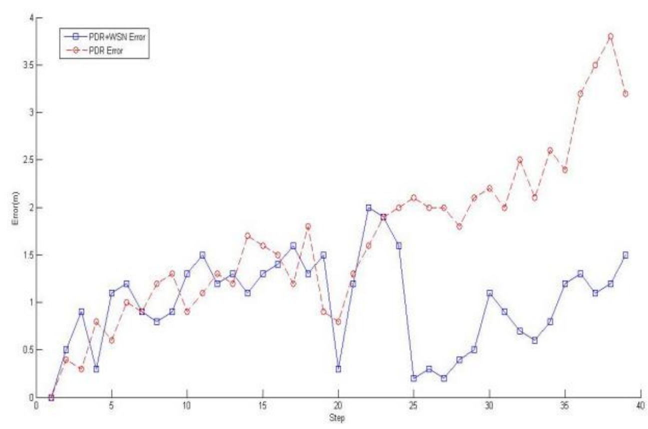

Fig.4. Position errors

VI. Conclusion

A new type of fusion method was provided in this paper to improve the position error in Pedestrian Dead Reckoning system and the stability of positioning in Wireless Sensor Network. Comprised of low-cost MEMS devices, IMU collected data of pedestrians' gait. Besides, through careful analysis of pedestrians' periodical features, Pedestrian Dead Positioning has been devised. Fused with positioning signal of Wireless Sensor Network, Extended Kalman Filtering calibrated PDR system. The results of experiments have proved that it reached better reckoning on pedestrians' walking distance and walking direction in partial area of ship environment. The pedestrian positioning system provided with effective positioning information and accurate positioning. Furthermore, it is valuable for ship-board information monitoring.

Acknowledgments

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