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Research on the Modeling of Random Drift Error and Filtering Technology of Low Cost MEMS Gyroscope

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Abstract

In order to improve the precision of the low cost MEMS gyroscope and reduce the influence of the random drift error on the measurement system. In this paper, the Allan variance method, mean filtering method, time series analysis method and Kalman filtering technique are used to analyze and filter the random error of static output of MEMS gyroscope. The results show that the amplitude of the random drift data is significantly reduced after filtering, the peak value of error data is 19.3% of that before filtering, and the variance is 3.1% of that before filtering. Main noises such as the angle random walk, the bias instability and the rate ramp are effectively suppressed. Above all, the method proposed in this paper can effectively reduce the random drift error of MEMS gyroscope and improve the output precision of MEMS gyroscope.

Key words

MEMS gyro, random drift error, Kalman filter, mean filter

1. Introduction

In recent years, MEMS (micro-electro-mechanical system) gyroscope as an important branch in the field of inertia, has obtained considerable development. Due to its advantages of low cost, small size, light weight and high reliability, it is widely used in low cost inertial system [1]. Although the MEMS gyroscope has many advantages compared with other traditional types of gyroscope, when compared with the optical fiber gyro and laser gyro, the accuracy of MEMS gyroscope is still very low. Due to the manufacturing process, the level of design and other reasons, the output signal of MEMS gyroscope has the disadvantages of high random noise, poor stability, and easy to be affected by external factors such as temperature, which will cause big error of the gyro output. And these errors can be used as the error source of attitude solution in the inertial navigation system, which will directly affect the precision of the system and greatly limits the application range of the MEMS gyroscope [2].

The error of the MEMS gyro mainly includes deterministic error and random error. The deterministic error as the system error can be eliminated by calibration etc [3]; random errors include random drift, trend drift and temperature drift. The mechanism of the random drift error is very complex, it has no rules and always changes with time, and can not be compensated by simple method. So it is the main reason for limiting the precision of gyroscope, and it is also one of the hot and difficult points in the field of inertial navigation at home and abroad [4]. Therefore, analyzing the characteristics of random error of MEMS gyroscope, modeling and filtering the random error of MEMS gyroscope, reducing the random drift error of MEMS gyroscope, have become the focus in the research of MEMS gyroscope [5].

In recent years, many scholars at home and abroad, aiming at the problem of MEMS gyroscope random drift, have proposed a variety of error correction methods, such as time series analysis, neural network, support vector machine and particle filter, etc [6]. The basic idea of these methods is to establish the error model after analyzing the random drift signal of MEMS gyroscope, and after parameter identification of model, the random drift error is estimated and compensated by filtering technology. The time series analysis method is to model the random error statistic characteristics of the gyroscope in the time domain by selecting the appropriate order model, which is a common method for the modeling of the gyro random drift error. The random drift signal of gyroscope is unstable, although approximate stable random drift error can be obtained after removing the trend and the constant value, there still exists some gross error and nonlinear interference signal, which will affect the precision of the model error and the effect of Kalman filter. In this paper, firstly some gross error and nonlinear interference signal in gyroscope random drift are eliminated by using mean filter, and the sources of various random drift error of MEMS gyroscope are characterized and analyzed through Allan variance. Secondly, the error model is established by combining with time series analysis method, and the Kalman filter is used for filter compensation. Finally, the compensation efficiency and precision of gyro performance has improved. The experimental results show that the method can effectively filter the random drift error of MEMS gyroscope.

2. Allan variance principle

The random error identification of MEMS gyroscope mainly includes the autocorrelation analysis method, the power spectrum density, the Allan variance and so on [7-8]. The data acquisition time of auto-correlation analysis method is very long; Power spectrum density is the frequency domain analysis method for random error, and it is very difficult to separate the random error by analyzing the function of power spectrum density [9]; Allan variance analysis method has the advantages of easy calculation and separation, which can easily characterize and identify various error sources, and estimate the coefficient of the error [10].

Assuming the sampling period of MEMS gyro is τ_0 **Erreur ! Source du renvoi introuvable.**; a total of N sample data is collected; after preprocessing, the data is a sample function of with stable and zero mean value $\{x_i = i = 1,2,3,\cdots N\}$**Erreur ! Source du renvoi introuvable.**; N data is divided into $M(M < N/2)$ **Erreur ! Source du renvoi introuvable.**groups, each group has m sample data; the correlation time is $\tau = (m-1)\tau_0$ **Erreur ! Source du renvoi introuvable.**, $\bar{x}_k$ represents average value of group k data, the number of such data is **Erreur ! Source du renvoi introuvable.**, as shown in the formula (1) [11].

$$\bar{x}_k(\tau) = \frac{1}{m}\sum_{j=0}^{k} x_{(k-1)m+j} \quad \textbf{Erreur ! Source du renvoi introuvable.} \tag{1}$$

The Allan variance is represented by the sample mean:

$$\sigma_x^2(\tau) \approx \frac{1}{2(M-1)}\sum_{k=1}^{M-1}\left[\bar{x}_{k+1}(\tau_m) - \bar{x}_k(\tau_m)\right]^2 \quad \textbf{Erreur ! Source du renvoi introuvable.} \tag{2}$$

In the formula, $\sigma_x^2(\tau)$ represents the Allan variance, which is an estimator. The square root of the Allan variance **Erreur ! Source du renvoi introuvable.** is called the Allan standard deviation. The curve of $\sigma_x(\tau) \sim \tau$ **Erreur ! Source du renvoi introuvable.** is obtained in coordinate systems of **Erreur ! Source du renvoi introuvable.** logarithmic coordinates, which is called Allan standard deviation curve or Allan standard deviation double logarithmic curve. Research shows that MEMS gyroscope mainly includes 5 kinds of random noise, which are quantization noise, angle random walk, zero bias instability, angular rate random walk and rate ramp [12]. Different noises in Allan standard deviation curve are shown as curves with different slope, and various kings of noise appear in different correlation time region. According to the above characteristics, we can identify the different noise in the test data of the random drift error of the gyroscope [13].

Allan variance is a measurement of the stability of MEMS gyroscope. Assuming the random error in the output data of MEMS gyroscope is generated by a specific and mutually independent noise source, and then there is a unique relationship between Allan variance and power spectral density (PSD) $S_{\Omega}(f)$ [14]:

$$\sigma_x^2(f)=4\int_0^{\infty} S_{\Omega}(f)\frac{\sin^4(\pi f\tau)}{(\pi f\tau)^2}df \quad \textbf{Erreur ! Source du renvoi introuvable.} \tag{3}$$

Formula (3) shows that when passing through a filter with the transfer function as $\sin^4(\pi f\tau)/(\pi f\tau)^2$ **Erreur ! Source du renvoi introuvable.**, the Allan variance is always proportional to the noise of the gyroscope, which can express and quantify the different noise terms in the random noise of the MEMS gyroscope, 5 main expressions of error Allan variance are shown in Table 1 [15]:

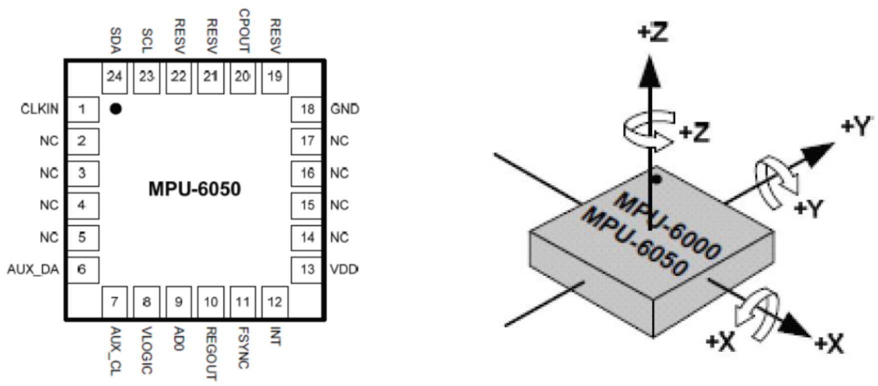
Table 1. Five typical Allan variance expressions of random error

Noise type	Parameter	Allan standard deviation	Unit	Slope of double logarithmic curve
Quantization noise	Q	$\sigma_Q=\sqrt{3}Q/\tau$	urad	-1
Angle random walk	N	$\sigma_N=N/\sqrt{\tau}$	$°/\sqrt{\mathrm{h}}$	-1/2
Zero bias instability	B	$\sigma_B=0.6643B$	$°/\mathrm{h}$	0
Angular rate random walk	K	$\sigma_K=K\sqrt{\tau/3}$	$°/\mathrm{h}^{\frac{3}{2}}$	1/2
Rate ramp	R	$\sigma_R=R\tau/\sqrt{2}$	$°/\mathrm{h}^2$	1

3. Test experiment and data processing

3.1 Data acquisition for drifts error of MEMS gyroscope

In this paper, MPU6050 gyroscope of Inven Sense Company is chosen as the research object, the model of this MEMS gyroscope is a kind of common low-cost space motion sensor chip, and its front view and axis view are shown in Figure 2.1. The 16 bit ADC is used to convert the analog quantity into digital quantity, its measurement range can be set by the register as $\pm 250°/\mathrm{s}$ **Erreur ! Source du renvoi introuvable.**, **Erreur ! Source du renvoi introuvable.**, **Erreur ! Source du renvoi introuvable.**, **Erreur ! Source du renvoi introuvable.**.



a) Front view b) Axis view

Fig.1. Front view and axis view of MPU6050 gyroscope

In this paper, the STM32F103ZET6 microcontroller is selected as the core interface processor. The static drift data of MEMS gyroscope in MPU-6050 is collected by simulating I2C signal through the I/O port, and the collected data is uploaded to the PC terminal via Bluetooth module. According to Nyquist sampling law, in order to ensure that the collected signal is not distorted, the sampling rate is at least 2 times the bandwidth of the sensor [16]. The bandwidth of the gyroscope is set to about 20Hz, and the sampling frequency of 50Hz is used to collect the data of MPU6050 gyroscope.

At room temperature, the MEMS inertial sensor is fixed on the horizontal test-bed through the fixture. After connecting the power line and data line, the drift data of the gyroscope is collected in the static state for 1.5h. When the MEMS gyroscope starts electrifying, due to the influence of temperature and other internal factors, the X axis sampled data for continuous 1 hour after the MEMS gyroscope is stable, is taken as the original output data of the gyroscope. The original signal of the random drift error of the gyroscope after converting is shown in Figure 2.2.

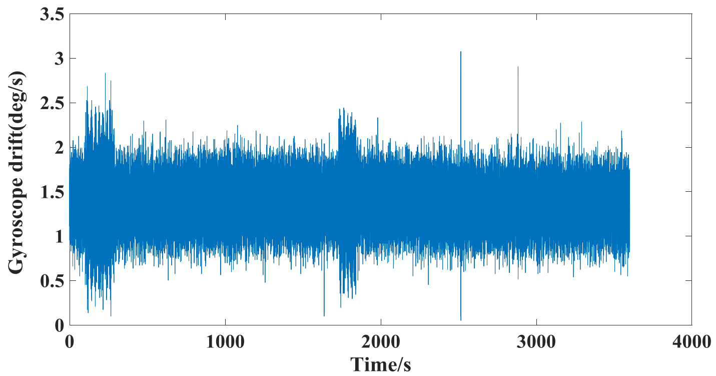


Fig.2. original drift data of X axis Output of MPU6050 gyroscope

3.2 Data preprocessing

In order to reduce the influence of the random drift error on the precision of the gyroscope, establishing accurate error model is the key part of this paper. At present, the correlation function method or time series method is usually used to establish the random error model of the gyroscope. However, because it is very easy to introduce additional error by the correlation function method, the time series analysis method is generally used to establish the mathematical model of stationary random process [17]. So in this paper, the time series analysis method is used to establish mathematic model of random drift error of MEMS gyroscope.

The requirements for the establishment of model by time series method are: the measured noise must be a stationary random process, and the expected value of the stationary random process is zero, the variance is constant, and they are not related to each other [18]. However, the original data measured by common gyroscope can't meet the above requirements. In order to get stable, normal and zero mean time series, the collected original signal must be tested and preprocessed.

3.2.1 Data test

(1) Zero mean value test: Zero mean value test is used to test whether the mean value of time sequence $\{x_t\}$ **Erreur ! Source du renvoi introuvable.** is 0, the **Erreur ! Source du renvoi introuvable.** is the implementation of the whole process rather than a sample. After the test, the drift sequence **Erreur ! Source du renvoi introuvable.** has non zero mean value of 1.367.

(2) Stability test: the stability test is the most important issue in the test of random drift data of gyroscope, and it is used to test whether the drift data has statistical characteristics that do not change over time. In this paper, a reverse u-test method of non-parametric test method is used. After testing, $u = -0.1632$ **Erreur ! Source du renvoi introuvable.**, when the significance level **Erreur ! Source du renvoi introuvable.**, and meets the conditions of $|u| < 1.96$, which can be considered that the drift data is a stationary sequence.

(3) Normality test. In order to test whether the stationary random data is normal or not, the probability density function of the data is needed to be calculated, and then be compared with the theoretical normal distribution. In this paper, the goodness of fit test with x^2 method is used for the non-parametric test. After testing, at the significance level of 5%, the probability distribution of drift data is approximate to normal distribution, which can be considered that the error data follows the normal distribution.

3.2.2 Data preprocessing

Usually, the gyroscope will be affected by factors such as the working environment, so the collected signal may contain constant values and trend term. After the collected data are pretreated, the data which removed the constant and trend term is shown in figure 2.3:

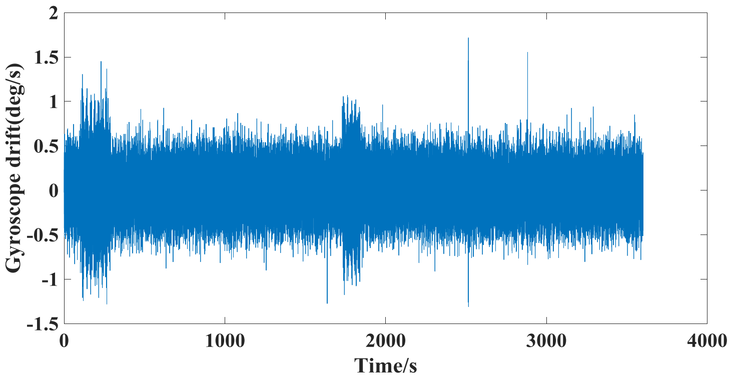


Fig.3. Random drift data after pretreatment

3.2.3 Allan variance analysis of random drift error of MEMS gyroscope

From the above that the sampling frequency $f = 50$ Hz**Erreur ! Source du renvoi introuvable.**, sampling interval time $\tau_0 = 0.02$ s**Erreur ! Source du renvoi introuvable.**. Through the treatment of drift data of gyroscope by formula (1) (2), the Allan standard deviation curve of the MPU6050X axis gyroscope can be obtained, as shown in Figure 2.3. The numerical values of the random noises in the data of random drift error data of gyroscope are also obtained, as shown in table 2.

Figure 2.3 and Table 2 shows that the main random error that affects the precision of MEMS gyroscope is angle random walk, zero bias instability and rate ramp.

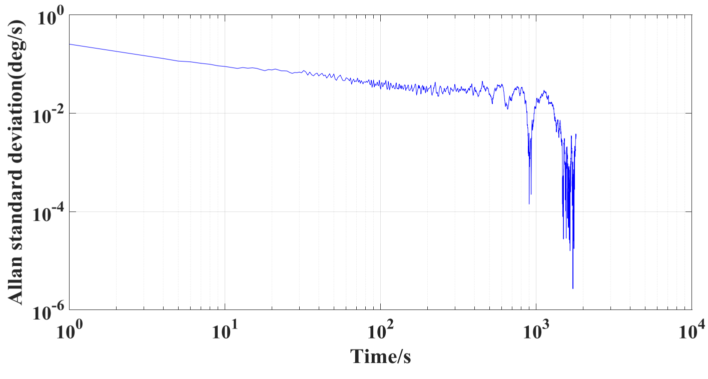


Fig.4. Allan standard deviation curve of X axis in MP6050

Table 2. Random noise figures of X axis gyroscope in MP6050

Error index	Drift data
Quantization noise(urad)	0.1663
Angular velocity random walk($°/\sqrt{h}$)	0.95164
Zero bias instability($°/h$)	0.60565
Rate random walk($°/h^{\frac{3}{2}}$)	0.07759
Rate ramp($°/h^2$)	0.43223

4. Mean filter and time series modeling

4.1 Average filtering algorithm

Time series model is very limited in time series prediction, and the quality of the model is depending on many aspects. In practical application, the time series has irregular nonlinear characteristics. So it is difficult to establish an ideal model for the gyro drift signal which is more than one kind of noise, which leads to the low precision of time series prediction. Therefore, the mean filter is used to estimate the partial gross error and nonlinear signals in the data of random drift error after pre-treatment, which can overcome the inaccurate estimation of the model parameters. The expression of the mean value estimation method is [19]

$$\hat{x}_n = \frac{1}{L}\sum_{i=n-L+1}^{n} x_i$$ **Erreur ! Source du renvoi introuvable.**

(4)

In the formula, x_i **Erreur ! Source du renvoi introuvable.** represents the elements in a data window, L **Erreur ! Source du renvoi introuvable.** represents the length of a data window, and $\hat{x}_n$ represents the result of mean value estimation. Because it is not the moving average, after average, the ratio of the **Erreur ! Source du renvoi introuvable.**output and **Erreur ! Source du renvoi introuvable.** output is $1/L$ **Erreur ! Source du renvoi introuvable.**. The greater the **Erreur ! Source du renvoi introuvable.** value, the lower the output rate, and the efficiency of the algorithm will be reduced, so the choice of L is very important. If the point number is too small, the average effect is poor, but if the point number is too big, it is not easy to remove the signal in the gross error signal. **Erreur ! Source du renvoi introuvable.**represents estimation result through the average of L historical data, and a threshold value r is set. Then a group of data **Erreur ! Source du renvoi introuvable.** is subtracted from **Erreur ! Source du renvoi introuvable.**, and the absolute value of the difference is compared with r, if it is greater than r, then **Erreur ! Source du renvoi introuvable.** is judged as a large signal, otherwise the data is valid. Finally, the mean value of the remaining valid data**Erreur ! Source du renvoi introuvable.** is calculated by the formula (4), as a result of the average filter output.

It can be found by observing the original data that gross error signal is generally not continuous in the short term. Therefore, in this paper, the selected L is 20, and r is 0.3. In practical application, L and r should be selected according to the need. After the averaging filter of output sequence, not only the influence of gross errors is eliminated, but also the variance of the output sequence is significantly reduced, as shown in Figure 3.1 below:

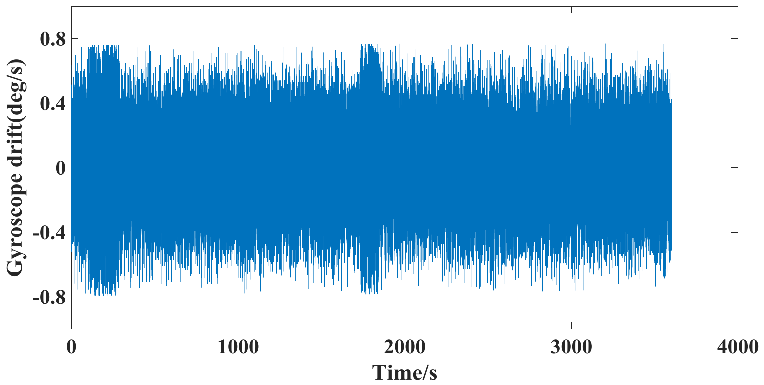


Fig.5. The data of random drift error of the gyroscope after mean filter

4.2 Data modeling

AR model is a linear dynamic model which is widely used in system analysis, prediction, identification and control, and it can describe the output noise of gyroscope. Suppose $\{x_k, k=1,2,\cdots N\}$**Erreur ! Source du renvoi introuvable.** as a stationary random sequence with zero mean value, the expression of the AR model is [20]:

$x_k = \varphi_1 x_{k-1} + \varphi_2 x_{k-2} + \cdots \varphi_p x_{k-p} + \alpha_k$ **Erreur ! Source du renvoi introuvable.** (5)

Where **Erreur ! Source du renvoi introuvable.** represents the time series, **Erreur ! Source du renvoi introuvable.** represents model parameters, **Erreur ! Source du renvoi introuvable.** represents white noise sequence with 0 mean value, and σ_a^2 variance.

In practical engineering projects, the general method for the determination order of the drift model of gyroscope is BIC criteria, AIC criteria, FPE criteria and least square method. In this paper, the AIC criterion is used for the determination order of the model [21].

AIC (An Information Criterion) guideline was proposed by Japanese scholar Akaike in 1973, based on the maximum amount of information extracted from the observation sequence, and it is applicable for ARMA model (includes AR, MA) to test definition criterion function, its structural form is [22]:

$$AIC(n) = NIn\sigma_a^2 + 2n$$ **Erreur ! Source du renvoi introuvable.** (6)

In the formula, N represents the length of the sample, σ_a^2 represents the estimation of noise variance, n represents the order estimation of model.

The order of error model of MEMS gyroscope is low, generally less than three-order. The parameters of the first three order model for the random drift error data of gyroscope after mean filter are estimated by using the Yule-Walker equation method, and the corresponding AIC values are calculated, the results are shown in table 3. It can be seen that the difference of AIC value is small when modeling the AR model with different order, and the AIC value of AR (1) is the smallest, so AR (1) model can basically meet the requirements of random drift characteristics of the MEMS gyroscope, the model of random drift error of the MEMS gyroscope is:

$$\begin{cases} x_k = -0.2855 x_{k-1} + a_k \\ a_k \sim N(0, 0.0577) \end{cases}$$ **Erreur ! Source du renvoi introuvable.** (7)

Table.3. Random drift model parameters of MEMS gyroscope

	AR(1)	AR(2)	AR(3)
φ_1	-0.2855	-0.2738	-0.2796
φ_2	0	-0.0411	-0.0802
φ_3	0	0	-0.1428
Variance white noise	0.0577	0.0576	0.0564
The value of AIC	-10266.9931	-10271.2378	-10345.0300

5. Kalman filter

5.1 Design of Kalman filter

Kalman filtering technique uses random drift error of gyroscope in navigation system as state variables, uses the discrete state equation to establish the model for describing the system, and uses the state equation and measurement equation to perform characteristics of the system. The optimal estimation of the system state variables can be obtained through the Kalman filtering process. In the inertial navigation system, the random error of the gyroscope can be reduced to a very low level by using Kalman filtering technique [23].

In the view of the system, the zero drift of the gyroscope can be regarded as the system output when the input is white noise. The Kalman filter uses the principle of recursive linear minimum estimation equation, and only the estimated values of the previous moment and the measured value of the current time are needed to introduce the best estimate of the current state, which can obtain the optimal linear filtering of the random signal in the estimation error of minimum mean square deviation [24]. Filtering principle is shown as follows:

Based on the AR (1) model, assuming the state equation of the system at k moment is:

$$\boldsymbol{X}(k) = \boldsymbol{A}\cdot\boldsymbol{X}(k-1) + \boldsymbol{B}\cdot\boldsymbol{W}(k)$$ **Erreur ! Source du renvoi introuvable.**

(8)

Where **Erreur ! Source du renvoi introuvable.** represents the state variable of system, $\boldsymbol{W}(k)$ represents the system noise.

From $x_k = -0.2855x_{k-1} + a_k$ **Erreur ! Source du renvoi introuvable.** that $\boldsymbol{A} = -0.2855$, $\boldsymbol{B} = 1$, the measurement equation for k moment is:

$$\boldsymbol{Z}(k) = \boldsymbol{H}\cdot\boldsymbol{X}(k) + \boldsymbol{V}(k)$$

(9)

Where **Erreur ! Source du renvoi introuvable.** represents the system output, **Erreur ! Source du renvoi introuvable.** represents the measurement of noise, $H = 1$.

Assuming that **Erreur ! Source du renvoi introuvable.** and **Erreur ! Source du renvoi introuvable.** are independent of each other and follow the normal distribution of white noise, that is:

$$\boldsymbol{W}(k) \sim N(0, Q)$$

(10)

$$\boldsymbol{V}(k) \sim N(0, R)$$

(11)

Among them, Q represents the covariance matrix of system noise, its value is $\sigma_a^2 = 0.0557$ **Erreur ! Source du renvoi introuvable.**, R represents the covariance matrix of measurement noise, and its value is the variance of the estimation error of the sample data. The recursive equation of the Kalman filter is:

Next state prediction of system:

$$\hat{\boldsymbol{X}}_{k,k-1} = \boldsymbol{A} \cdot \hat{\boldsymbol{X}}_{k-1}$$

(12)

State estimation:

$$\hat{\boldsymbol{X}}_k = \hat{\boldsymbol{X}}_{k,k-1} + \boldsymbol{K}_k \cdot \left(\boldsymbol{Z}_k - \boldsymbol{H} \cdot \hat{\boldsymbol{X}}_{k,k-1} \right)$$

(13)

Filter gain:

$$\boldsymbol{K}_k = \boldsymbol{P}_{k,k-1} \cdot \boldsymbol{H}^T \cdot \left(\boldsymbol{H} \cdot \boldsymbol{P}_{k,k-1} \cdot \boldsymbol{H}^T + \boldsymbol{R} \right)^{-1}$$

(14)

One-step estimation of covariance matrix:

$$\boldsymbol{P}_{k,k-1} = \boldsymbol{A} \cdot \boldsymbol{P} \cdot \boldsymbol{A}^T + \boldsymbol{B} \cdot \boldsymbol{Q} \cdot \boldsymbol{B}^T$$

(15)

Estimation of covariance matrix:

$$\boldsymbol{P}_k = \left(\boldsymbol{I} - \boldsymbol{K}_k \cdot \boldsymbol{H} \right) \cdot \boldsymbol{P}_{k,k-1}$$

(16)

The initial value of P is: $P_0 = 0$ **Erreur ! Source du renvoi introuvable.**, The first value of gyroscope output is selected as the initial value of $\boldsymbol{X}$, namely $\hat{x}_0 = Z_0$ **Erreur ! Source du renvoi introuvable.**. According to the measurement **Erreur ! Source du renvoi introuvable.** of k moment, the state estimation **Erreur ! Source du renvoi introuvable.**of k moments can be obtained by recursive calculation.

5.2 Performance test of Filter

Based on the Kalman filter to filter the drift data of gyroscope, the curve of drift data of gyroscope before and after filtering is shown in Figure 4.1. The drift amplitude of gyroscope after filtering decreases significantly, and peak value of error data after filtering is 19.3% of that before filtering. Therefore, the majority of the interference noise can be filtered by Kalman filter.

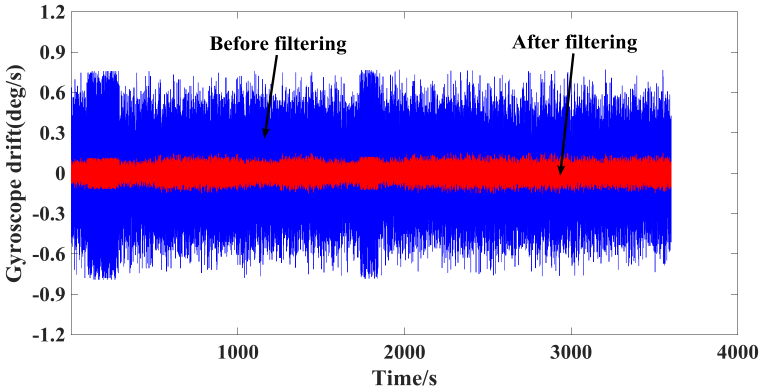


Fig.6. Comparison of random drift error of gyro before and after filtering

The variance of the filter before and after filtering is shown in table 3. It can be seen that the variance of the data is significantly reduced after Kalman filtering, and is only 3.1% of the variance before filtering, which indicates that the filtering method can effectively suppress the random drift error of the MEMS gyroscope.

Table.3. Comparison of variance in random drift error data before and after filtering

Parameter	Raw data	Mean filter	Kalman filter
Variance	0.0667	0.0528	0.0021

By comparing the various noise coefficient of the gyroscope before and after filtering that, the statistical effect of various data can be effectively improved, and the random drift error can be significantly suppressed after the Kalman filtering. The main random error which influences the precision of the MEMS gyroscope such as the random walk, zero bias instability and the noise figure of the rate ramp are obviously reduced. The noise coefficient of angle random walk decreases by 96.45%, and the noise coefficient of zero bias instability decreases by 94.47%, and the noise coefficient of rate slope decreases by 77.87%.

Table.4. Comparison of various random error coefficients of gyroscope before and after filtering

Noise figure	Raw data	Kalman filtering
Quantization noise(urad)	0.1663	3.526×10^{-4}
Angular velocity random walk(**Erreur ! Source du renvoi introuvable.**)	0.95164	0.03816
Zero bias instability(°/h)	0.60565	0.03352
Rate random walk(**Erreur ! Source du**	0.07759	0.01568

renvoi introuvable.)		
Rate ramp(**Erreur ! Source du renvoi introuvable.**)	0.43223	0.09564

6. Conclusions

In this paper, aiming at the low precision of MEMS gyroscope, the Allan variance method, mean filter method, time series analysis method and Kalman filtering technique are used to analyze and filter the random error of static output of MEMS gyroscope. And the noise coefficient of variance and random drift error of MEMS gyroscope are used as measure index to carry out the simulation research, and the results shows that:

(1) The amplitude of the random drift data after filtering is significantly reduced, the peak value of the error data after filtering is 19.3% of that before filtering, and the variance of the error data after filtering is 3.1% of that before filtering. Obviously, time series mathematical modeling method and filter design method used in this paper can effectively reduce the random drift error of MEMS gyroscope and improve the precision of MEMS gyroscope, and has certain practical value to the inertial navigation system with low cost MEMS gyroscope.

(2) Comparing random error coefficients before and after Kalman filtering, the random error of the gyroscope has significantly reduced after filtering. The noise coefficient of angle random walk of the main random error which affects the precision of MEMS gyroscope has reduced by 96.45%, the noise coefficient of zero bias instability has reduced by 94.47% and the noise coefficient of rate ramp has reduced by 77.87%, which indicates that the Kalman filtering technique can effectively filter the main random error term in the random drift error of MEMS gyroscope.

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