Research on Noise Reduction Optimization of MEMS Gyroscope Based on Intelligent Technology

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Abstract. By analysing the principle of the threshold denoising algorithm in the wavelet analysis method, according to the mathematical model of the MEMS gyroscope signal drift, the wavelet threshold denoising method is used to denoise the output of the MEMS gyroscope in real time. And the algorithm After being applied to a MEMS gyroscope strapdown inertial navigation system based on DSP, the system's MEMS gyroscope is tested for zero drift. Through the analysis of the whole system test results, the wavelet threshold denoising method is used to suppress the zero drift of the MEMS gyroscope and improve the MEMS gyroscope. The zero-bias stability of the MEMS gyroscope has a good effect, which confirms the ideal effect of the wavelet threshold denoising method in the noise processing of the MEMS gyroscope.

Keywords: MEMS gyroscope, signal drift, wavelet analysis, threshold denoising method.

1. Introduction
MEMS gyroscopes are used in low-cost inertial navigation systems because of their small size, low cost, and strong shock resistance. The random error in the MEMS gyroscope itself is the main factor restricting the improvement of the accuracy and stability of the device, and the existing processing technology limits the effective suppression of the random error in the physical structure of the gyroscope. The research work around MEMS gyroscope random error separation technology mainly focuses on the refinement of the device model and the research on denoising methods. At present, domestic and foreign scholars have proposed new methods such as support vector machine (SVM), particle filter, and genetic algorithm to optimize neural network for the random error problem of MEMS gyroscope [1]. Due to the random time-varying nature of MEMS gyroscope drift, it is difficult to establish an accurate and stable autoregressive (AR) model, and the low-order AR model has fewer parameters, and it is difficult to completely describe the characteristics of gyroscope drift data, so non-stationary time series must be considered Modelling and forecasting methods. At present, MEMS gyroscopes used in China generally have the disadvantage of relatively large drift error. In this paper, the wavelet threshold denoising method is used to denoise the output signal of the MEMS gyroscope. By selecting the optimal base, the decomposition scale is increased and improved. Methods such as threshold selection have achieved better filtering results.
2. Mathematical model of MEMS gyroscope

Because the accuracy of the MEMS gyroscope is relatively poor, the drift can reach 70°/h~80°/h, so the cross-quadratic term in the output signal of the MEMS gyroscope can be ignored, taking into account the scale factor error, installation error and drift. In the case of MEMS gyroscope output model can be described as

\[ W(t) = w_0 + S_k w(t) \]  

(1)

Where: \( W(t) \) is the output value of the MEMS gyroscope, in °/s; \( w_0 \) is the drift of the MEMS gyroscope, in °/s; \( S_k \) is the scale factor of the MEMS gyroscope. Gyro drift is determined by the constant of the MEMS gyroscope. Value drift, period drift and white noise composition, namely

\[ 0 \sum_0^2 \Gamma \sin \left( 2\pi f + \theta_0 \right) + \Gamma(t) \]  

(2)

Where: \( X_d \) is the zero bias of the three-axis MEMS gyroscope, which is approximately a constant in a short time; \( K_d \) is the amplitude of the periodic components of the three axes; \( f \) is the frequency of the periodic components of the three axes; \( \theta_0 \) is the three The initial phase of the three axes; \( \Gamma(t) \) is the zero mean Gaussian white noise of the three axes [2].

3. Selection of wavelet denoising algorithm

The energy of the image itself corresponds to the wavelet coefficients with larger amplitudes, mainly concentrated in high frequencies; the noise energy corresponds to the wavelet coefficients with smaller amplitudes, and is dispersed in all the coefficients after wavelet transformation. According to this feature, set a threshold, consider that the main component of wavelet coefficients greater than the threshold is a useful signal, and retain it after shrinking; wavelet coefficients less than the threshold, the main component of which is noise, is eliminated, so that denoising can be achieved the goal of.

3.1. Wavelet threshold denoising method

The basic idea of wavelet threshold denoising is: (1) First, perform wavelet transformation on the noisy signal \( f(k) \) to obtain a set of wavelet coefficients \( W_{j,k} \); (2) By thresholding \( W_{j,k} \), the estimated coefficient \( W_{j,k}^\text{est} \) is obtained, so that \( W_{j,k} \) and \( W_{j,k}^\text{est} \) are both The difference of is as small as possible; (3) Use \( W_{j,k}^\text{est} \) for wavelet reconstruction to obtain the estimated signal \( f(k) \), which is the signal after denoising.

Donoho proposed a very concise method to estimate the wavelet coefficient \( W_{j,k} \). After several continuous wavelet decompositions of \( f(k) \), there is a signal with uneven spatial distribution \( s(k) \). The wavelet coefficients \( W_{j,k} \) on each scale have larger values at certain specific positions. These points correspond to the oddly changed positions and important information of the original signal \( s(k) \), and \( W_{j,k} \) in most other positions is small; for white noise \( n(k) \), its corresponding wavelet coefficient \( W_{j,k} \) is uniformly distributed on each scale, and as the scale increases, the amplitude of the \( W_{j,k} \) coefficient decreases. Therefore, the usual denoising method is to find a suitable number \( \lambda \) as the threshold (threshold), and set the wavelet function \( W_{j,k} \) lower than \( \lambda \) (mainly caused by the signal \( n(k) \)) to zero, and for the wavelet function higher than \( \lambda \) \( W_{j,k} \) (Mainly caused by the signal \( s(k) \)), it is retained or contracted to obtain the estimated wavelet coefficient \( W_{j,k}^\text{est} \), which can be understood as basically caused by the signal \( s(k) \), and then \( W_{j,k}^\text{est} \) is reconstructed to reconstruct the original signal [3].
3.2. Algorithm description
The wavelet threshold denoising method proposed in this paper can be described in 5 steps:

(1) Perform s-layer orthogonal redundant wavelet transformation on the noisy image \( g(l,j) \) to obtain a set of wavelet decomposition coefficients \( W_{g(l,j)}(s,j) \), where \( j = 1,2,\cdots,s \) and \( s \) represent the number of wavelet decomposition layers.

(2) The noise variance \( \sigma_{n,j} \) is estimated in each direction of each decomposition layer, and the noise variance \( \sigma_{n,j} \) can be estimated as follows:

\[
\hat{\sigma}_{n,j}(s,j) = \frac{\text{median}(|W_{g(j,j)}(s,j)|)}{0.6745}
\]  

(3) Calculate the parameters needed for the threshold: estimate the variance \( \sigma_{i,j} \) of the wavelet coefficients of the image. Since it obeys the Gaussian distribution,

\[
\hat{\sigma}^2_{i,j}(s,j) = \frac{1}{N^2(j)} \sum_{i,j=1}^{N(j)} W_{g(i,j)}^2(s,j)
\]  

(4) Calculating the threshold coefficient \( \beta \): the threshold value of each high-frequency sub band in each decomposition layer is adjusted by the threshold coefficient \( \beta \).

\[
\beta = \sqrt{\log\left(\frac{L_j}{j}\right)/4.08}
\]  

Where \( L_j \) is the length of the wavelet coefficients of the k-th layer of wavelet decomposition coefficients, and \( j \) is the number of layers of wavelet decomposition.

(5) Find the expression of the new threshold from the above items

\[
T_{[s,j]} = \beta \frac{\hat{\sigma}_{n,j}(s,j)}{\hat{\sigma}_{i,j}(s,j)}
\]  

Perform wavelet soft threshold processing on each high-frequency coefficient of each layer to obtain new wavelet coefficients:

\[
\hat{W}_{g(i,j)}(s,j) = WST\left(W_{g(i,j)}(s,j)\right)
\]
Among them, $WST(\bullet)$ represents soft threshold function processing. Then, perform inverse wavelet transformation on the processed wavelet coefficient $\tilde{W}_{s,j}(s,j)$ to obtain a denoised image.

4. Result analysis
Install the existing MEMS gyroscope in the laboratory on the three-axis inertial test turntable and return the turntable to zero. After 30 minutes of static preheating, data is continuously collected for 6 hours at a sampling frequency of 100 Hz, and 1 hour of the data is intercepted for analysis and processing, and the gyro shown in Figure 1 is obtained. The original drift curve of the instrument [4].

![Figure 1. Original drift of MEMS gyroscope](image)

In this paper, compressive sensing-based wavelet filtering method and wavelet soft threshold filtering method are used to denoise the output signal of low-precision MEMS gyroscope, and then the gyroscope bias stability after denoising by the two methods is calculated, and the two methods are compared. The method has the effect of denoising the output signal of low-precision MEMS gyroscope. In this paper, Daubechies4 is used as the wavelet base to decompose the output value of MEMS gyroscope in 4 scales. The wavelet soft threshold filtering method uses the "Hers're" heuristic threshold, and the compression ratio $M/N$ in the wavelet filtering method based on compressed sensing is set to 0.5, 0.25 and 0.125, so as to analyse the influence of compression ratio on the denoising effect of low-precision MEMS gyroscope signal [5].

In the experiment, the low-precision MEMS gyroscope was fixed on the levelled turntable, and the turntable was installed on the vibration isolation foundation. The PC104 industrial computer was used to collect and process the data. Due to the large error of the low-precision MEMS gyroscope, the rotation angle rate of the earth could not be distinguished., So there is no need to consider the azimuth error of the gyroscope installation. The experiment process is to measure the same azimuth angle, the signal sampling interval is 10ms, and the sampling length is 8192. The test results are shown in Figure 2.
In the figure, the wavelet soft threshold filtering method and the wavelet filtering method based on compressed sensing are used to denoise the output signal of the low-precision MEMS gyroscope. The amplitude of the output signal of the gyroscope decreases significantly, and the signal after denoising the glitch reduction shows that both methods can filter out a large part of the noise signal. However, the signal glitches after denoising based on the compressed sensing wavelet filtering method are less than the wavelet soft threshold filtering method, which shows that the signal after denoising using this method is more stable. Therefore, using this method can obtain better MEMS gyroscope bias stability Table 1 compares the zero-bias stability of the gyroscope after denoising by the wavelet filtering algorithm and the algorithm in this paper, and shows the denoising effect of the algorithm in different compression ratios [6].

The random error of the inertial device after the digital filter noise reduction and Kalman filter estimation compensation is reduced, and the gyro random drift amplitude after Kalman filter is reduced more obviously, indicating that the Kalman filter can affect the disturbance information in the output data of the inertial device. It can be more effectively suppressed. The mean and standard deviation of random drift before and after filtering in different motion states are shown in Tables 1 and 2, respectively. Among them, the standard deviation of the gyro data after Kalman filtering is significantly improved compared with that before filtering and the digital filtering method, which further verifies the conclusion that the data dispersion is reduced.

| Table 1. Comparison of mean and standard deviation before and after filtering on static base |
|-------------------------------------------------------------|
| Before filtering | Mean value (°/s) | Standard deviation |
|------------------|-----------------|--------------------|
|                  | -3.4059×10-2    | 5.6526×10-2        |
| Digital filtering| -3.4588×10-2    | 3.5300×10-2        |
| Kalman filter    | -3.4462×10-2    | 7.1186×10-3        |

| Table 2. Comparison of mean and standard deviation before and after base filtering |
|----------------------------------------------------------------------------------|
| Before filtering | Mean value (°/s) | Standard deviation |
|------------------|-----------------|--------------------|
|                  | -6.5693×10-2    | 9.8812×10-1        |
| Digital filtering| -6.5643×10-2    | 6.8943×10-1        |
| Kalman filter    | -3.7209×10-2    | 4.2424×10-1        |
5. Conclusion
In this paper, the wavelet filtering method based on compressed sensing is applied to the denoising of low-precision MEMS gyroscopes, and the wavelet filtering method based on compressed sensing is analysed through experiments. The experimental results show that the wavelet filtering method based on compressed sensing can effectively remove the noise in the output signal of the MEMS gyroscope, although the denoising effect will decrease slightly as the compression ratio decreases, it has a good effect on improving the stability of the bias of the low-precision MEMS gyroscope, and can solve the low-precision problem in engineering. The noise reduction problem of MEMS gyroscope provides a new idea.

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