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Research on Combined Denoising Algorithm Based on Wavelet Filtering and Adaptive Filtering

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Abstract

Aiming at the problem of large random error of MEMS gyroscope, which leads to low measurement accuracy, a wavelet denoising and adaptive filtering method is proposed. First, perform wavelet denoising on the data, and then introduce an adaptive algorithm based on the predicted value feedback to reduce the random noise of the MEMS gyroscope. Using Allan variance to analyze and compare the data before and after filtering, the results show that the angle random walk, the bias instability, and the angular rate random walk are at least an order of magnitude smaller, and the standard deviation is significantly reduced, indicating that the improved algorithm effectively suppresses random noise. Improve the performance of MEMS..

Keywords

MEMS gyroscope; wavelet filter; predictive feedback; adaptive algorithm; combined filter.

1. Introduction

Although Micro Intertial Measurement Uint (MIMU) has been widely used in various fields such as drones, pods, and inertial positioning and navigation. However, due to the low accuracy and large drift of Micro Electro Mechanical System (MEMS) inertial devices, the measurement accuracy and performance of the system are limited, and error analysis and compensation for MEMS gyroscopes are of great significance [1-4] .

MEMS gyroscope error includes systematic error and random error [5]. Among them, the random drift error is caused by the gyroscope's deviation from the original direction under the action of various external interferences. It is constantly changing with time and external environmental conditions, and it is difficult to calibrate and deal with [6]. Random errors have become one of the main factors that limit the accuracy of MEMS inertial devices. The methods currently used for error analysis of MEMS inertial devices mainly include time series analysis, Allan analysis of variance, wavelet neural network, etc. [7].

In this paper, wavelet filtering and adaptive filtering algorithms based on predictive feedback are used to reduce the random noise of MEMS gyroscopes, and then combined with MEMS gyroscopes for experiments, and the Allan variance method is used to compare and analyze the effects before and after filtering.

2. Time Series Analysis and Modeling

2.1. Determination of The Time Series Model

After the data is preprocessed by removing gross errors, removing trend items, and removing periodic items, time series model modeling can be carried out [8]. Identify the model structure of the time series through the "tailing/censoring" properties of the autocorrelation function graph (Auto Correlation Function, ACF) and the partial correlation function graph (Partial Auto

Correlation Function, PACF) [9]. Perform autocorrelation and partial autocorrelation tests on the MEMS gyroscope used in the experiment, and then identify the type of model based on the characteristics of tailing/cutting. The autocorrelation function and partial autocorrelation graphs are shown in Figure 1, Figure 2.

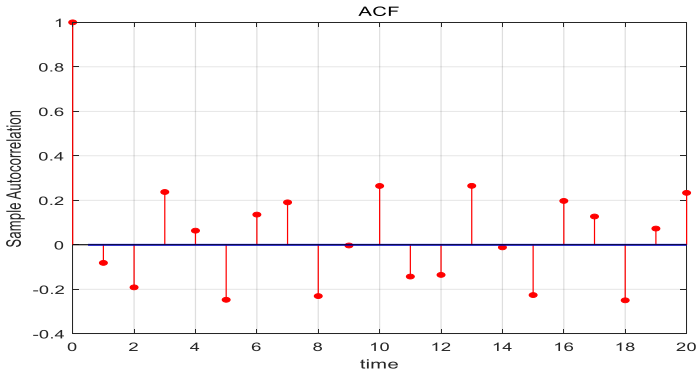

Fig. 1 Sample autocorrelation graph

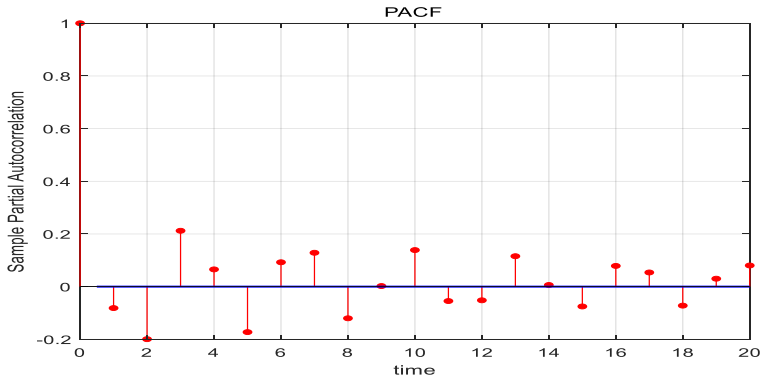

Fig. 2 Sample partial autocorrelation graph

From the figure, it can be concluded that the ACF graph of the MEMS gyroscope used in the experiment shows tailing characteristics, and the PACF graph shows tailing characteristics. It is judged that the AR model is used for modeling the gyroscope. The AR(p) model of stationary and normal time series x_k is [6]:

$$\begin{cases} X_t = \phi_1 X_{t-1} + \ldots + \phi_P X_{t-p} + \varepsilon_t \\ \phi_p \neq 0, \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \delta_\varepsilon^2 \\ E(\varepsilon_t \varepsilon_s) = 0, s \neq t \\ E(X_s \varepsilon_t) = 0, \forall s < t \end{cases} \tag{1}$$

2.2. AR Model Order and Parameter Determination

To determine the order of the AR model, the commonly used judgment methods include AIC criterion, BIC criterion, FPE criterion and innovation value, etc. [10]. In this modeling, AIC and BIC criteria are used to determine the order of the model.

Akaike information criterion (AIC) is an excellent metric for estimating the order of a random sequence model [10]. The formula is shown in formula (2):

$$\mathrm{AIC(p)} = -\ln \sigma^2{}_{(p)} + 2p \tag{2}$$

Among them, $AIC_{(p)}$ is the function of p, and $\sigma^2_{(p)}$ is the estimated value of innovation variance.

Bayesian Information Criterion (Bayesian Information Criterion, BIC), similar to AIC, is used to select the model order [10]. The formula is shown in formula (3):

$$\mathrm{BIC}(p) = -2\ln(L) + p\ln(N) \tag{3}$$

Among them, L is the maximum likelihood function, and N is the total number of samples.

The AR model of the MEMS gyroscope used in this article is AR(3) calculated by AIC and BIC criteria. The parameters of the AR model in this paper are estimated by the autoregressive approximation method [11], and the estimated parameters are: $\phi_1 = -0.055372$, $\phi_2 = -0.17875$, $\phi_3 = 0.21211$. The expression of the x-axis AR model of the MEMS gyroscope used in the experiment is:

$$\mathrm{x}_k = -0.055372\, x_{k-1} - 0.17875\, x_{k-2} + 0.21211\, x_{k-3} + \varepsilon_k \tag{4}$$

3. Filtering Algorithm Design

Because the MEMS gyroscope is easily affected by the surrounding environment and is prone to generate large noises, wavelet filtering is performed before adaptive filtering of the data to reduce the wavelet coefficients generated by removing the noise and weaken a part of the noise in the data.

Introduce an adaptive filtering algorithm based on predictive feedback, and feed back the predictive value to the wavelet filtered data to complement each other. The state equation and measurement equation of the system can be expressed as:

$$\begin{cases} \mathrm{x}_k = A_{k/k-1}\mathrm{X}_{k-1} + B_{\mathrm{k}/k-1}\mathrm{Q}_{k-1} \\ z_k = H_k \mathrm{x}_k + V_k \end{cases} \tag{5}$$

In the formula, $A_{k/k-1}$ represents the state transition matrix of the system; $X_{k-1} = [x_{k-1} \quad x_{k-2} \quad x_{k-3}]^T$; $B_{k/k-1}$ represents the noise matrix of the system; Q_{k-1} represents the system noise at time k-1; H_k is the measurement matrix at time k; V_k is the measurement noise at time k.

The initial value fed back through the predicted value:

$$\mathrm{y}_{k(k)} = c_{i1} + c_{i2} y_{k(k-1)} + \cdots c_{ij} y_{k(k-j)}, (i = 1,2,3;\ j = 1,2,\ldots,n) \tag{6}$$

Where parameter c_{ij} is an element in the feedback matrix, The feedback matrix is:

$$\mathrm{C_k} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ c_{31} & c_{32} & \cdots & c_{3n} \end{bmatrix} \tag{7}$$

The value of each parameter changes with the input signal. The short-term innovation is curve-fitted, and then the innovation is updated through complementarity. The curve parameters are updated using the recursive least squares method.

In view of the instability of the measured noise parameters, the attenuation coefficient is added to the filtering algorithm, and the attenuation memory weighting algorithm is used to adaptively estimate it to weaken the unstable characteristics at the beginning of the filtering [4]. The Kalman filter algorithm after introducing the feedback matrix and attenuation coefficient is

$$\begin{cases} \beta_k = (1-b)/(1-b^{k+1}) \\ P_k^- = A_{k/k-1}P_{k-1}A_{k/k-1}^T + B_{k/k-1}Q_kB_{k/k-1}^T \\ \hat{x}_{k/k-1}^- = A_{k/k-1}\hat{x}_{k-1} \\ y_k = H_kC_kx_k + V_k - H_kx_{k/k-1}^- \\ K_k = P_{k/k-1}H_k^T/(H_kP_{k/k-1}H_k^T + R_k) \\ \hat{x}_k = \hat{x}_{k/k-1}^- + K_ky_k \\ P_k = (I-KH)P_k^- \\ \hat{z}_k = H_kx_k + V_k \\ R_k = (1-\beta_k)R_{k-1} + \frac{1}{2}\beta_k(\hat{z}_k - \hat{z}_{k-1})^2 \end{cases} \tag{8}$$

In the formula, b is the attenuation coefficient, 0<b<1, in this MEMS gyroscope test, the attenuation coefficient b is 0.98.

4. Data Analysis and Result Verification

In the experiment, the laboratory self-developed MEMS inertial device was used for testing. The turntable used a certain type of three-axis speed position turntable with a sampling frequency of 200Hz to test the reliability of the filtering method and the compensation effect of the device. Before data collection, the MEMS inertial device was fixed on the three-axis speed turntable and adjusted to the level, and the laboratory temperature was controlled at room temperature. The output is measured at room temperature and under zero excitation conditions. The measured data were analyzed by wavelet filtering and Kalman filtering, and wavelet filtering and adaptive filtering based on predictive feedback. Some data test results are as follows:

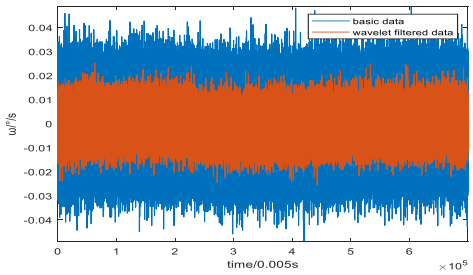

Fig. 3 Wavelet filtering results

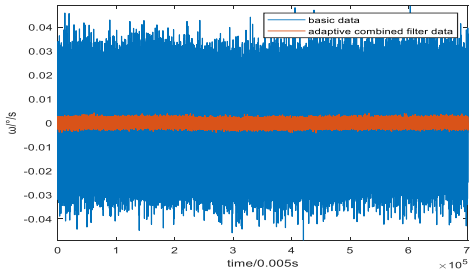

Fig. 4 The combined filtering result of wavelet and adaptive algorithm

From Figures 3 and 4, it can be seen intuitively that wavelet filtering can only reduce a part of the noise, and the filtering effect is not very ideal. However, the data fluctuation after combined filtering is obviously reduced. Combined filtering is based on wavelet filtering and adaptive filtering is added. The noise of the data has a good suppression effect, and the data is smoother in comparison, and there is no obvious sudden change value. The results in Table 1 are obtained through Allan analysis.

Table 1 Comparison of raw data and filtering results

	raw data	wavelet filtered data	wavelet and adaptive filtering data
standard deviation	0.0107	0.0047	7.767×10-4
angle random walk	0.039957	0.036742	0.004781
bias instability	1.992704	1.972311	0.247063
angular rate random walk	13.019911	12.019916	2.123519

It can also be seen from the standard deviation comparison of Table 1 that the probability of data dispersion before and after filtering is reduced, the accuracy of angular random walk is increased by 1.09 and 8.36 times, the accuracy of bias instability is increased by 1.01 and 8.07 times, and the accuracy of angular rate random walk is improved. 1.08 and 6.13 times.

The test results show that the standard deviation after the combined filtering significantly reduces the probability of sudden changes in the data before and after filtering, including angular random walk, bias instability and angular velocity random walk, and the results are at least one order of magnitude smaller. Experiments show that the algorithm based on wavelet filtering and adaptive filtering effectively suppresses the sudden change of the data, the random error is obviously smaller, and the accuracy of the MEMS gyroscope is improved.

5. Summary

This article first introduces the analysis method of random error, and the combined filtering algorithm of wavelet filtering and adaptive filtering is used to filter and compensate the data. Allan analysis shows that the experimentally established ARMA model and the proposed algorithm are suitable for the MEMS gyroscope used in this article, and the filtering effect is significant, which significantly reduces the random noise and improves the performance of the MEMS gyroscope.

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