Research on Information Fusion Technology of MEMS Gyro Array

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Abstract. The measurement accuracy of MEMS gyroscopes is relatively low. Starting from the software level, the multi-sensor information fusion technology of MEMS gyroscope array (MGA) is used to reduce the drift of MEMS gyroscopes. Firstly, a signal acquisition and processing system for communicating with ADXRS810 gyroscope based on field-programmable gate array (FPGA) is designed. Secondly, the collected drift data of the gyroscope array is preprocessed. Long-term drift trend terms are obtained by ensemble empirical mode decomposition (EEMD) and the linear function fitting, and the trend terms are filtered out to obtain a smooth and normal drift signal. Then, the data fusion model based on time series analysis is built for the gyroscope array and the error analysis is performed by Allan variance. Finally, based on the AR (1) model, the moving horizon optimization Kalman filter method is used to filter the drift data of the gyroscope array. The experiment shows that when the time domain length N=3, the bias instability of gyroscopes 1, 2, 3 and 4 decreases from 9.716 o/h, 8.5682 o/h, 13.484 o/h and 26.414 o/h to 1.2922 o/h, 0.61147 o/h, 1.4184 o/h and 1.6964 o/h, respectively, and the average noise coefficient decreases by more than 85%. Compared with the ordinary Kalman filter method, the bias instability has been significantly improved.

Keywords: MEMS gyroscope array; time series analysis; ensemble empirical mode decomposition; the moving horizon optimization; Allan variance; Kalman filter.

1. Introduction
MEMS gyroscope is a sensing device used to measure the rotation angle or angular displacement of a moving carrier relative to inertial space. It has the advantages of small size and low cost, but because its accuracy is relatively low, it is difficult to meet the needs of high-performance products, so there is an urgent need to improve its measurement accuracy. The gyroscope array based on the combination of multiple MEMS gyroscopes uses Kalman filter, "virtual gyroscope" [5], OBE smoothing algorithm [6] and other methods to fuse the collected data of the array gyroscope, which can improve measurement accuracy without significantly increasing cost. It has high practical value to improve the measurement accuracy. This article further improves the measurement accuracy of the MEMS gyroscope array through experimental modeling and the moving horizon optimization Kalman filter.
2. Design of FPGA signal acquisition system
The signal acquisition system for MEMS gyroscope array simultaneously collects data from multiple gyroscopes through the FPGA controller [7]. Fig. 1 shows the signal acquisition system, which chooses Cyclone IV series FPGA minimum system as the controller, and the peripheral and power circuit of the ADXRS810 series gyroscope is designed. The software part realizes the design of the start module, the SPI timing module, the storage module and the serial port sending module. The SPI communication of the gyroscope is simulated and analyzed through the Modelsim SE software. Finally, the online monitoring of the Quartus II is used for real-time observation and the function of real-time data transmission to the host computer through the serial port is realized.

(a) Structure of the signal acquisition system for MGA

(b) The practical hardware

Fig. 1 The signal acquisition system based on FPGA.

3. Time Series Analysis of Random Drifting Signal

3.1. Signal preprocessing of MEMS gyroscope array
Pre-processing of the drift data is required before building the time series model. The original collected data will have some outliers with large errors, which belong to gross errors. In this paper, the pauta criterion is used to eliminate gross errors.
When the gyro is in a static state for a long time, an unstable drift trend item will appear. The ensemble empirical mode decomposition (EEMD) is used to decompose the random drift signal into intrinsic mode function (IMF) components, and then the trend term is extracted. EEMD is a noise-assisted data analysis method proposed by Huang on the basis of EMD [8]. After the trend term is extracted by the EEMD algorithm, it is fitted into a linear equation through a fitting function, and the time trend term is subtracted before the actual data processing to reduce error interference. The EEMD algorithm step process is shown in Fig. 2. Add a set of white Gaussian noise signal \( w_i(t) \) to the zero-drift data \( z(t) \) to get the signal \( Z(t) \); perform EMD decomposition on the signal \( Z(t) \) to get a set IMF component and a residual signal; add different Gaussian white noise signals \( w_i(t) \) to the original signal \( z(t) \), repeat the above steps, the number of repetitions \( n \) is 100. Based on the principle that the mean value of white Gaussian noise spectrum is zero, the original time series data is obtained by taking the mean value and eliminating the additional white noise.

**Fig. 2** Flow chart of the EEMD algorithm.
Fig. 3 shows the intrinsic mode function components of the EEMD decomposition of gyro 1 in gyroscope array. The top layer is the original signal waveform after removing the gross errors, and c1-c15 are the IMF1–IMF15 components, with the IMF15 component as the reference for trend term fitting extraction.

In order to obtain an accurate trend item, 4 groups of 10-hour random drift data were collected for gyro 1, and the trend item extraction and linear fitting were performed based on the EEMD algorithm, as shown in Fig. 4.

It can be observed from Table I that the difference between the various parameters is very small. The parameters of the linear equation of the trend term can be obtained by averaging. The average of the
four sets of parameters is: \( y = -0.0485x + 391.9026 \). Fig. 5 shows the result of filtering out the trend term on the original data of gyro 2 and gyro 3.

Table 1. Parameters of the fitting function

| Function parameters | First group | Second group | third group | Fourth group | average value |
|----------------------|-------------|--------------|-------------|--------------|---------------|
| First order parameter \( a \) | -0.0435 | -0.0472 | -0.0463 | -0.0570 | -0.0485 |
| Constant \( b \) | 403.8712 | 413.2497 | 360.0591 | 390.4299 | 391.9026 |

Fig. 5 The trend removing of the gyroscope 2 and 3.

The error of MEMS gyroscope data usually includes quantization noise QN, angle random walk ARW, speed random walk RRW, rate ramp RR, etc. Allan variance analysis is performed on the MEMS gyroscope array after data preprocessing [9], and the Allan variance curve of the gyroscope is shown in Fig. 6, and the calculation results of each error term are shown in Table 2.
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Zero drift 2

Allan Standard deviation

Relevant time/s

(b) Allan variance of the gyroscope 2

Zero drift 3

Allan Standard deviation

Relevant time/s

(c) Allan variance of the gyroscope 3

Zero drift 4

Allan Standard deviation

Relevant time/s

(d) Allan variance of the gyroscope 4

Fig. 6 Allan variance curves of the MGA.

Table 2. Allan variance value of the MGA

| Data group | Noise Figure | Quantization noise /μrad | Speed ramp (°)/h^2 | Bias instability (°)/h | Rate random walk (°)/h^1/2 | Angle random walk (°)/h^1/2 |
|------------|--------------|--------------------------|---------------------|------------------------|---------------------------|-----------------------------|
| Gyro 1     | 64.833       | 12.856                   | 9.716               | 38.365                 | 8.8887                    |                             |
| Gyro 2     | 145.3        | 9.4162                   | 8.5682              | 12.286                 | 7.6104                    |                             |
| Gyro 3     | 301.62       | 14.214                   | 13.484              | 67.5739                | 6.756                     |                             |
| Gyro 4     | 397.89       | 8.2752                   | 26.414              | 29.302                 | 6.1195                    |                             |

3.2. Time series analysis

Time series models are divided into three types: autoregressive model AR(p), moving average model MA(q), autoregressive moving average model ARMA(p,q). Before modeling, it is necessary to determine the order of the model. This article chooses AR (1), AR (2), AR (3), ARMA (1,1), ARMA (1,2) and ARMA (2,1) as time series models for comparison. The final prediction error (FPE) criterion is selected to determine the model order. Table 3 shows the FPE value of each model. It can be seen that the FPE value is not much different, and the value of the AR (1) model is the smallest, so the AR (1) model is selected as the time series analysis model of the MEMS gyroscope array.
Table 3. FPE value of the time series model

| Gyro | AR (1)       | AR (2)       | AR (3)       | ARMA(1,1)    | ARMA(1,2)    | ARMA(2,1)    |
|------|--------------|--------------|--------------|--------------|--------------|--------------|
| 1    | 0.019809     | 0.019811     | 0.019810     | 0.019811     | 0.019813     | 0.019814     |
| 2    | 0.019652     | 0.019653     | 0.019685     | 0.019669     | 0.019683     | 0.019665     |
| 3    | 0.019369     | 0.019368     | 0.019368     | 0.019349     | 0.019451     | 0.019351     |
| 4    | 0.019413     | 0.019414     | 0.019415     | 0.019416     | 0.019416     | 0.019416     |

For the AR (1) model, the parameters estimated by the ordinary least squares are shown in Table 4.

Table 4. Parameter values of the AR (1) model

| Data group | Gyro 1            | Gyro 2            | Gyro 3            | Gyro 4            |
|------------|-------------------|-------------------|-------------------|-------------------|
|           | -0.0084537        | -0.0096885        | -0.0088450        | -0.0039511        |

4. Kalman filter design based on rolling time domain estimation

The filter structure of the random drift signal of the MEMS gyroscope array is constructed based on the time series model. The filter is based on the Kalman update to perform the rolling time domain optimization estimation (MHE) processing on the AR (1) model.

4.1. Rolling time domain estimation

Introduce the concept of "data time domain length N", that is, when solving the optimization estimation problem online, the number of data to be processed is kept at time T; When T>N, the measurement data sequence discards the oldest data after receiving the new measurement value, and calculates based on the latest N measurement values to maintain the data time domain length unchanged, thereby reducing the complexity of data processing [10].

4.2. Rolling optimization based on AR model

In practical applications, the continuously output gyroscope measurement value is related to the last moment or the last few moments. Therefore, a rolling optimization algorithm with time domain constraints is used for processing.

Table 5. Allan variance with moving horizon optimization under different time domain length

| Error index                     | original data | MHE(N=1) | MHE(N=2) | MHE(N=3) |
|---------------------------------|---------------|----------|----------|----------|
| Quantization noise Q/μrad       | 64.833        | 29.919   | 20.579   | 5.6515   |
| Angle random walk N/(°)/h^{1/2} | 8.8887        | 4.8228   | 3.0765   | 1.9345   |
| Bias instability B/(°)/h        | 9.7167        | 5.2457   | 2.6858   | 1.2922   |
| Angular rate random walk K/(°)/h^{3/2} | 38.365   | 20.812   | 11.603   | 6.3571   |
| Speed ramp R/(°)/h^{2}          | 12.856        | 6.978    | 4.0579   | 2.3604   |

Table 5 shows the Allan variance analysis results of the optimized output value obtained by the rolling estimation filtering algorithm under different time domain lengths of gyro 1. When the time domain length N=1, the error item of various noises is reduced by more than 50%; when the time domain length N=2, the error item is reduced by more than 70%; when N=3, the bias stability is reduced to 1.2922 o/h and the error coefficient of various noises is reduced by more than 85%. Considering the
filtering effect and computational complexity, the time domain length N is selected as 3. The filtering results of the zero bias data of gyro 2, gyro 3 and gyro 4 when N=3 are shown in Fig. 7.

(a) Filtering result of the gyroscope 2 when N=3  (b) Allan variance of the gyroscope 2 when N=3

(c) Filtering result of the gyroscope 3 when N=3  (d) Allan variance of the gyroscope 3 when N=3

(e) Filtering result of the gyroscope 4 when N=3  (f) Allan variance of the gyroscope 4 when N=3

Fig. 7 Filtering result of the MGA when N=3

Fig. 7 (a), (c), and (e) are the filtering results obtained by rolling time domain optimization for gyro 2, 3, and 4, respectively, when the time domain length is N=3. Fig. 7 (b), (d), (f) are the corresponding Allan variance curves.
Table 6 shows the Allan variance analysis results after the MEMS gyroscope array is optimized in the rolling time domain. Comparing Table II, the bias instability of gyros 1, 2, 3 and 4 are reduced from 9.716 o/h, 8.5682 o/h, 13.484 o/h and 26.414 o/h to 1.2922 o/h, 0.61147 o/h, 1.4184 o/h and 1.6964 o/h, respectively. The noise figure is reduced by more than 85% on average.

Table 6. Filtering result with moving horizon optimization

| Data group | Noise Figure | Quantization noise /urad | Speed ramp /(^o)/h^2 | Bias instability /(^o)/h | Rate random walk /(^o)/h^1/2 | Angle random walk /(^o)/h^1/2 |
|------------|--------------|--------------------------|----------------------|-------------------------|-----------------------------|-------------------------------|
| 1          | 5.6515       | 2.3604                   | 1.2922              | 6.3571                  | 1.9345                      |
| 2          | 29.879       | 1.0314                   | 0.61147             | 3.7652                  | 1.7426                      |
| 3          | 45.565       | 0.4233                   | 1.4184              | 0.83653                 | 1.643                       |
| 4          | 29.965       | 0.0631                   | 1.6964              | 0.7282                  | 1.7134                      |

The results of the MEMS gyroscope array after ordinary Kalman filter processing are shown in Table 7. The bias instability of gyros 1, 2, 3 and 4 are reduced to 5.2457 o/h, 4.694 o/h, 7.3628 o/h and 14.398 o/h, respectively, and the noise figure is reduced by more than 50% on average. Compared with Table VII, the rolling time domain optimization estimation filtering algorithm is obviously better than the ordinary Kalman filtering.

Table 7. Filtering result with ordinary Kalman filter

| Data group | Noise Figure | Quantization noise /urad | Speed ramp /(^o)/h^2 | Bias instability /(^o)/h | Rate random walk /(^o)/h^1/2 | Angle random walk /(^o)/h^1/2 |
|------------|--------------|--------------------------|----------------------|-------------------------|-----------------------------|-------------------------------|
| 1          | 29.919       | 6.978                    | 5.2457              | 20.812                  | 4.8228                      |
| 2          | 85.026       | 1.2693                   | 4.694               | 6.6307                  | 4.1247                      |
| 3          | 169.43       | 1.9221                   | 7.3628              | 2.0188                  | 3.6626                      |
| 4          | 219.13       | 4.5095                   | 14.398              | 15.971                  | 3.3284                      |

5. Conclusion
This article focuses on how to improve the accuracy of the MEMS gyroscope array. The hardware signal acquisition circuit and software filter program of the MEMS gyroscope array are designed. The FPGA minimum system of EP4CEF15F17C8 is selected as the signal acquisition controller to realize the real-time reading of data from the host (FPGA) to the slave (MEMS gyroscope array). The trend item is extracted by EEMD, and the noise figure of the MEMS gyroscope array is analyzed using the Allan variance method. Based on the time series AR (1) model, the corresponding observation equation and state equation are established. When the time domain length is N=3, the rolling time domain estimation (MHE) algorithm based on Kalman filter is used to filter the MEMS gyroscope array. Allan variance calculation results show that the noise figure has dropped by more than 85% on average, which is significantly improved compared to the common Kalman filtering algorithm.

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