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Noise Reduction Based on Kalman Filter of Low Precision Gyroscope

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Abstract. The precision of the gyroscope data output by the MEMS device of the ordinary mobile phone is experimentally known that the error caused by the zero drift in the stationary state seriously affects the measurement of the attitude angle. In this paper, the dynamic performance of Kalman filter (KF) is analyzed. A low-cost mobile phone gyroscope denoising method based on composite Kalman is proposed. By integrating the raw data of gyroscope and accelerometer with large error, Filter noise reduction processing to reduce offset drift and noise and improve sensor accuracy. The test results show that when the carrier is in motion, the method can effectively reduce the drift error of the gyroscope and improve the accuracy of the attitude angle measurement. After filtering under dynamic conditions, the attitude angle data is stable, the error size is controlled at about 4%, the error is within the acceptable range, and the comprehensive noise reduction effect is about 77.36%, which proves that the algorithm can effectively improve the measurement accuracy of low-cost MEMS gyroscopes.

Keywords: low precision gyroscope, Kalman filter, reduce the noise, the accelerometer

1 Introduction

The microelectromechanical systems (MEMS) gyroscope featuring low cost, small device size, low power consumption and high reliability leads to increasing applications in various inertial fields. Cai et al. [1] and Liang et al. [2] hoped to replace the traditional fiber-optics gyroscopes or as complementary sensors in the field of aviation and aerospace where requires compact sensors. However, the performance of MEMS gyroscope quickly degrades over time because of high level of the noise and drift, and to date the lower accuracy is the major shortcoming that limits the application of MEMS gyroscope [3].

When using low precision gyroscope to make a joint pose, it is difficult to obtain accurate attitude information because of the error of gyroscope and accelerometer output data. The drift error of a low precision gyroscope is especially severe. To solve this problem, we can reduce the noise and improve the accuracy of attitude determination by using the Kalman filtering that accelerometer data correct and fuse gyro data [41]. The experimental results show that the denoising method based on Kalman filter can effectively improve the pose accuracy. The angle obtained by the accelerometer is subject to the response time. For example, when a cell phone is shaken violently, the accelerometer will not respond, and the specific data transmission will lag behind [4]. The main methods of noise reduction include random error compensation, dynamic error model and static error model. The more primitive filtering methods include

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IIR filter, smoothing filter and so on. Wavelet analysis, neural network, AMRA model and Allan variance analysis are applied in engineering [36]. The gyro drift signal is nonlinear, and the neural network can approximate the nonlinear functions obtained by the system indefinitely. There are software filtering and data fusion technology for gyro drift modeling [37]. In this paper, the Kalman filtering method is used to fuse the measurement information of accelerometer and gyroscope, and the measurement accuracy is improved according to their respective characteristics [5]. It has been demonstrated that the bias drift is a crucial factor that affects the measurement precision of a MEMS gyroscope. Therefore, to estimate and compensate for the bias drift is an important aspect for enhancing the performance of MEMS gyroscope along with the improvement of sensors itself [38-39]. IMU inertial navigation device will gradually drift until divergence, autonomous positioning error increases exponentially with the time. The quality of inertial sensors in smartphones is generally poor and is often accompanied by a large number of errors. By integrating the original data of the gyro, the angle of the carrier rotation can be obtained, but the integral operation makes the original error accumulate a little bit. It will eventually find that the error is piling up. Based on the paper [6], this paper proposes a method. A low-cost mobile phone gyroscope denoising method based on composite Kalman is proposed.

The second chapter reviews the research status of the Kalman filter and gyroscope noise reduction technology. Section 3 introduces the system framework and Kalman filtering method. Section 4 discusses the implementation of a low-precision gyroscope noise reduction method based on Kalman filtering. Section 5 presents the results of experimental validation and statistical analysis. Section 6 summarizes the paper and outlines future research trends.

2 Related Work

Limited by its own working principle, structure and manufacturing process, the research on noise reduction of low-cost MEMS gyroscope can effectively improve the performance without increasing the hardware cost, which has strong practical engineering significance. The error of MEMS gyroscope can be divided into determination error and random error. The determination error can be compensated by means of test and calibration. This paper will not discuss it. There are two kinds of compensation technologies for the random drift error of gyroscope.

The first is to adopt the gyroscope drift error model. The modeling methods of gyroscope random error include neural network, wavelet analysis, and time series analysis. Currently, Pakniyat and Salarieh [7] proposed the methods for estimating and compensating for the stochastic drift and reducing the noise of MEMS gyroscope mainly include several approaches such as time series analysis, power spectral density, neural network [40] and wavelet transformation [8]. These methods are usually based on the analysis of a mathematical equation for modeling the gyroscope's drift and then obtain the model equation of drift characteristics. Consequently, in designing an integrated system, the model equation can be added into the system model to improve accuracy. The common feature of these methods is that the drift errors are usually modeled and estimated to compensate for the outputs of a MEMS gyroscope [9]. Xue Liang et al. [10] proposed a new method for processing the output signals of microelectromechanical systems (MEMS) gyroscopes to reduce bias drift and noise. Zhang Shilei, et al [13] proposed a Kalman filter denoising model based on BP neural network is proposed. In view of the large noise of MEMS (micro-electro-mechanical systems) gyroscope, an improved noise reduction algorithm based on wavelet transform is proposed. the error models established by the approaches of wavelet transformation and a neural network usually have higher order, making them hard to implement using a Kalman filter (KF), because the dimensions of the system coefficient matrix and noise covariance matrix become very large and complicate the KF operation, especially for MEMS gyroscope with a lower accuracy [16]. In recent years, a novel method was proposed to improve the measurement precision of MEMS gyroscope through fusing the multiple outputs of a MEMS gyroscope array. Numerous studies have been undertaken on the multi-data fusion of the gyroscope array [17]. LIU Hui-ting, et al. [18] proposed for the underwater robot MEMS gyroscope, there is noise. In order to improve navigation accuracy and solve the problem that high and low-frequency noise is difficult to distinguish and eliminate, the Complementary Ensemble Empirical Mode Decomposition (CEEMD) and Correlation Theory are proposed. A combined approach optimizes the noise reduction algorithm. Cheng Cheng, et al. [42] proposed by analyzing the limitations of traditional wavelet threshold filtering, the wavelet sensing method based on compressed sensing is applied to the signal denoising of low-precision MEMS (micro electro mechanical system) gyroscope, and compared with the wavelet threshold filtering method.

The second is to estimate and compensate the random error by a filtering technique. The filtering technologies mainly include Kalman filtering, nonlinear filtering and the enhancement and improvement of these filtering technologies. Wang et al. [6], for the low cost and low precision of gyro sensors in mobile phones, using the basic idea of information fusion to complement the static and dynamic characteristics of gyroscopes and accelerometers, using Kalman The filtering effectively solves the serious zero drift problem of the gyroscope. Bao et al. [11] proposed for the problem that the inertial navigation accuracy of the sea cucumber fishing device is significantly reduced due to the random drift noise contained in the output signal of the MEMS gyroscope, the time series analysis method and the Kalman filtering algorithm are used to study the problem of the reduction of the random drift noise of the MEMS gyroscope. Zhang Min, et al. [12] proposed aiming at the problem of low measurement accuracy caused by random drift error of MEMS gyroscope output signal. Sun et al. [14] proposed for the micro-electromechanical system (MEMS) gyroscope random error becomes the main factor that restricts its accuracy and application range, a Kalman filter estimation method based on the regression sliding average (ARMA) model is proposed. Lu and Li proposed [20] the Kalman filtering algorithm is put forward to select the appropriate state error matrix and observation error array and optimize the positioning accuracy, so as to improve the location performance of the robot room. Mathematical reasoning and simulation results show that the probability of positioning error is 80% when Kalman filter is not used, and the positioning error is controlled within 1.2m after Kalman filter, which effectively improves the positioning effect of indoor robots.

Kalman filter is widely used in mobile robot localization [21-22]. In view of the unstable transmission and poor positioning accuracy of indoor wireless sensor network communication, an autonomous dynamic positioning system for mobile robots is proposed, by real-time selection of adjacent beacon nodes, determination of boundaries, and drawing of local grid space, the dynamic positioning of the robot is realized [23-24]. Based on the standard Kalman filter, when the sensor measurement error exists, the positioning accuracy is improved by adjusting the size of the state covariance matrix to resist the filtering divergence caused by the pose error.

In the above studies, Literature [6, 11-12, 14] conducted noise reduction studies on low-cost gyroscopes, which are similar to the research in this paper. The results of the research are shown in Table 1.

Table 1. Experimental results chart

research method	noise reduction effect	instructions
Literature [6]	70%	
Literature [11]	--	Only the strapdown inertial navigation (SINS) results are directly presented in this literature. No error data before and after filtering is given.
Literature [12]	68.9%	This value is calculated from the error reduction factor is given in the literature.
Literature [14]	43.3%	This value is calculated from the mean before and after the error of the filter given in the literature.

3 Noise Reduction of Low Precision Gyroscope Based on Kalman Filtering

3.1 Analysis of Low Precision Gyroscope Error

In this paper, the core method is the Kalman Filter. The raw data is the acceleration measured by the accelerometer and the angular velocity measured by the gyro. Two kinds of information are fused by the filter to get an accurate results. In the experiment, has selected the two platforms were verified, using the MPU6050 module (module line carrying the gyroscope and accelerometer of the module and the majority of Android mobile phone) to provide data on the algorithm are studied. The actual sensor data of the Android mobile phone is collected to verify the algorithm. The direction of motion of the object equipped with the sensor can be measured by an accelerometer. Under normal circumstances the accelerometer is used to calculate the displacement, but also can be used to correct point of view, this is the content of this paper, using the measure of the gyroscope is modified to improve the measuring precision of angle.

For the gyroscope of the mobile phone, although the angular acceleration values obtained from the direct integral angle value can be obtained, but the noise is very significant, for the poor accuracy, so the data using the accelerometer data of gyroscope needs to be corrected. According to the classical mechanical formula, If the carrier changes simultaneously in translation and pose, It is impossible to solve the attitude angle change simply according to the acceleration of three axes. But the general motion control system for UAV translational acceleration control and attitude control are separated, so in a certain range, linear estimates of angular acceleration we can use the accelerometer, based on the assumption of the uniform motion vector. It should be noted that this estimate is not very accurate, but it can meet the needs of the general application, and the concrete calculation and analysis [25] are as follows.

Rename the Pitch in the gyroscope of mobile phone, to elevation angle theta, and Roll to roll back angle gamma. The accelerometer acquisition data is still defined by fx, fy, fz , and assumes that the vectors are uniformly moving. Then, when the attitude of the object changes, the change of the accelerometer value is caused by the change of angle. At this point, we can calculate the elevation angle and roll angle according to Formula (1)

$$\begin{cases} \gamma = asin(fz / sqrt(fy^2 + fz^2)) \\ \theta = -asin(fx / sqrt(fx^2 + fy^2 + fz^2)) \end{cases} \quad \textbf{(1)}$$

The angle can be calculated by integrating the angular velocity of the gyro output, and the two kinds of data can be fused to obtain more accurate attitude information.

3.2 The Basic Principle of Kalman Filtering

The greatest advantage of the Kalman filtering method is that the dynamic state of the system can be estimated from the measured noise data when the measurement variance is known. The implementation of the Kalman filter requires the use of two sets of data, the two sets of data named system state quantities and system view measurements. The filtering result (estimate) of the current time is produced by the combination of the estimate obtained from the last moment system and the observation of this time system. The iteration process [26] is shown in Fig. 1.

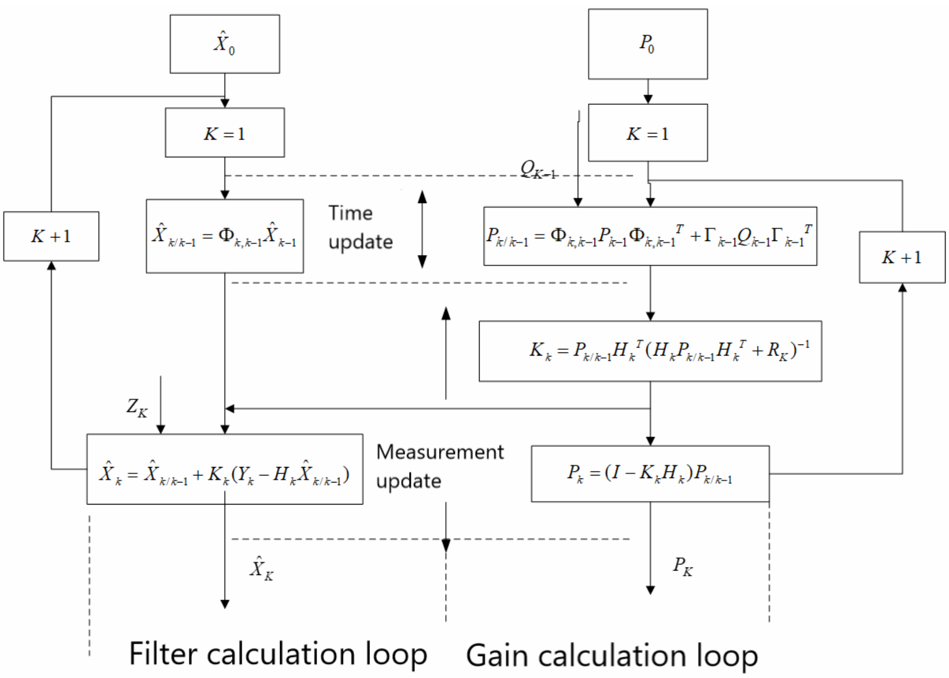


Fig. 1. The principle of Kalman Filter in which noise changes at all times

The specific Kalman Filter process [27] is as follows:

For the state prediction algorithm, three specified representative values of the state quantity are obtained: the state prediction value ($\tilde{x}_k^-$), the optimal estimation value ($\tilde{x}_k$), and the true value ($\tilde{x}_k$). The principle of Kalman filtering is to use Kalman. The gain is used to correct the state prediction value to approximate the true value.

For us to understand more easily, the Kalman filter derivation process is simplified. The first process is the state estimation covariance P_k derivation, that is, the cost function is obtained; the second step is to derive the relevant criterion derivation.

(1) State Estimation Covariance P_k.

(2) Before the state estimation covariance P_k is obtained, several representations of the state matrix of the state in the state estimation algorithm are introduced.

(3) The true value of the $x_k - \rightarrow$ state.

(4) $\tilde{x}_k - \rightarrow$ status estimate.

(5) $\tilde{x}_k - \rightarrow$ state optimal estimate.

The state prediction value ($\tilde{x}_k^-$) is obtained from the state prediction equation:

$$-\tilde{x}_k^- = A * \tilde{x}_{k-1} + A * u_k \tag{2}$$

The state-optimal estimate ($\tilde{x}_k$) can be obtained from the state update equation:

$$\tilde{x}_k = \tilde{x}_k^- + K(z_k - H * \tilde{x}_k^-) \tag{3}$$

From the above equation, we can know that the Kalman gain K is the ratio of the error of the model prediction and the measurement error in the optimal estimation of the state represented, ie. $K \in [0, 1]$. When $K = 0$, the prediction error is 0, the system state value is only related to the predicted value ($\tilde{x}_k = \tilde{x}_k^-$); and when $K = 1$, the measurement error is 0, the state value of the system is completely dependent on The number of side values.

$$K = \text{Predicted error/(Predicted error + Measurement error)} \tag{4}$$

Therefore, it can make:

$$\tilde{e}_k^- = x_k - \tilde{x}_k^- \tag{5}$$

$$e_k = x_k - \tilde{x}_k \tag{6}$$

$$P_k^- = E[e_k^- * e_k^{-T}] \tag{7}$$

$$P_k = E[e_k * e_k^{-T}] \tag{8}$$

among them:

(1) $e_k^- - \rightarrow$ a priori state error.

(2) $e_k - \rightarrow$ posterior state error.

(3) $P_k^- - \rightarrow$ covariance between the true value and the predicted value.

(4) $P_k - \rightarrow$ Covariance between the true value and the optimal estimate.

As can be seen from equations (2) and (4),

$$\tilde{x}_k = \tilde{x}_k^- + K(H * x_k + v_k - H * \tilde{x}_k^-] \tag{9}$$

$$\tilde{x}_k = \tilde{x}_k^- + KH * x_k - KH * \tilde{x}_k^- - K_{v_k}] \tag{10}$$

The transformed equation,

$$\tilde{x}_k - x_k = \tilde{x}_k^- - x_k + KH(x_k - \tilde{x}_k^-) + K_{v_k} \tag{11}$$

The simultaneous equation (5) (6) shows that

$$e_k = (I - KH) * e_k^- - K * v_k \tag{12}$$

Therefore, from equation (8), the estimated error variance matrix P_k is:

$$P_k = E[e_k * e_k^T] = (I - KH) * P_k^- * (I - KH) - K * R * K^T \tag{13}$$

Expand to know

$$P_k = P_k^- - KHP_k^- - P_k^- H^T K^T + K(HP_k^- H^T + R)K^T \tag{14}$$

State variables

The Kalman filter estimation criterion is to minimize the covariance P_k of the optimal state and make it infinitely close to the true value. So, its objective function is:

$$J = \Sigma_{min} P_k \tag{15}$$

It is not difficult to know the partial derivative of the Kalman gain matrix K:

$$\frac{\partial P_k}{\partial K} = -2(HP_k^-)^T + 2K(HP_k^- H^T + R) = 0 \tag{16}$$

It can be seen that the Kalman gain matrix K under the optimal estimation condition is

$$K = P_k^- H^T (HP_k^- H^T + R)^{-T} \tag{17}$$

The simultaneous equation (11) (14) can know that the estimated error variance matrix is

$$P_k^- = (1 - KH) * P_k^- \tag{18}$$

The state of the last piece of gold is estimated by the covariance , which is known by equation (5):

$$e_k^- = x_{k+1} - \tilde{x}_{k+1}^- = (A * x_k + Bu_k + w_k) - (A * \tilde{x}_k + Bu_k) \tag{19}$$

Simplification can be known:

$$e_{k+1}^- = E[e_{k+1}^- * e_{k+1}^{-\,T}] = E[(Ae_k + w_k)(Ae_k + w_k)^T] \tag{20}$$

It can be known from equation (7):

$$P_{k+1}^- = E[e_{k+1}^- * e_{k+1}^{-\,T}] = E[(Ae_k + w_k)(Ae_k + w_k)^T] \tag{21}$$

$$P_{k+1}^- = E[(Ae_k)(Ae_k)^T] + E[w_k (w_k)^T] \tag{22}$$

It is not difficult to know from equation (20) that the prediction covariance matrix P_{k+1}^- is:

$$P_{k+1}^- = AP_k A^T + Q \tag{23}$$

The specific process of Kalman filter state prediction and state update:

$$\hat{x}_k^- = A\hat{x}_k^- + Bu_k \tag{24}$$

$$P_k^- = AP_{k-1}^- A^T + Q \tag{25}$$

$$P_k^- = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{26}$$

$$\hat{x}_k^- = \hat{x}_k^- + K_k (z_k - H\hat{x}_k^-) \tag{27}$$

$$P_k = (1 - K_k H) P_k^- \tag{28}$$

3.3 Modeling of Low Precision Gyroscope Noise Reduction

Work according to [6], The corresponding concrete calculation process [43] is shown in formula (29) to (36).

The angular acceleration of the gyro output has a fixed deviation. The deviation corresponding to the observation angle value is b, Then, for the system according to the angle and angular velocity, the following equation can be obtained, such as equation (12). The angular velocity value obtained by gyroscope is the corresponding noise error:

$$\begin{bmatrix} \dot{\varphi} \\ \dot{b} \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varphi \\ b \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \omega_g + \begin{bmatrix} n_g \\ 0 \end{bmatrix} \tag{29}$$

The sampling period of the system is T, and the above formula can be rewritten as:

$$\begin{bmatrix} \varphi(k) - \varphi(k-1) \\ b(k) - b(k-1) \end{bmatrix} = T * (\begin{bmatrix} 0 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varphi(k-1) \\ b(k-1) \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} \omega_g + \begin{bmatrix} n_g \\ 0 \end{bmatrix}) \tag{30}$$

Set state vector, Then the state equation of the system is shown as follows:

$$X(k) = \begin{bmatrix} 1 & -T \\ 0 & 1 \end{bmatrix} X(k-1) + \begin{bmatrix} T \\ 0 \end{bmatrix} \omega_g (k-1) + \begin{bmatrix} T \\ 0 \end{bmatrix} n_g \tag{31}$$

The observation equations of the system are established based on the accelerometer. According to the foregoing calculation method, there are three accelerations in the formula (1). Angle values can be calculated directly. Therefore, the observation equation is shown as follows: n_a stands for the noise of the accelerometer.

$$Z(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} X(k) + n_a \tag{32}$$

Referring to the realization principle of Kalman Filter, we can obtain the covariance matrix of two noises [36], Q and R. In this example, Q and R are shown in formula (16). q_a q_g r_a determined [37] by component parameters

$$Q = \begin{bmatrix} q_a & 0 \\ 0 & q_g \end{bmatrix},\ R = \begin{bmatrix} r_a \end{bmatrix} \tag{33}$$

The above is for a single angle calculation. Each vector is extended when both the pitch angle and the roll angle gamma are calculated simultaneously. The system equations involve the matrices A, B, and Q, as shown in the following formula:

$$A = \begin{bmatrix} 1 & -T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & -T \\ 0 & 0 & 0 & 1 \end{bmatrix},\ B = \begin{bmatrix} T & 0 \\ 0 & 0 \\ 0 & T \\ 0 & 0 \end{bmatrix}, Q = \begin{bmatrix} q_{a\theta} & 0 & 0 & 0 \\ 0 & q_{g\theta} & 0 & 0 \\ 0 & 0 & q_{a\gamma} & 0 \\ 0 & 0 & 0 & q_{g\gamma} \end{bmatrix} \tag{34}$$

State vector X and control vector U [29]:

$$X(k) = \begin{bmatrix} \theta(k) \\ b_\theta(k) \\ \gamma(k) \\ b_\gamma(k) \end{bmatrix}, U(k) = \begin{bmatrix} \omega_{g\theta}(k-1) \\ \omega_{g\gamma}(k-1) \end{bmatrix} \tag{35}$$

The matrix H and R, and the observation vector Z (K):

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix},\ R = \begin{bmatrix} r_{a\theta} & 0 \\ 0 & r_{a\gamma} \end{bmatrix}, Z(k) = \begin{bmatrix} \theta_a \\ \gamma_a \end{bmatrix} \tag{36}$$

4 Program Simulation of Filtering Model of Low Precision Gyroscope Based on Kalman

4.1 Program Realization of Filtering Model

Write the filter program file according to the above model.

The main flowchart of the filtering program is shown in Fig. 2.

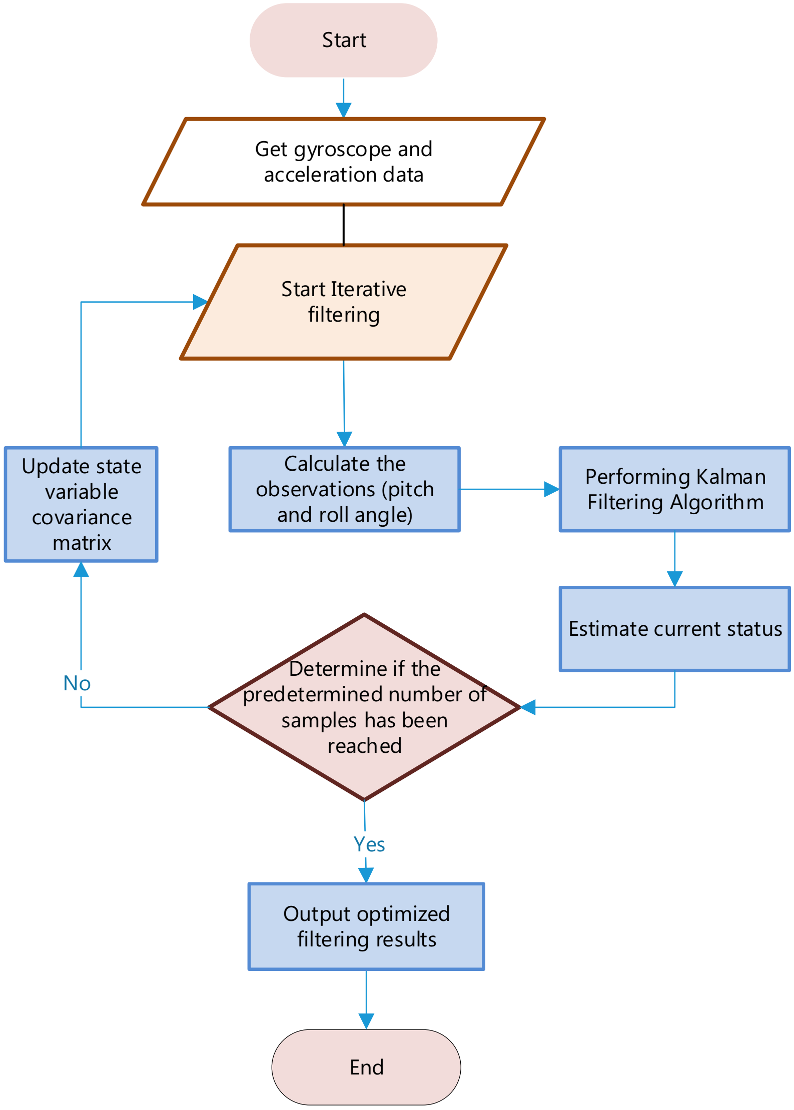


Fig. 2. Main program flow chart of Kalman filter

Filter program is divided into: 1. read the experimental data obtained; 2. calculate the attitude angle from acceleration, and as the observed value; 3. for the Kalman Filter; 4. get the state prediction value of four steps.

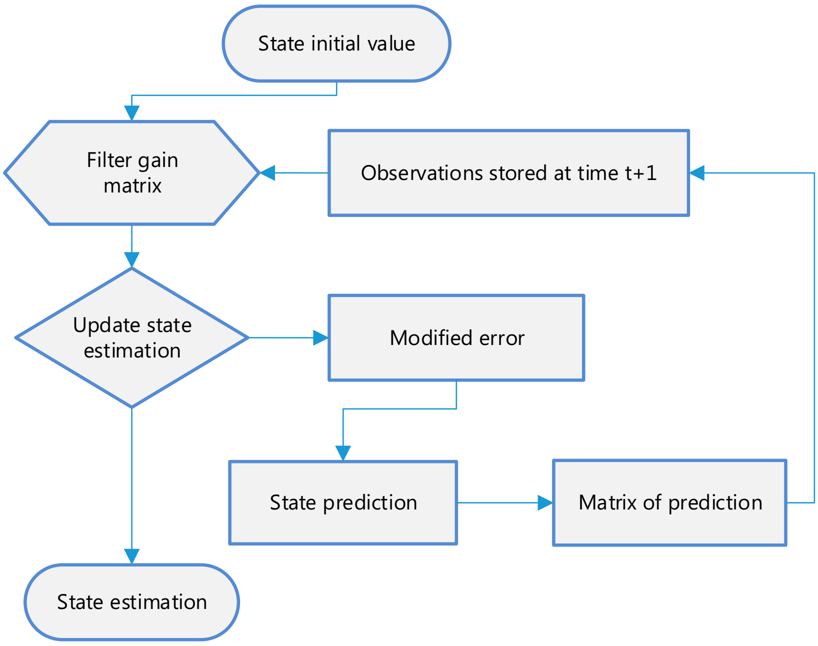


Fig. 3. Kalman filter subroutine flow chart

The final program implementation is shown below:

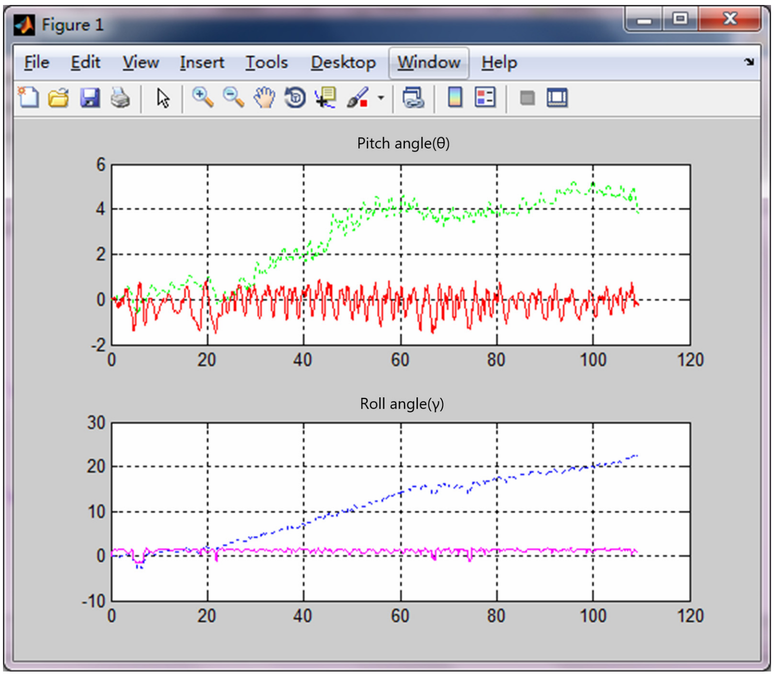


Fig. 4. Kalman filtering procedure

(Remark: the unit of the X-axis is seconds and the unit of the Y-axis is degrees)

4.2 Simulation Results of the Filtering Model and Error Analysis of Gyroscope and Accelerometer

The collected data is processed by the program in the appendix, as can be seen from the diagram, the filtering effect [30] is obvious (T=0.05s, as the angular movement of the circle, moves constantly).

When the gyroscope is in motion, although the signal-to-noise ratio is reduced, the effect of noise accumulation will continue to appear as time goes on. The variation of the bias noise of the gyro relative to the deviation of the unbiased output in the ideal state is called the gyro drift rate (the rate of variation of the angular velocity in the unit time). Gyro drift rate [31] is considered as the standard to measure the accuracy of a gyroscope. In practice, the gyro drift rate can be divided into two categories: 1., systematic drift rate 2., random drift rate. The rate of systematic drift is regular, and the compensation of this drift is simple and mature. 2. random drift rates (stochastic, irregular) are the focus of the study [45]. The error of accelerometer is 1. fixed deviation 2., scale factor deviation 3., cross-coupling error 4., random error [32].

Remark 1. fixed deviation: the device has a fixed error in a certain state of motion.

Remark 2. scale factor error: the ratio of the change in the current value of the final output of the device to the change in the acceleration of the output.

Remark 3. Cross-coupling error: because of the device changes between the three axes of the XYZ, it has a greater impact on the accelerometer.

Remark 4. random error: determined by the stability of the device.

5 Realization of Filtering Model for Low Precision Gyroscope

5.1 Experimental Preparation

This article uses MATLAB's support package for Android sensors to record data from the sensors supported by Android devices or to view the latest available data.

(1) hardware preparation: Android phone, computer, and on the same LAN.

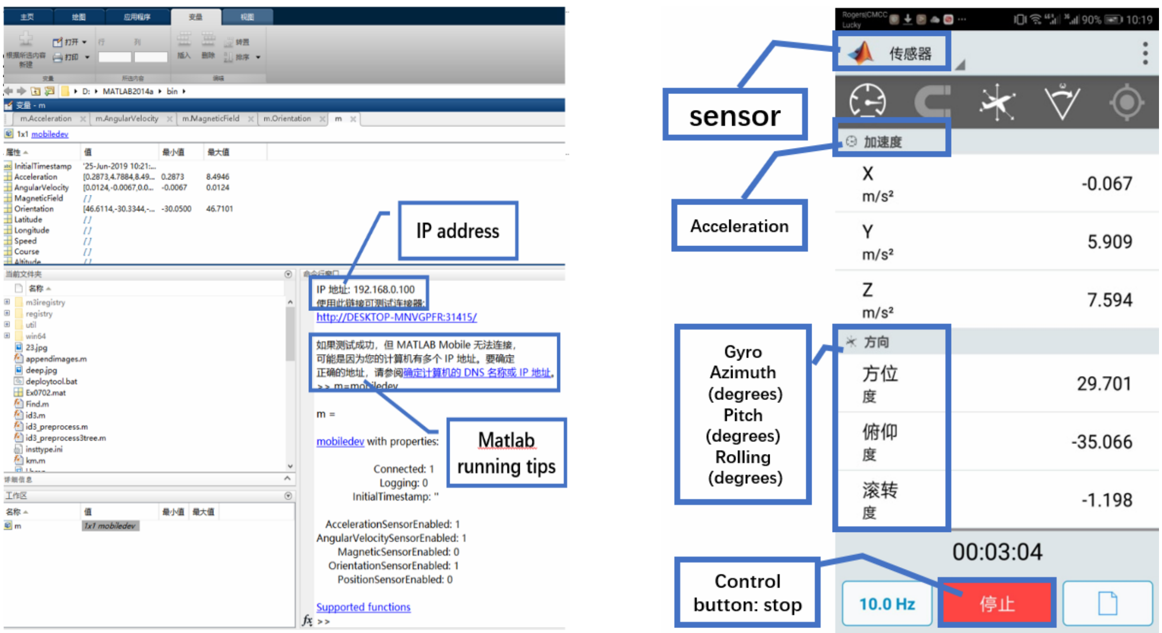
(2) software preparation: Android mobile phone installation MATLABmobile; computer installation MATLAB, this article is used for R2014a and installed MATLAB Support Package for Android Sensors in MATLAB.

(3) Establish a connection with mobile in MATLAB, and enter the connector on the MATLAB command line to establish a connection.

(4) Open Mobile, enter the IP address (the computer's LAN address) and password, the port defaults, click Connect to the computer.

(5) After the connection is successful, create a mobiledev object in MATLAB.

(6) Start/end data acquisition and sensor value acquisition.



(a) Computer operating environment screenshot (b) Android phone running environment screenshot

Fig. 5. Screenshot of the experimental running environment

The running effect is as shown Fig. 2.

5.2 Experimental Results

After collecting the data based on the above experimental steps, the filter program is run, and the result is shown in Fig. 6.

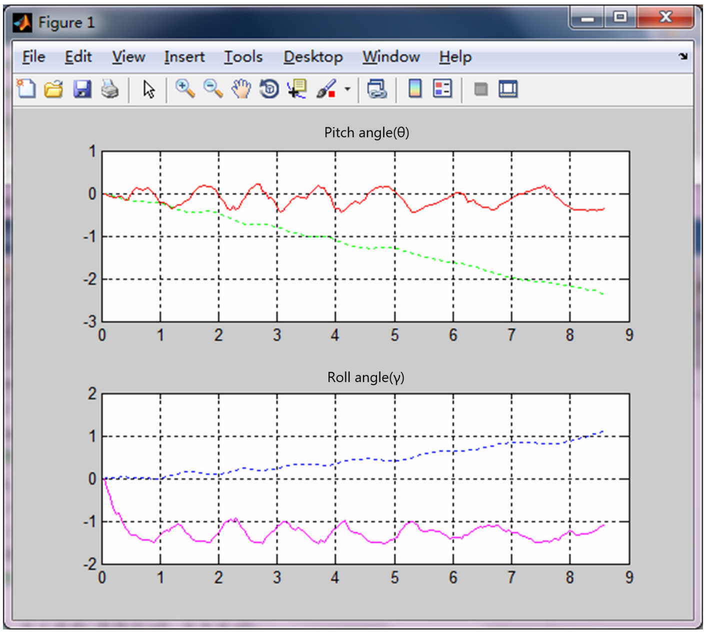


Fig. 6. Mobile phone data filtering results

(Remark: the unit of the X-axis is seconds and the unit of the Y-axis is degrees)

As can be seen from the figure above, the filter significantly reduces the effect of gyro drift. Analysis of the attitude angle information before filtering shows that under dynamic conditions: the drift error of the pitch angle is about 27.6 degrees at 200s (the dynamic drift rate is about 0.138°/s), and the drift error of the roll angle within 200s is about 34.4 degrees (the dynamic drift rate is approximately 0.172°/s). After filtering, the attitude angle data is stable, and the error size is controlled at about 4%.

Obviously, with the increase of time, the error accumulates and the data gradually diverges. The filtering well restrains the divergence trend of drift error when the gyroscope is at rest, effectively controls the error and improves the availability of the low-cost gyroscope.

The method in the literature [6] by Takashi SASAKI, the action is complete and then read the sensor data in mobile sensors record, constant parameters of the Kalman filter, adopts directly set method, the final results for the dynamic drift rate are 0.143 °/s, the method adopts composite Kalman filter structure, based on Matlab directly from the phone reads the raw data, process noise covariance of them, the error of measurement noise covariance and covariance matrix of parameters selected for the actual test, finally told parameters for optimal performance, The dynamic drift rate in this paper is 0.138°/s, the comprehensive noise reduction efficiency after 200s is more than 75%, which is better than that in literature [6].

Table 2. Experimental Results Chart

Time	100	150	200
X-axis pre-filtering error (rad)	0.247	0.373	0.485
X-axis filtered error (rad)	0.122	0.123	0.119
X-axis noise reduction effect	50.61%	67.02%	75.46%
Y-axis pre-filtering error (rad)	0.296	0.447	0.598
Y-axis filtered error (rad)	0.118	0.122	0.124
Y-axis noise reduction effect	60.14%	72.71%	79.26%
average noise reduction effect	55.37%	69.87%	77.36%

5.3 The Problems that Exist in the Current Works

Based on the composite Kalman filter the accuracy of random drift data of gyroscope is improved significantly. The shortcoming is that this paper only involves six-axis degrees of freedom in the plane direction. When the application needs in the future, the directional Angle information and magnetometer information can also be optimized by adjusting the filtering parameters to improve the efficiency of low-cost inertial navigation devices.

6 Conclusion

In this paper, based on the measured data of low-cost gyroscopes of ordinary mobile phones, a new method for improving the measurement accuracy of MEMS gyroscopes by combining multiple outputs of low-cost gyroscopes by composite Kalman filtering is proposed. The actual Kalman data filter is verified by the real data generated by the phone. The use of sensor UDP and sensor groups is described. In the experiment, more abundant data acquisition conditions were designed. The filter fusion method is deeply analyzed. Based on the composite Kalman filter, the filter divergence caused by the pose error is reduced. The experimental results show that the Kalman filter can effectively reduce the drift error and fixed error of the gyroscope and accelerometer when the carrier linear velocity and angular velocity change. The test results show that the noise drift of the gyroscope after the noise reduction is more than 75% lower than that of the original sampling signal of the gyroscope, which significantly improves the precision of the random drift data of the gyroscope. In the future, the Kalman filter will have a wider range of applications [32-35].

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