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# Allan variance method for gyro noise analysis using weighted least square algorithm

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ABSTRACT

The Allan variance method is an effective way of analyzing gyro's stochastic noises. In the traditional implementation, the ordinary least square algorithm is utilized to estimate the coefficients of gyro noises. However, the different accuracy of Allan variance values violates the prerequisite of the ordinary least square algorithm. In this study, a weighted least square algorithm is proposed to address this issue. The new algorithm normalizes the accuracy of the Allan variance values by weighting them according to their relative quantitative relationship. As a result, the problem associated with the traditional implementation can be solved. In order to demonstrate the effectiveness of the proposed algorithm, gyro simulations are carried out based on the various stochastic characteristics of SRS2000, VG951 and CRG20, which are three different-grade gyros. Different least square algorithms (traditional and this proposed method) are applied to estimate the coefficients of gyro noises. The estimation results demonstrate that the proposed algorithm outperforms the traditional algorithm, in terms of the accuracy and stability.



## 1. Introduction

The navigation system provides essential information for the vehicle's control system. Inertial navigation system (INS) is one of the most popular navigation systems, which can measure vehicle's position, velocity and attitude without receiving signals from external equipments [1]. Gyros are the critical components of the INS. They can provide angular velocity information for the INS [2].

The navigation accuracy of the INS is greatly affected by gyros' errors. The analysis of gyros' errors has two purposes. One is to evaluate gyros' performances and list them on their specifications. This work is usually done by producers. Another is to provide the reference for the filter parameters setting of the INS-based integrated navigation system. This work is usually done by users. Gyro error falls into two categories: the deterministic errors and the stochastic errors [3,4]. The deterministic errors include bias and scale factor errors, whose models and the parameters are easy to obtain. The stochastic errors contain a variety of complex stochastic noises, which are difficult to model. Several methods including the Allan variance method can be utilized to analyze the stochastic noises [5,6].

The Allan variance method, which is the effective way to analyze stochastic noises, is widely applied in the field of gyro signal analysis, including laser gyros [7], fiber optical gyros (FOGs) [8], and micro electro mechanical systems (MEMS) gyros [9]. The Allan variance method mainly consists of two steps [10]: the first step is to calculate the Allan variance values from the gyro's sample data; the second step is to estimate the gyro's stochastic coefficients by fitting Allan variance values. Both steps affect the coefficients estimation accuracy, and this work focuses on the second step.

At present, the ordinary least square algorithm is usually applied to fit Allan variance values [11], but problem remains. Allan variance values are essentially random variables with different variance. Therefore, the accuracy of each Allan variance value is different from others [12]. The different accuracy violates the prerequisite of the ordinary least square algorithm. As a result, it is not valid to estimate the gyro's stochastic coefficients using the ordinary least square algorithm. Some research work [13,14] tried to remove the Allan variance values which had large estimation errors and used the rest part of the values in the ordinary least square algorithm. However, the solution partly decreased the errors but not completely solved the problem, because the estimation errors of the rest Allan variance estimates were still not in the same level.

In this study, a weighted least square algorithm is proposed to solve the problem. In the new algorithm, the Allan variance values are weighted according to their relative estimation accuracy, so that

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the Allan variance values are normalized and the fitting errors are reduced.

The rest of this paper is organized as follows. In Section 2 we briefly introduce the commonly used gyro's stochastic models and their Allan variances, and then the fitting process of the model coefficients is analyzed using the ordinary least square. In Section 3 the defects of the traditional algorithm are discussed and the new algorithm is described in detail. Simulations are carried out in Section 4, which are based on the noise characteristics of three types of gyros, i.e. SRS2000, VG951 and CRG20. The performances of different least square algorithms are compared.

## 2. Allan variance method and gyro stochastic noises

There are usually several types of stochastic noises in the gyro's signal. Since the Allan variance method can identify different types of noises in the given data set, it is appropriate for the gyro noise study.

### 2.1. Gyros' stochastic noises

The gyro's stochastic error is complex, which is usually described as the combination of several stochastic noises. Quantization noise, angle random walk, bias instability, rate random walk and rate ramp are five common stochastic noises existing in the gyro's output [15]. The sources of the five noises are the electronic components in gyros, which lead to stochastic errors and decrease the gyros' accuracy. The five noises' characteristics, which can be described by their power spectrums, are different from each other. In this paper, the coefficients of the five noises are identified by using the Allan variance method.

### 2.2. Allan variance values

The first step of the Allan variance method is to calculate Allan variance values from the gyro's data. The gyro's sample data series is denoted as $\omega_k$, the sampling frequency is $f$ and the sample size is $N$. The calculation process of Allan variance values is as follows:

(1) $m$ ($m = 1, 2, \ldots, [N/2]$) data points are made as one cluster, so we can get $J = [N/m]$ clusters, where $[x]$ represents the floor of $x$.
(2) To take the average of each cluster as $\bar{\omega}_k(m)$:

$$\bar{\omega}_k(m) = \frac{1}{m}\sum_{i=1}^{m}\omega_{(k-1)\times m+i}, \quad k = 1, 2, \ldots, \left[\frac{N}{2}\right]. \tag{1}$$

(3) $\tau_m = m/f$ is defined as the correlation time of each cluster and the Allan variance is defined as

$$\sigma^2(\tau_m) = \frac{1}{2(J-1)}\sum_{k=1}^{J-1}\left[\bar{\omega}_{(k+1)}(m) - \bar{\omega}_k(m)\right]^2. \tag{2}$$

If the gyro signal is composed of the five noises, i.e. quantization noise, angle random walk, bias instability, rate random walk and rate ramp, whose coefficients are denoted as $Q$, $N$, $B$, $K$ and $R$, its Allan variance can be derived as [16]

$$\sigma^2(\tau_m) = \frac{3Q^2}{\tau_m^2} + \frac{N^2}{\tau_m} + (0.664B)^2 + \frac{K^2\tau_m}{3} + \frac{R^2\tau_m^2}{2}. \tag{3}$$

It can be seen from Eq. (3) that the Allan variance is a function of the correlation time, which can be described by a log–log curve called the Allan variance curve. The properties of different stochastic noises can be reflected in the curve.

### 2.3. Model parameters identification

The purpose of the Allan variance method is to identify the noises' coefficients. In Eq. (3), $\sigma^2$ and $\tau_m$ are known variables and $Q$, $N$, $B$, $K$, $R$ are five unknown coefficients. Intuitively, we may use five Allan variance values, plugging into Eq. (3) to solve these five unknown coefficients algebraically. However, each Allan variance value has the uncertainty (see Section 2.2), which may have negative impact on the solution of the coefficient. To overcome the uncertainty, curve-fitting or regression methods can be utilized here to estimate the coefficient instead of solving it algebraically. Since the Allan variance is a polynomial function of the five unknown coefficients, a polynomial fitting method (the ordinary least square algorithm) can be used to obtain the coefficients [13]. The fitting model can be written as

$$\begin{cases} \sigma_1^2 = 3Q^2\tau_{m1}^{-2} + N^2\tau_{m1}^{-1} + (0.664B)^2 + K^2\tau_{m1}/3 + R^2\tau j_{m1}^2/2 + w_1 \\ {\sigma_2}^2 = 3Q^2\tau_{m2}^{-2} + N^2\tau_{m2}^{-1} + (0.664B)^2 + K^2\tau_{m2}/3 + R^2\tau_{m2}^2/2 + w_2 \\ \vdots \\ {\sigma_i}^2 = 3Q^2\tau_{mi}^{-2} + N^2\tau_{mi}^{-1} + (0.664B)^2 + K^2\tau_{mi}/3 + R^2\tau_{mi}^2/2 + w_i \end{cases}. \tag{4}$$

where $\sigma_i$ is the calculated Allan variance value, $w_i$ is the corresponding estimation error which is assumed as white noise, and $\tau_{mi}$ is the correlation time. Define the system in the matrix form, we can have

$$\boldsymbol{y} = \boldsymbol{X}\beta + \boldsymbol{e}. \tag{5}$$

where

$$\boldsymbol{y} = \begin{bmatrix} \sigma_1^2 \\ \sigma_2^2 \\ \vdots \\ \sigma_i^2 \end{bmatrix}, \quad \boldsymbol{X} = \begin{bmatrix} \tau_{m1}^{-2} & \tau_{m1}^{-1} & 1 & \tau_{m1} & \tau_{m1}^2 \\ \tau_{m2}^{-2} & \tau_{m2}^{-1} & 1 & \tau_{m2} & \tau_{m2}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tau_{mi}^{-2} & \tau_{mi}^{-1} & 1 & \tau_{mi} & \tau_{mi}^2 \end{bmatrix},$$

$$\beta = \begin{bmatrix} 3Q^2 \\ N^2 \\ (0.664B)^2 \\ K^2/3 \\ K^2/2 \end{bmatrix}, \quad \text{and} \quad \boldsymbol{e} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_i \end{bmatrix}. \tag{6}$$

According to the ordinary least square algorithm, the coefficients matrix $\beta$ can be solved as

$$\beta = \left(\boldsymbol{X}^T\boldsymbol{X}\right)^{-1}\boldsymbol{X}^T\boldsymbol{y}. \tag{7}$$

where $\boldsymbol{X}^T$ is the transposed matrix of $\boldsymbol{X}$.

The gyro's performance can be evaluated by its noises' coefficients. In the real-time INS, gyro's main stochastic noises are usually extended to the filter equation as state variables, and then the stochastic noises can be estimated and compensated. The navigation accuracy will be improved accordingly [17].

## 3. Limitations of the ordinary least square algorithm and its solution

From Eq. (2), the Allan variance values are calculated based on finite sample data. The Allan variance accuracy varies with the number of samples (clusters). The different Allan variance accuracy violates the important prerequisite of the same level of accuracy in the ordinary least square algorithm. In this section, the traditional solution is introduced and its defects are analyzed, and then an improved solution is proposed.

### 3.1. The traditional solution and its defects

Since the estimation error of the Allan variance values becomes bigger as the correlation time increases, the most common solution is to use the Allan variance values with short correlation time. The solution removes the samples with large estimation errors and reduces the relative differences between the samples' estimation errors, so the coefficients' identification accuracy improves in some degree. However, this solution has some defects:

(1) Even if the Allan variance values of low estimation accuracy are abandoned, the estimation errors of the rest values are still different, so the problem is not totally solved.
(2) The selection principle of the Allan variance values is usually taken as follows: values whose estimation error exceeds 30% to 40% are not used [13,14]. But this percentage is got empirically, and the effects are different when it is applied to different types of gyros.
(3) According to Eq. (3), the Allan variance values with big errors mainly represent the characteristics of the stochastic noises in long correlation time, which are bias instability, rate random walk and rate ramp. When those three noises possess a large proportion of the gyro signal, the fitting errors of the quantization noise and angle random walk are still big after removing the less reliable samples.

### 3.2. The improved solution

According to the above analysis, the ordinary least square algorithm is not suitable for the Allan variance method. In order to solve the problem, we propose a weighted least square algorithm, in which the Allan variance values are weighted according to their estimation accuracy.

The $1-\sigma$ accuracy of the root Allan variance value for $J$ clusters can be expressed by [12]

$$\%\text{error} = \frac{100}{\sqrt{2(J-1)}} \tag{8}$$

From Eq. (8), the estimation accuracy decreases as the reduction of the cluster's number. Since the Allan variance is the function of $\tau_m$, which is inversely proportional to $J$, it can be concluded that Allan variance estimation error grows as $\tau_m$ increases. In Eq. (4), the variance of $w_i$ varies with $\tau_m$, so we can express $w_i$ as $e(\tau_{mi})$ $w$, where $w$ is the white noise with variance 1 and $e(\tau_{mi})$ is the variance of $w_i$. Then $\sigma_i^2$ can be written as

$$\sigma_i^2 = 3Q^2\tau_{mi}^{-2} + N^2\tau_{mi}^{-1} + (0.664B)^2 + \frac{K^2\tau_{mi}}{3} + \frac{R^2\tau_{mi}^2}{2} + e(\tau_{mi})\cdot w. \tag{9}$$

In order to normalize the estimation error of $\sigma_i^2$, both sides of Eq. (9) are divided by $e(\tau_{mi})$, we can get

$$\frac{\sigma_i^2}{e(\tau_{mi})} = \frac{3Q^2}{\tau_{mi}^2 e(\tau_{mi})} + \frac{N^2}{\tau_{mi} e(\tau_{mi})} + \frac{(0.664B)^2}{e(\tau_{mi})} + \frac{K^2\tau_{mi}}{3e(\tau_{mi})} + \frac{R^2\tau_{mi}^2}{2e(\tau_{mi})} + w. \tag{10}$$

In Eq. (10), all samples' estimation errors have the same variance, which satisfies the prerequisite of the least square algorithm. Eq. (8) presents the relative estimation accuracy of the root Allan variance values under different correlation time. It can be concluded that $e(\tau_{mi})$ is approximately inversely proportional to the number of clusters, so Eq. (10) can be written as

$$\sigma_i^2 J_i = \frac{3Q^2 J_i}{\tau_{mi}^2} + \frac{N^2 J_i}{\tau_{mi}} + (0.664B)^2 J_i + \frac{K^2\tau_{mi}J_i}{3} + \frac{R^2\tau_{mi}^2 J_i}{2} + w. \tag{11}$$

where $J_i$ is the clusters' number corresponding to $\tau_{mi}$. Define the system in matrix form, we can have

$$\boldsymbol{y}' = \boldsymbol{X}'\beta + \boldsymbol{e}'. \tag{12}$$

where $\beta$ is the same as in Eq. (5), and

$$\boldsymbol{y}' = \begin{bmatrix} \sigma_1^2 J_1 \\ \sigma_2^2 J_2 \\ \vdots \\ \sigma_i^2 J_i \end{bmatrix}, \quad \boldsymbol{e}' = \begin{bmatrix} w \\ w \\ \vdots \\ w \end{bmatrix},$$

$$\boldsymbol{X}' = \begin{bmatrix} J_1\tau_{m1}^{-2} & J_1\tau_{m1}^{-1} & J_1 & J_1\tau_{m1} & J_1\tau_{m1}^2 \\ J_2\tau_{m2}^{-2} & J_2\tau_{m2}^{-1} & J_2 & J_2\tau_{m2} & J_2\tau_{m2}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ J_i\tau_{mi}^{-2} & J_i\tau_{mi}^{-1} & J_i & J_i\tau_{mi} & J_i\tau_{mi}^2 \end{bmatrix}. \tag{13}$$

According to the least square algorithm, the coefficients matrix $\beta$ can be solved as

$$\beta = \left(\boldsymbol{X}'^T\boldsymbol{X}'\right)^{-1}\boldsymbol{X}'^T\boldsymbol{y}'. \tag{14}$$

During the above fitting process, the Allan variance values are weighted before being used in the least square algorithm. Therefore, we call the new algorithm as a weighted least square algorithm. The new algorithm satisfies the prerequisites of the least square algorithm, so it has a better performance than the traditional algorithm. Comparing Eq. (14) with Eq. (7), it can be concluded that calculation load of the new algorithm is similar as the traditional one. In fact, since $J$ can be recorded when calculating the Allan variance values, the new algorithm is easy to carry out.

## 4. Simulation and analysis

In order to prove the effectiveness and superiority of the proposed algorithm, outputs of SRS2000, VG951 and CRG20 are simulated, which are three different-grade gyros. SRS2000 and VG951 are two types of fiber optical gyros, and CRG20 is a type of MEMS gyro. Allan variance methods, with traditional and improved least square algorithms, are used to analyze them. The stochastic noises' coefficients, which are identified by different methods, are compared with the setting values, and then conclusions are made. The specific steps are as follows:

(1) The static tests of the three gyros are done, and the collected gyro data are analyzed to get their stochastic noises' coefficients. Fig. 1 shows the gyro data acquisition process. Gyros are fixed on a turntable to keep away from the ground vibration, which influences their accuracy. A data acquisition card (DAQ) is used to collect gyros' outputs, and then data are analyzed by the software in a computer. Fig. 2 is the experimental scenario of SRS2000 static test.
(2) Since the true stochastic noises' coefficients of those gyros are unknown, the effects of different algorithms can't be compared through the experimental data. Therefore, simulations are carried out based on the characteristics of SRS2000, VG951 and CRG20 which were analyzed in step one.

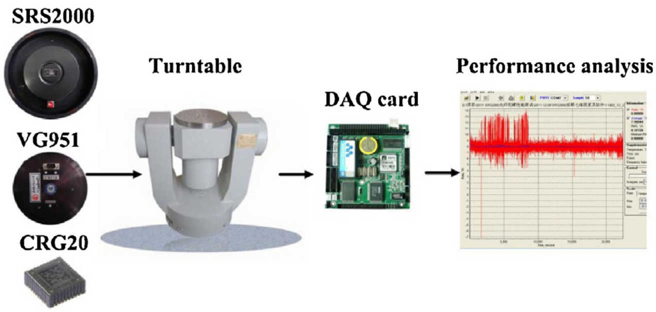


**Fig. 1.** Data acquisition and analysis process for SRS200, VG951 and CRG20.

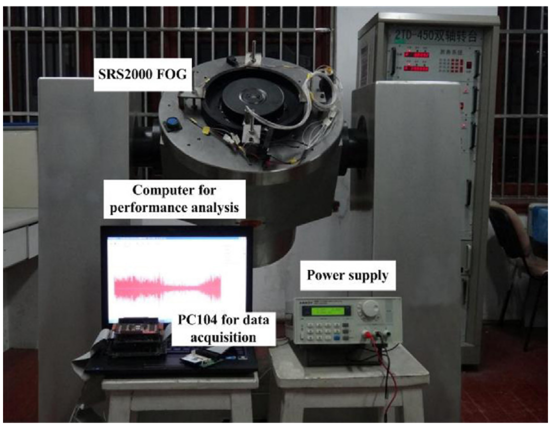


**Fig. 2.** Experimental scenario of SRS2000 static test.

**Table 1**
Random noise parameters of SRS2000.

| Gyro type | Quantization noise (μrad) | Angle random walk (deg/h$^{1/2}$) | Bias instability (deg/h) |
|---|---|---|---|
| SRS2000 | 6.870e – 03 | 8.587e – 05 | 6.773e – 03 |

### 4.1. SRS2000 Allan variance analysis

SRS2000 is a navigation-grade fiber optical gyro, whose stochastic drift is about 0.005 deg/h. The static experimental results are shown in Table 1 and the Allan variance curve is shown as Fig. 3. It can be seen that only quantization noise, angle random walk and bias instability are contained in SRS2000.

Thirty simulation experiments are done under the condition of Table 1. The sample time is set as 0.1 s, and the total time is 4 h. The ordinary least square algorithm (with all Allan variance values), the ordinary least square algorithm (with Allan variance values less than 40% error) and the weighted least square algorithm (with all Allan variance values) are applied to the Allan variance method, respectively, and gyro noises' coefficients are estimated by the three algorithms as shown in Table 2.

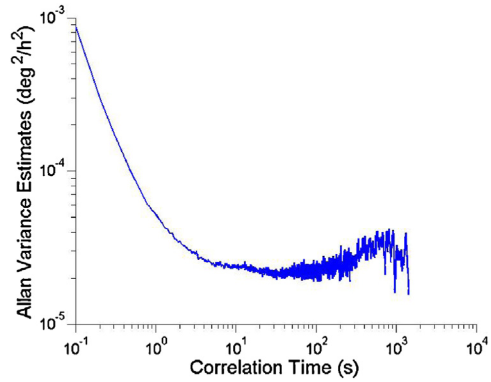


**Fig. 3.** The Allan variance curve of SRS2000.

**Table 3**
Random noise parameters of VG951.

| Gyro type | Quantization noise (μrad) | Angle random walk (deg/h$^{1/2}$) | Bias instability (deg/h) |
|---|---|---|---|
| VG951 | 7.555e – 2 | 7.636e – 3 | 1.246e – 1 |

Table 2 shows that when all Allan variance values are used in the ordinary least square algorithm, the coefficient identification accuracy is low. Improvement is quite noticeable when abandoning values with more than 40% error. In addition, the weighted least square algorithm brings better results than the ordinary least square algorithm. Both accuracy (judged by the estimation error percentage) and stability (judged by the standard deviation) are improved by more than 5 times for quantization noise and angle random walk, and 2 times for bias instability.

### 4.2. VG951 Allan variance analysis

VG951 is a tactical-grade fiber optical gyro, whose stochastic drift is about 0.3 deg/h. Table 3 shows the static experimental results and the Allan variance curve is shown as Fig. 4. Similar with SRS2000, VG951 stochastic noise only contains quantization noise, angle random walk and bias instability. 30 simulation experiments are done under the condition of Table 3, and results are shown in Table 4.

From Table 4, it is clear that accuracy improvement is also obvious when using high accuracy Allan variance values instead of all values in the ordinary least square algorithm. Comparing the new algorithm with the traditional one, accuracy and stability are improved by more than 1.5 times for quantization noise and angle random, and it's almost the same for bias instability.

**Table 2**
Accuracy comparison of different least square algorithms for SRS2000.

| Method | | Quantization noise (μrad) | Angle random walk (deg/h$^{1/2}$) | Bias instability (deg/h) |
|---|---|---|---|---|
| True value | | 6.870e – 03 | 8.587e – 05 | 6.773e – 03 |
| Traditional least square (all data) | Mean value | 8.651e – 03 (25.9%) | – | 9.312e – 03 (37.5%) |
| | Standard deviation | 8.971e – 03 | – | 1.021e – 02 |
| Traditional least square (40% error) | Mean value | 7.249e – 03 (5.5%) | 7.398e – 05 (13.8%) | 7.306e – 03 (7.9%) |
| | Standard deviation | 3.804e – 03 | 7.130 – 05 | 4.984e – 03 |
| Weighted least square | Mean value | 6.920e – 03 (0.7%) | 8.389e – 05 (2.3%) | 7.007e – 03 (3.5%) |
| | Standard deviation | 8.662e – 04 | 1.664e – 05 | 1.783e – 03 |

*Note*: value in brackets represents estimation error percentage. The symbol '–' means that estimation value is negative, which has no physical meaning.

**Table 4**
Accuracy comparison of different least square algorithms for VG951.

| Method | | Quantization noise (μrad) | Angle random walk (deg/h$^{1/2}$) | Bias instability (deg/h) |
|---|---|---|---|---|
| True value | | 7.555e − 2 | 7.636e − 3 | 1.246e − 1 |
| Traditional least square (all data) | Mean value | 1.170e − 1 (54.9%) | 7.450e − 3 (2.4%) | 1.650e − 1 (32.4%) |
| | Standard deviation | 1.123e − 1 | 2.071e − 3 | 1.299e − 1 |
| Traditional least square (40% error) | Mean value | 8.571e − 2 (13.4%) | 7.595e − 3 (0.5%) | 1.358e − 1 (8.9%) |
| | Standard deviation | 6.844e − 2 | 1.261e − 3 | 8.583e − 2 |
| Weighted least square | Mean value | 7.862e − 2 (4.1%) | 7.620e − 3 (0.2%) | 1.346e − 1 (8.0%) |
| | Standard deviation | 4.392e − 2 | 8.279e − 04 | 8.912e − 2 |

**Table 5**
Random noise parameters of CRG20.

| Gyro type | Quantization noise (μrad) | Angle random walk (deg/h$^{1/2}$) | Bias instability (deg/h) |
|---|---|---|---|
| CRG20 | 1.868e + 1 | 1.492 | 2.079e + 1 |

**Table 6**
Accuracy comparison of different least square algorithms for CRG20.

| Method | | Quantization noise (μrad) | Angle random walk (deg/h$^{1/2}$) | Bias instability (deg/h) |
|---|---|---|---|---|
| True value | | 1.868e + 1 | 1.492 | 2.079e + 1 |
| Traditional least square (all data) | Mean value | 2.657e + 1 (42.1%) | 1.449 (2.8%) | 3.016e + 1 (45.1%) |
| | Standard deviation | 2.038e + 1 | 3.755e − 1 | 2.352e + 1 |
| Traditional least square (40% error) | Mean value | 1.915e + 1 (2.5%) | 1.489 (0.2%) | 2.183e + 1 (5.0%) |
| | Standard deviation | 1.081e + 1 | 2.017e − 1 | 1.810e + 1 |
| Weighted least square | Mean value | 1.895e + 1 (1.4%) | 1.490 (0.1%) | 2.077e + 1 (0.1%) |
| | Standard deviation | 9.626 | 1.812e − 1 | 1.306e + 1 |

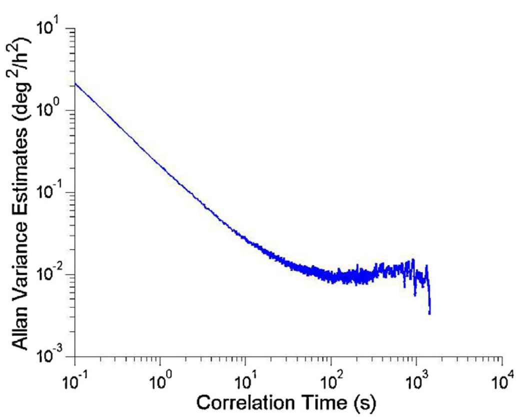


**Fig. 4.** The Allan variance curve of VG951.

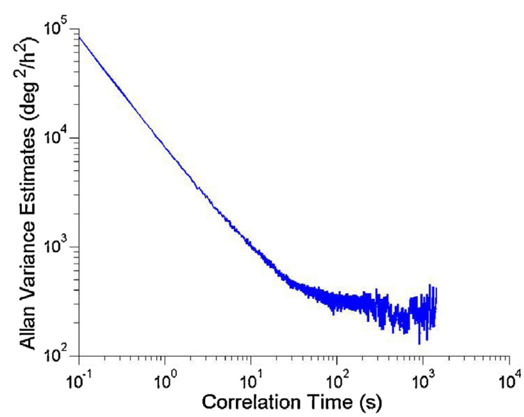


**Fig. 5.** The Allan variance curve of CRG20.

### *4.3. CRG20 Allan variance analysis*

CRG20 is a MEMS gyro, whose stochastic drift is about 10 deg/h. Table 5 shows the static experimental result and the Allan variance curve is shown as Fig. 5. It's clear that only quantization noise, angle random walk and bias instability are contained in CRG20, which is the same with the other two gyros. 30 simulation experiments are done under the condition of Table 5, and results are shown in Table 6.

Same with the above two simulation results, Table 6 shows that estimation accuracy is much better when abandoning Allan variance values with more than 40% error in the ordinary least square algorithm. Comparing the new algorithm with the traditional one, accuracy and stability are improved by about 2 times for quantization noise and angle random, and the accuracy of bias instability is improved by about 50 times.

Simulation results show that both estimation accuracy and stability of stochastic noise coefficients are improved by using the new method.

## 5. Conclusions

A weighted least square algorithm was proposed for the Allan variance method to improve the identification accuracy of gyros' stochastic noises. The weight was set based on the relation of estimation accuracy of all Allan variance values, and the error brought by the fitting process was reduced. Simulations were carried out referred to the characteristics of SRS2000, VG951 and CRG20 three different-grade gyros, and the superiority of the new algorithm was proved. The following conclusions can be drawn:

(1) When the ordinary least square algorithm is applied to the Allan variance method, the estimation error is large if all Allan variance values are used in curve fitting. The accuracy can be improved much by removing the values whose errors are more than 40%.
(2) Both accuracy and stability are improved when the weighted least square algorithm is used. But the extent is different when it's applied to different gyros.

Through the theoretical analysis and simulation, it's clear that the weighted least square algorithm is more suitable to the Allan variance method than the ordinary least square algorithm.

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