Hierarchical calibration architecture based on Inertial/magnetic sensors for indoor positioning

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Abstract—**Indoor positioning system based on MEMS (Micro-electromechanical Systems) technology is really self-measurement technology which does not depend on any external signal and other infrastructure. Inertial/magnetic sensors based on MEMS technology are typically composed of three orthogonal gyroscopes, three orthogonal accelerometers and three orthogonal magnetometers, which can form AHRS (attitude heading reference system) and pedestrian dead reckoning system. However, the inertial/magnetic sensors can offer good short term positioning in indoor environments, but the absolute position fixes of medium-to long- term have always been the research hotspot and difficulty. Therefore, a hierarchical calibration architecture based on inertial/magnetic sensors is proposed creatively, including the data layer—a axial-based temperature variation model is proposed to calibrate the raw data from MEMS sensors by the analysis and modeling of sensor error characteristics; the signal layer—a triple zero velocity update method is proposed to update integral initial value according to the pedestrians' gait characteristic; the information layer—an intelligent information fusion method is proposed based on machine learning to calibrate the orientation and positioning. Besides, a 3-D indoor positioning platform is set up based on MPU9250, and the effectiveness of the proposed hierarchical calibration architecture is verified based on the platform.**

Keywords—Indoor positioning; attitude heading reference system; pedestrian dead reckoning; hierarchical calibration architecture; inertial/magnetic sensors.

I. INTRODUCTION

The urgent market demands have provided broad space for further growth in terms of IPS (Indoor Positioning System), which is expected to become the next huge market of billion-dollar order in the field of navigation and LBS (Location -based Service). Although there is a variety of available indoor positioning technology, there is not a mature indoor positioning scheme in terms of reliability, accuracy and power consumption can well satisfy the user experience. The research on current indoor positioning is mainly based on the structured environment [1-5]. In order to create the database, extra hardware platform is usually established and manual testing is also needed, which is time-consuming and labor-intensive. Yet, the challenges of indoor positioning are as follows:

a) The radio signal cannot be used or severely attenuated in indoor environments.

b) The embedded MEMS(Micro-electromechanical Systems) sensor in the intelligent device is sensitive to the environment.

c) The Various technologies have problems of compatibility because of the lack of unified indoor positioning standards and protocols.

d) Indoor environment is complex, such as NLOS (Non Line Of Sight), multipath effect and human interference.

e) There may be frequent and severe electromagnetic interference in indoor environments, which affects the robustness of indoor positioning technology.

f) The form of pedestrians' movement is diversified and unpredictability, which restricts the generality and extensibility of motion model of pedestrians.

MEMS sensor with small volume, low weight, low cost, good reliability, and the advantages of large measuring range, is an ideal way to provide indoor positioning and navigation, besides, the positioning process doesn't depend on any external signal. Usually, inertial/magnetic sensors based on MEMS technology are typically composed of three orthogonal gyroscopes, three orthogonal accelerometers and three orthogonal magnetometers, which can form AHRS (attitude heading reference system) and pedestrian dead reckoning system. However, the inertial/magnetic sensors can offer good short term positioning in indoor environments, but the absolute position fixes of medium- to long- term have always been the research hotspot and difficulty.

In recent years, the experts and scholars have proposed a number of combination methods based on MEMS inertial sensors and other technologies, i.e., using maps to eliminate the accumulated error of inertial sensors [6]; using ultra wideband and inertial sensors for indoor positioning [7]; using building layout and spatial physical information to assist the inertial MEMS sensor for indoor positioning [8-9]; fusing Wi-Fi and inertial sensor for indoor positioning [10-11]; combing visual sensor and inertial sensor for indoor positioning [12]; all the methods mentioned above are to use other technologies to make up for the accumulated error of MEMS inertial sensor. However, the application scenario is based on the structured environment. Besides, it adds new hardware equipment, which increases the cost of the system as well as the complexity of the algorithm.

There are also many indoor positioning algorithms only based on MEMS inertial sensors. By studying ZVU (zero velocity updates) and its improved algorithm [13] to suppress accumulated error of the MEMS sensor over time. Although these methods can be used as prior information, the errors are corrected when the carrier remains static or quasi-static, and some sensor errors are estimated, such as gyro zero bias. In reality, because of the unpredictable movements of pedestrian, it is usually difficult to judge the state of static or quasi-static. Although there are scholars research the gait characteristics of pedestrian [14- 15], motion model [16] and so on. While the motion models, such as walking, running, climbing, jumping and so on, are difficult to be expanded and transplanted, which makes it difficult to ensure the long-term accuracy of indoor positioning when pedestrians change their motion frequently.

In order to explore the solution to accurate, rapid and long-term indoor pedestrian positioning in unknown environments, we have done a lot of research work with regard to data layer, signal layer and information layer, respectively. Therefore, a hierarchical calibration architecture based on inertial/magnetic sensors is proposed creatively. The data layer will discuss how to calibrate the raw data from MEMS sensors by the analysis and modeling of sensor error characteristics; the signal layer will discuss how to update the navigation solution online according to the motion models of pedestrians; the information layer will discuss the calibration of orientation and positioning based on machine learning. The paper is organized as follows. Section II describes the architecture's design process. And then the experimental results and discussion are given in section III. Finally, section IV summarizes the conclusion and future work of this study.

II. HIERARCHICAL CALIBRATION ARCHITECTURE

The general block diagram of the hierarchical calibration architecture based on inertial/magnetic sensors is as shown in Fig. 1. The basic idea of the proposed architecture is as follows. The hierarchical calibration architecture consists of three parts. They are the underlying part − data layer, the intermediate calibration part−signal layer and the top level calibration part− information layer, respectively. The data layer will discuss how to calibrate the raw data from MEMS sensors by the analysis and modeling of sensor error characteristics, besides the axial-based temperature variation model is proposed; the signal layer will discuss how to update integral initial value according to the human motion model, besides, a Triple Zero Velocity Update method is proposed; the information layer will discuss the calibration of orientation and positioning based on machine learning, besides, an intelligent information fusion method is proposed. More details will be introduced in the following subsections.

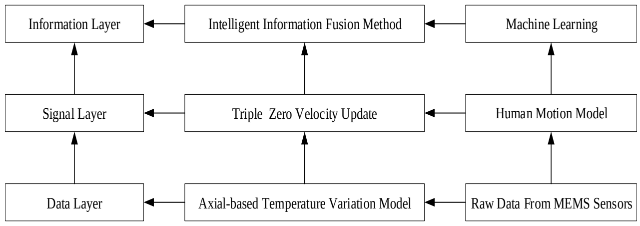

Fig.1 Hierarchical calibration architecture based on inertial/magnetic sensors—the general block diagram of calibration of orientation and positioning.

A. *Data Layer*

Usually, ellipsoid calibration method and dot product invariance method are the most common methods to calibrate the magnetometer, and N location method is used to calibrate the accelerometer. Compared with the calibration method of the gyroscope, the calibration method of magnetometer and accelerometer is relatively mature. Besides, the magnetometer and accelerometer are insensitive to temperature. However, the gyroscope is easily affected by the environment, especially the temperature.

Therefore, the modeling and compensation of MEMS sensors here mainly give priority to the gyroscope. The classification of MEMS gyro's error is classified into constant error, random error and induced environment error. The constant error and induced environment error can be compensated easily after simple experiment, while the random error is not easy to compensate, even though a large quantity of experiments are conducted to study the statistical features of the data source.

Generally, the random errors fall into the followings major groups [17-18].

1) *Error of Angle's Random Surfer*

It represents the angle's error when white noise surfers randomly in a long time, and its mathematical model is as shown in (1).

$$\sigma^2(\tau) = \frac{N^2}{\tau} \tag{1}$$

Where N indicates the coefficient of angle's random surfer.

2) Error of Angle Velocity's Random Surfer

It is the result of integral of the power spectral density function of the broadband angular of angle acceleration, and its mathematical model is as shown in (2).

$$\sigma^2(\tau) = \frac{K^2\tau}{3} \tag{2}$$

Where K indicates the coefficient of angle velocity's random Surfer.

3) Error of Zero Deviation Instability

It is derived from the circuit noise and environmental noise of gyro, which is the deviation fluctuation in the data, and its mathematical model is as shown in (3).

$$\sigma^2(\tau) = \frac{2B^2}{\pi}\left[ln2 - \frac{sin^3x}{2x^2}(sinx + 4xcosx) + \cos 2x - \cos 4x\right] \tag{3}$$

Where $x = \pi f_0 t$, and B indicates the coefficient of zero deviation instability.

4) Error of Rate Slope

It includes more deterministic error e.g., the trends, which comes from the one-way change of electron drift and environment, and its mathematical model is as shown in (4).

$$\sigma^2(\tau) = \frac{R^2\tau^2}{2} \tag{4}$$

Where R indicates the coefficient of rate slope.

5) Error of Quantization Noise

It is caused by A/D transformation during data collection, and the noise intensity depends on the accuracy of the data acquisition system, and its mathematical model is as shown in (5).

$$\sigma^2(\tau) = \frac{3Q^2}{\tau^2} \tag{5}$$

Where Q indicates the coefficient of quantization noise.

The coefficients of (1) - (5) can be obtained by the method of Allan variance estimation. However, its obvious disadvantage is that it does not take temperature effect into consideration, besides, parameter estimation by Allan variance is only a rough approximation. In fact, according to our previous studies, we have known that the temperature has different influence on the different axes of the same MEMS, e.g., some axes are sensitive to temperature variation, some not. Therefore, on the basis of previous research work, and in order to clear the physical significance of the error source, we propose a more simple and effective model, i.e., axial-based temperature variation model. Its core idea is to collect a large amount of raw data of the gyro, by modeling the random sequence, extract the parameters of error sources, and then to simplify the relationship of input and output with a projection matrix **Ke**, and the effect of the temperature on the sensor is equivalent to zero bias **D(t)** which is the function of temperature. The flow chart of time sequence analysis and modeling of gyro random error is as shown in Fig. 2.

By stepwise regression analysis, massive data processing, we can extract the projection matrix parameters, as shown in formula (6) [9].

$$\begin{bmatrix} N_x \\ N_y \\ N_z \end{bmatrix} = \begin{bmatrix} K_{gx} & K_{gx}E_{gxy} & K_{gx}E_{gxz} \\ K_{gy}E_{gyx} & K_{gy} & K_{gy}E_{gyz} \\ K_{gz}E_{gzx} & K_{gz}E_{gzy} & K_{gz} \end{bmatrix} \begin{bmatrix} w_x \\ w_y \\ w_z \end{bmatrix} + \begin{bmatrix} Dx(t) \\ Dy(t) \\ Dz(t) \end{bmatrix} \tag{6}$$

Where $\mathbf{w}=(w_x\ w_y\ w_z)^T$ and $\mathbf{N}=(Nx\ Ny\ Nz)^T$ indicates the input and output of the sensor of the coordinate components of the 3 dimensions vector field respectively. The vector $\mathbf{D(t)} = (Dx(t)\ \ Dy(t)\ \ Dz(t))^T$ and the matrix $\mathbf{Ke} = (Ke_{ij})_{3\times3}$ include all the linear and time-invariant sensor errors. The sensor bias, electromagnetic interference and other errors are included in **D(t)**. Errors caused by the scale factors and misalignments are included in **Ke**.

B. Signal Layer

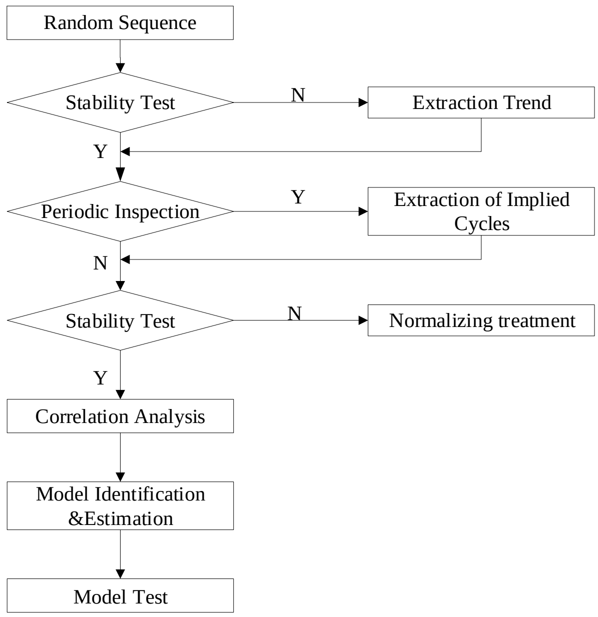

Fig.2.The time sequence analysis and modeling of gyro random error.

Fig.3 The block diagram of signal layer.

The IMU (Inertial Measurement Unit) is attached on the ankle, as shown in Fig.3.

Our previous research showed that the Earth's magnetic field is relatively weak in modern buildings, filled with metal and conducting wires, can overpower the natural signal, leading to local periodic disturbances with the gait period. Besides, the accelerometer is sensitive to both gravity and bodily acceleration, which makes their discrimination difficult, especially as the speed of pedestrian changes. Similarly, the Coriolis force, which affects the output of the gyro directly, should be corrected when the pedestrian's motion state changes. In a word, the data from MEMS sensors contains too much ambiguous information when pedestrian walks in indoor environments.

As to the analysis above, we proposed our solution as shown

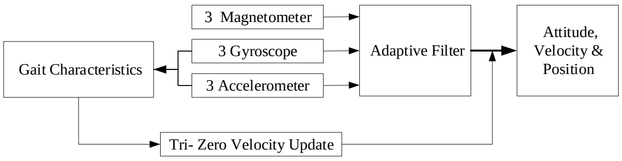

Fig.4 The block diagram of signal layer.

in Fig. 4. After the data calibration of inertial/magnetic sensors, the calibration focus on signal layer will be carried out. On the one hand, adaptive filter e.g., complementary filter [19] and Kalman filter can be used to get the navigation solution—attitude, velocity and position. On the other hand, the gait characteristics of pedestrian can be acquired from gyro and accelerometer, then the triple zero velocity update method can be used to eliminate the ambiguous information mentioned above when pedestrian walks in indoor environments. The idea of triple zero velocity update method is derived from the traditional ZVU (zero velocity update). In the proposed method the velocity, attitude and magnetic distortion can be calibrated in just one gait cycle.

C. Information Layer

The study of artificial intelligence and machine learning is very hot. The traditional algorithms based on machine learning for indoor positioning are as follows.

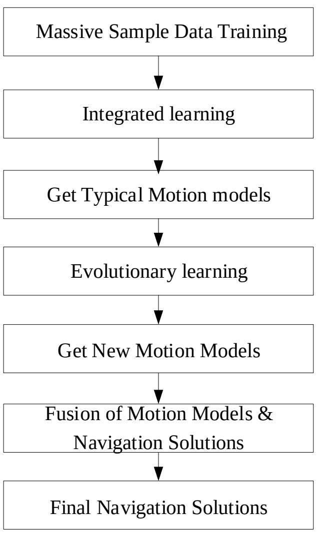

Fig.5 The block diagram of information layer.

- Decision trees [20] are the most frequently used machine learning algorithms in the world. A decision tree is a hierarchical structure that contains decision nodes, branches, and leaf nodes, which represent attributes, conditions, and class, respectively. Information gain or information entropy is usually used to create nodes in a decision tree. Each attribute node contains a condition to determine the branch that is connected to the node. If the condition is true, the algorithm will perform one of the branches, otherwise the algorithm selects another branch. When the algorithm executes to the leaf node, the label that the leaf node stored is returned to the upper node as a class.
- The naive Bayes classifier [21] is based on Bayesian theory of supervised learning algorithm. It is robust, easy to build, high precision, fast speed, suitable for large database and complex classification model. It assumes that each property is independent and equally important, so it is easy to calculate the probability of each attribute.
- Bayesian network algorithm [22] is widely used in classification. Based on Bayesian theory, the conditional probability of each node is calculated and the Bayesian network is formed. The Bayesian network contains both qualitative and quantitative conditional probability tables. The topological structure is a distribution of the data of each node. The conditional probability table enumerates the possible combinations of the property values of all parent class nodes and the conditional probabilities of each node.
- The K neighbor classifier [23] is also based on the distance classifier, which means that the instance of distance is similar and belongs to the same class. It is one of the most popular algorithms in machine learning algorithms.
- The sequence minimum optimization algorithm [24] was proposed by John C. Platt when using the polynomial and radial basis functions to train the support vector machine classifier. It is one of the most common algorithms of SVM (Support Vector Machine) concerning large boundary classification. SVM is based on the neural network, using the classification technique of statistical learning theory, which aims to find a linear hyperplane to maximize the separation spacing between positive and negative classes. In fact, most of the data is not linearly separable, and in order to be separable, you usually have to convert it with a kernel function. The nonlinear mapping is used to transform input into the feature space of higher dimensions.
- AdaBoost (Adaptive Boosting) [25] is a kind of integrated learning method. Overall, it can achieve higher accuracy by integrating many weak classifiers. It has the advantages of simple implementation, fast calculation. Besides, the algorithm is not easy to overfitting.
- When the sample appeared frequently, bagging [26] is formed by the random selection of different subsets in training data, and the process is called guide replication of training data. The idea is that each subset training a

classifier, and use of these subsets to generate a variety of classifier.

The following will discuss our calibration solution in information layer. Multiple source intelligent information fusion method is proposed based on machine learning in information layer. The main idea is as shown in Fig. 5. Through the classification method, we can train the motion model of pedestrians e.g., walking, running, jumping, upstairs and downstairs, turning et.al. And then more models can be evolved by using evolutionary learning algorithm, i.e, generating new models through the crossover or mutation of the existing models. It is similar to the biological evolution. After the evolution, the information from motion model and the navigation solution obtained from signal layer can be fused, and then the navigation solution can be corrected. More details will be discussed in the following.

1) Integrated learning

By integrated learning method, we can train the motion models e.g. sitting, standing, walking, jogging et al. The steps are as follows. Through a large number of sample data, extract n attributes, and assume that n=100. Here we use a combination of random forest and the RegionBoost. The random forest and the RegionBoost belong to the integrated learning algorithm, as shown in Fig. 6.

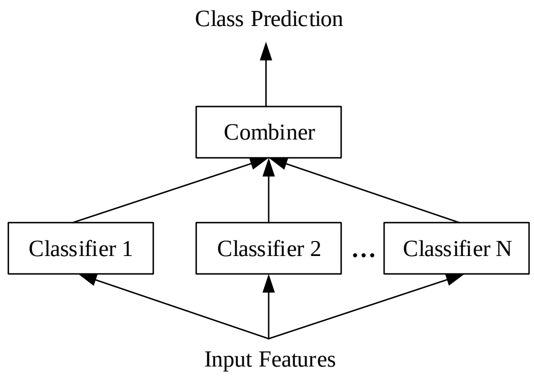

Fig.6 The block diagram of integrated learning.

The generation process of random forest is as follows. The number of feature attributes of sub classifier is $\sqrt{n} = 10$. And then we can select 10 properties randomly from 100, and the total number of permutations is C_{100}^{10}, namely, there are C_{100}^{10} decision trees forming a random forest.

$$1 - \lim_{n\to\infty}\left(1 - \frac{1}{n}\right)^{n} = \frac{2}{3} \tag{7}$$

(7) shows that the more the decision trees are generated, the closer the training set is 2/3 of the total set, remaining 1/3 of the total set as a test set automatically. The algorithm itself can be automatically determined randomly training set and testing set without artificial regulation. In addition, a single decision tree has the drawback of over learning, but the random forest which many decision trees forming do not. Besides the classification accuracy is high. However, each classifier in random forests has the same weight, which is not appropriate in the complex and dynamic indoor environments.

In order to make the weight of each classifier can be adjusted dynamically as the environment changes, we introduce RegionBoost algorithm to solve this problem. The block diagram of RegionBoost algorithm is as shown in Fig. 7. The fusion of random forest and RegionBoost can not only guarantee the random forest high utilization rate, but also can adjust the weight of each classifier dynamically, to adapt to the

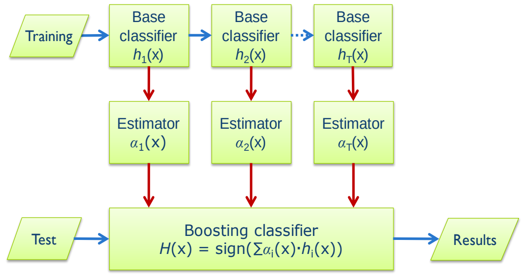

Fig.7 The block diagram of RegionBoost algorithm.

dynamic change of indoor environments.

2) Evolutionary learning

In order to increase the robustness of the system, it requires the algorithm has the ability of self-learning. Through the training and self-evolution, the algorithm also has some fault tolerance to the motion state which is unknown. Here we use the idea of genetic programming, which belongs to the category of evolutionary learning, whose block diagram is shown in Fig. 8. We can generate new models through the crossover or mutation of the existing models. It is similar to the biological evolution, such as selection, recombination and mutation. The new models generated by the old ones have a good ability to cope with the complex movement of pedestrians.

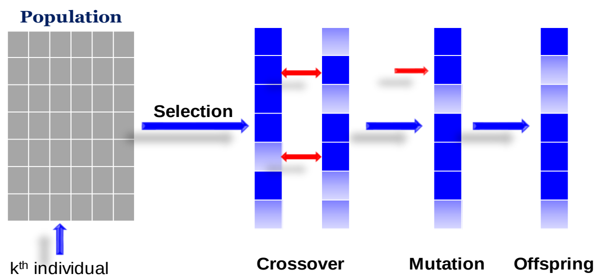

Fig.8 The block diagram of evolutionary learning.

3) Fusion of Motion Models and Navigation Solutions

Strapdown inertial navigation algorithms have been well studied and the standard approach to limit drift is to use an EKF in the complementary or indirect form [27-28]. In this paper, the navigation solution calculated from signal layer is treated as measurement model and the motion model of pedestrians as the state model. To better illustrate the rationale of the EKF, let $\hat{O}_k$ and $\hat{Z}_k$ indicate the sequence of the state and measurement, respectively. Besides, v and n are assumed to be zero-mean Gaussian distributed with known covariance S and R, respectively. The steps of EKF for secondary fusion are described as follows:

a. Employing the current state to predict the next state:

$$\hat{O}_k = \hat{A}_k \hat{O}_{k-1} \quad (8)$$

b. Predicting the error covariance matrix of the next state:

$$\hat{C}_k = \hat{A}_k \hat{C}_{k-1} \hat{A}_k^T + S \quad (9)$$

c. Computing the Kalman gain that minimizes the error covariance matrix:

$$\hat{K}_k = \hat{C}_k \hat{H}(\hat{H}\hat{C}_k \hat{H}^T + R)^{-1} \quad (10)$$

d. Updating the pedestrian's state using measurements and Kalman gain:

$$\hat{O}_{knew} = \hat{O}_k + \hat{K}_k(\hat{Z}_k - \hat{H}\hat{O}_k) \quad (11)$$

e. Updating the error variance matrix using Kalman gain:

$$\hat{C}_{knew} = (I - \hat{K}_k \hat{H})\hat{C}_k \quad (12)$$

In the equations above, $\hat{A}_k$ and $\hat{H}$ are denoted as

$$\hat{A}_k = \frac{\partial f(\hat{O}, v)}{\partial \hat{O}} \Big|_{\hat{O}=\hat{O}_{k-1}, v=0} \quad (13)$$

$$\hat{H} = \frac{\partial h(\hat{O}, n)}{\partial \hat{O}} \Big|_{\hat{O}=\hat{O}_k, n=0} \quad (14)$$

In the process of fusion, a 20-state model is used: one state to model attitudes, and nine states to model the biases of accelerometer, gyroscope and magnetometer, besides the remaining ten states to model the motion state. The fusion of the measurement model and state model can be realized by EKF algorithm mentioned above to further revise and update the navigation solution.

The simulation results of the proposed algorithm are analyzed in section III.

III. Experimental Verification And Discussion

A. Axial-based Temperature Variation Model

A 3-D indoor positioning platform is set up based on MPU9250. The proposed model is verified as follows. Take the x, y and z axis in turn as the center of rotation, and turn 5 circles clockwise and counterclockwise respectively to get the integral result of the axes of gyro, in total 6 groups. The group can be represented by symbol [X/Y/Z] <+->, where symbol [*] indicates the rotation axis and symbol <+-> indicates the direction of rotation, e.g. '+' indicates the direction is clockwise and '-' indicates the direction is counterclockwise, as shown in Table 1, Table 2 and Table 3. In theory, the integral result of rotation axis is 1800° or -1800°, and both of the integral results of the other two axes are 0°. The calibration effect is compared with the traditional Allan variance method.

Compared with the traditional Allan variance method, the proposed calibration model has improved the accuracy greatly. However, when the gyro rotates at high speed, e.g. 250° per second, the proposed calibration model is not ideal. One of the important reasons is that in the proposed model, the parameter of **Ka** is the first order approximation from the mathematical expression of all kinds of error source. And when gyro continues to rotate at high speed, the first-order approximation is unreasonable. For this reason, we are working toward to researching the second-order axial-based temperature variation model. The idea is to use the first order model to calibrate the gyro cursorily. And then take the advanced features of error source into consideration, introducing auxiliary projection matrix. Finally, the gyro is finely calibrated.

TABLE I. The Integral Results of Axes of Gyro Before Calibration

Rotation Direction	X(°)	Y(°)	Z(°)
X+	1983.0	49.1	12.6
X-	-2018.5	24.2	16.7
Y+	-31.1	2029.4	-27.1
Y-	-12.5	-1948.8	4.4
Z+	-21.9	29.9	1972.9
Z-	18.0	58.5	-2021.4

TABLE II. The Integral Results of Axes of Gyro According to the Traditional Allan Variance Estimation Method.

Rotation Direction	X(°)	Y(°)	Z(°)
X+	1802.3	7.0	13.5
X-	-1800.5	5.1	6.9
Y+	-3.3	1807.7	14.1
Y-	-7.9	-1795.6	12.6
Z+	5.2	8.7	1804.2
Z-	5.1	7.1	-1805.2

TABLE III. The Integral Results of Axes of Gyro According to the Proposed Calibration Method.

Rotation Direction	X(°)	Y(°)	Z(°)
X+	1800.5	0.0	4.5
X-	-1800.5	1.9	3.5
Y+	-1.4	1799.7	9.4
Y-	-1.8	-1799.6	9.0
Z+	3.1	2.5	1800.7
Z-	1.7	0.3	-1800.8

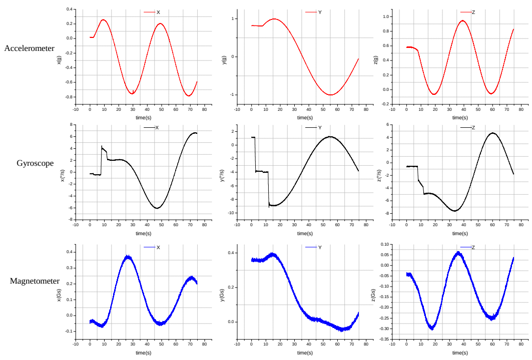

Fig.9 The raw data of 9-axes MEMS sensors.

B. *Turntable Experiment*

The positioning platform is mounted on a rotating turntable. All the three axes of the turntable spin simultaneously, and as shown in Fig. 9 and Fig. 10. The roll and yaw have a continuous variation between +180° and -180° ,respectively. The pitch has a continuous variation between +90° and -90°. The solution of the attitude angle is verified by the turntable experiment and the results show the basic function of the proposed method has no problem, the performance of the proposed method can be verified by other experiments in the flowing.

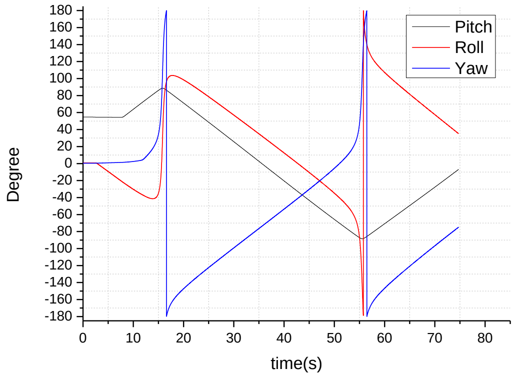

Fig.10 The attitude calculated by the proposed method.

C. *Centrifugal Experiments*

We conducted a series of centrifugal experiments to test the performance of the proposed method. As shown in Fig. 11, the centripetal acceleration increased gradually and stabilized to 0.8 g. As shown in Fig.12, the RMSE (root-mean-square error) of the proposed method is less than 1.5°, however the RMSE of the traditional method (e.g. CF, KF and so on) is higher than 10°. Obviously, the proposed method performs better.

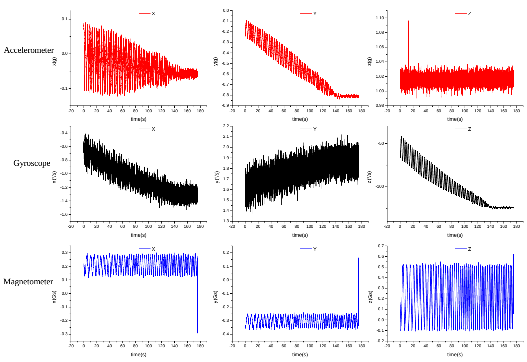

Fig.11 The raw data of 9-axes MEMS sensors.

D. *Anti Noise Performance Test*

To further test the proposed method's performance, we conducted the following test. Put the positioning platform on the horizontal table and apply external forces (±8g, see in

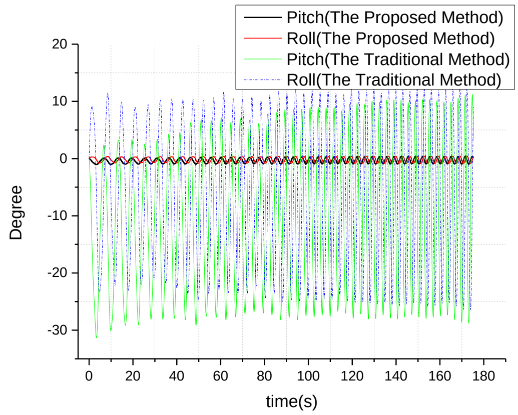

Fig.12 The attitude calculated by the proposed method.

Fig.13) in the horizontal plane. Theoretically, both of pitch and roll should be close to 0°. A comparison of Fig.14 and Fig.15 show that the proposed method has a strong anti-noise capability.

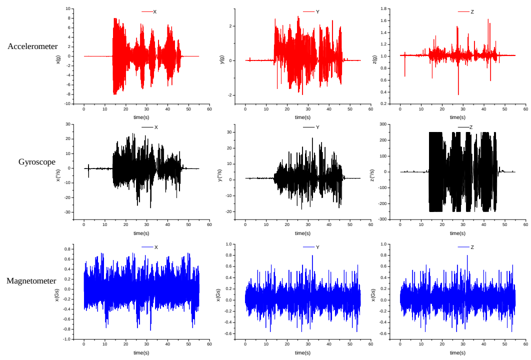

Fig.13 The raw data of 9-axes MEMS sensors.

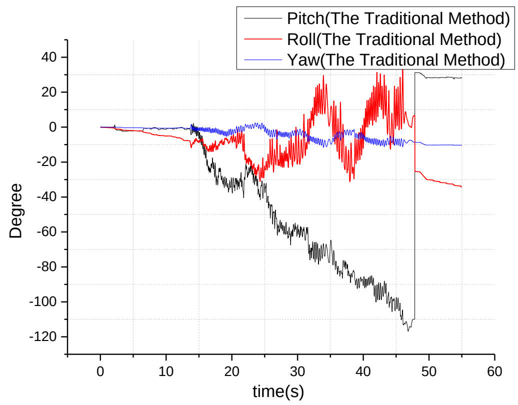

Fig.14 The attitude calculated by the traditional method.

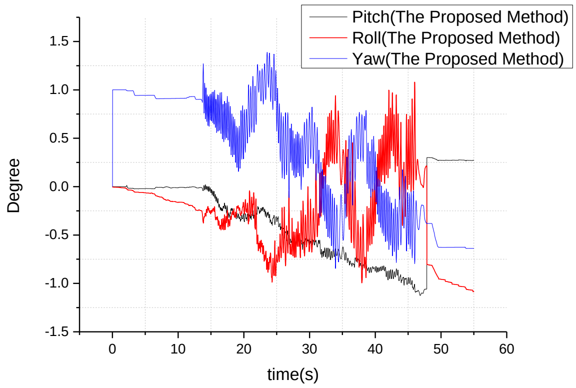

Fig.15 The attitude calculated by the proposed method.

E. *Walk Test*

A comparison of the traditional calibration method and the calibration method proposed in this paper is as shown in Fig. 16, and the result show that the proposed method has high positioning accuracy. The distance error is 0.5/220, namely, 0.23%.

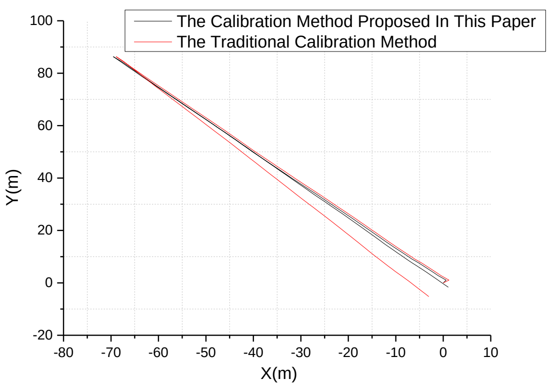

Fig.16 The camparison of positioning results calculated by the traditional calibration method and the proposed method in this paper, respectively.

IV. CONCLUSION

This paper proposed a hierarchical calibration architecture based on inertial/magnetic sensors for indoor positioning. The hierarchical calibration architecture is a good combination of hard technology and soft power. The proposed architecture is convenient for comprehensive and systematic understanding the nature of calibration. The data layer is the cornerstone of the calibration system, and the signal layer as a bridge of data and information layer. The information layer gives the whole system more flexible and intelligent. In a word, the three calibration levels are an organic unity. Through training and evolution of human motion models, we can get the new measurement as well as the state, which adds the space-time dimensions of calibration. This paper provides the necessary theoretical guidance and certain technical support for indoor pedestrian positioning in the unknown environment.

In the future, our work will focus on intelligent fusion algorithms and evolutionary circuits, as well as new ways to explore indoor positioning in unknown environments.

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