

An enhanced random noise suppression method for fiber optic gyroscopes to improve gyrocompass performance

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ABSTRACT

This paper presents a method for reducing random noise and zero-bias instability in the signal of a fiber optic gyroscope, based on a hybrid algorithm that combines an autoregressive mathematical model with an adaptive Kalman filter using a Sage sliding window. The results of the study demonstrate that this approach shortens the gyrocompass initialization time while maintaining the accuracy of defining initial orientation parameters, particularly the initial azimuth angle. Consequently, it enhances the overall performance of the gyrocompass in strapdown inertial navigation systems, especially in scenarios requiring rapid startup.

Keywords: Gyrocompass; Fiber optic gyroscope; Inertial sensor; Strapdown Inertial Navigation System (SINS); Adaptive Kalman filter.

1. INTRODUCTION

In recent years, the Fiber Optic Gyroscope (FOG) has become a core component in modern Strapdown Inertial Navigation Systems (SINS), particularly in gyrocompass applications, due to its high accuracy and stable performance under conditions of strong external disturbances. FOG-based gyrocompasses are widely employed in a range of platforms, including submarines, unmanned aerial vehicles (UAVs), cruise missiles, marine navigation systems, and autonomous vehicles. Despite these advantages, a major limitation of FOG-based systems is the extended initialization time, primarily due to the necessity of filtering random noise (RN) and reducing bias instability (BI) in the FOG signal. During the initial alignment (IA) process, particularly in gyrocompass applications, FOGs are employed to measure the Earth's rotation rate, which is then used to determine the system's azimuth angle [1]. However, the measured signals are inevitably affected by RN and BI, which introduce errors in the computation of the initial azimuth angle. To achieve the required accuracy, the system typically requires a sufficiently long convergence time to average the signals, resulting in an extended startup duration (usually between 8 and 15 minutes). Therefore, effective filtering of RN and reduction of BI are critical factors in minimizing the startup time while maintaining the accuracy of the gyrocompass system.

Over the past decade, numerous methods have been researched and developed to reduce RN and BI in inertial sensors [2], particularly in FOGs. The main approaches include: Adaptive Kalman Filter (AKF) [3]; Statistical models (AR, ARMA, ARIMA, MA) [4]; Machine learning techniques (SVR, Deep Learning) [5]; Sage-Husa Kalman Filter (SHKF) [6]. Despite considerable advancements in noise reduction techniques for FOGs, several challenges remain unresolved. Most existing methods predominantly assume that FOG noise is white noise; however, in practice, the measured signals often exhibit both colored noise and zero-bias drift, which degrade filtering accuracy and lead to significant errors [2-4]. Machine learning approaches such as Support Vector Regression (SVR) demonstrate promising results but suffer from performance degradation under varying real-world conditions, thus limiting their effectiveness in real-time applications [5]. Furthermore, while some studies account for bias drift, they do not assess the accuracy of the filtered and averaged signal, potentially introducing deviations in the estimation of Earth's rotation rate critical for gyrocompass alignment [6]. These limitations highlight the urgent need for a novel

noise reduction approach capable of simultaneously handling both RN and BI in FOG signals. The desired approach should ensure high output accuracy immediately after filtering, thereby improving the practical applicability of the system, particularly for dynamic platforms that require rapid gyrocompass initialization. This paper presents a noise reduction method aimed at minimizing both RN and BI in FOGs, by integrating an Autoregressive (AR) model with an Adaptive Kalman Filter utilizing a Sage sliding window referred to as the Sage Window Adaptive Kalman Filter (SWAKF). The proposed method shortens the gyrocompass initialization time and enhances the accuracy of azimuth angle estimation during the Initial Alignment (IA) phase of the Strapdown Inertial Navigation System (SINS). The subject of this study is the IMU500 inertial measurement unit (IMU) developed by Optolink, which consists of a three-axis FOG - TRS500 and three accelerometers. The proposed solution is implemented in two steps. In the first step, a mathematical model of the FOG's output noise is constructed using an AR model [4]. In the second step, a state-space model and measurement equation are formulated for the SWAKF to simultaneously minimize RN and BI, thereby improving the accuracy of the output signal. To evaluate the effectiveness of the proposed method, the authors conducted a series of experiments using the IMU500 installed on a three-axis turntable. The measured signals were processed using the proposed approach to estimate the azimuth angle. Key performance indicators, including initialization time and azimuth accuracy, were assessed and compared with the reference values provided by the manufacturer.

2. PROBLEM

2.1. Mathematical modeling of FOG output noise

The mathematical model of FOG output noise is constructed using an AR model. The structure and order of the AR model are determined based on the analysis of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) derived from the measured FOG signals. These statistical tools provide insight into the temporal dependencies within the signal, enabling accurate selection of the AR model order. The type and order of the Autoregressive Moving Average (ARMA) model are determined based on the analysis of the ACF and PACF plots, following the criteria outlined in table 1 [7].

Table 1. Criteria for selecting ARMA model based on ACF and PACF plots.

ACF Plot	PACF Plot	Model and order
Gradual decay	Sharp cutoff	AR(p)
Sharp cutoff	Gradual decay	MA(q)
Gradual decay	Gradual decay	ARMA(p,q)

Figure 1 illustrates the ACF and PACF plots of the measured FOG signal from the IMU500 inertial measurement unit. From figure 1, it can be observed that the ACF plot exhibits a sharp cutoff at lag 1 with a negative value for ACF(1), while the PACF plot gradually decays towards zero. Therefore, a first-order Moving Average model (MA(1)) is deemed appropriate for modeling the noise in the FOG signal of the IMU500 unit. The mathematical representation of the MA(1) model is expressed as follows:

$$y_k = \mu_k + \varepsilon_k + \theta_1 \varepsilon_{k-1} \tag{1}$$

where y_k is the measured value from the FOG at time step k , μ_k is a constant proportional to the mean value of the effective signal; ε_k and ε_{k-1} are white noise terms at time steps k , $k-1$, and θ_1 is the coefficient of the MA(1) model.

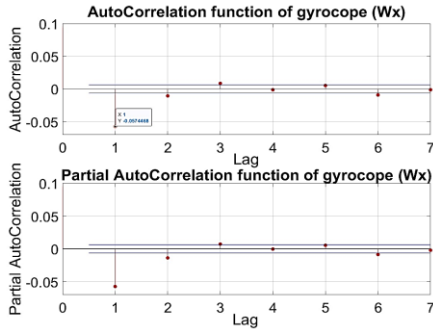


Figure 1. ACF and PACF plots of FOG signal from the IMU500.

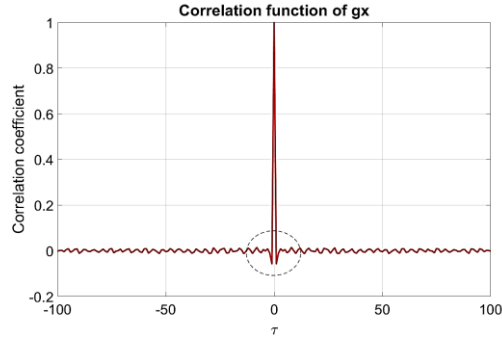


Figure 2. Autocorrelation function plot of the FOG signal along the x-axis in the IMU500.

The autocorrelation function plot of the FOG signal is presented in figure 2. Analysis of figure 2 reveals oscillatory components within the autocorrelation function of the FOG signal. Additionally, equation (1) contains a sum of two white noise terms at time steps k and $k - 1$, indicating the nonlinear nature of the system. To linearize this nonlinear component and enable the application of the Kalman filter, the MA(1) model has been transformed into an infinite-order Autoregressive model, AR(∞). The detailed mathematical derivation of this transformation is provided in reference [8]. The resulting AR(∞) model equation is expressed as follows:

$$y_k = \varphi_1 y_{k-1} + \varphi_2 y_{k-2} + \dots + \varphi_n y_{k-n} + c + \varepsilon_k, \tag{2}$$

where, $\varphi_i = (-1)^{i+1} \theta_1^i, i = 1, 2, \dots, \infty$; $c = \mu(1 - \varphi_1 - \varphi_2 - \dots - \varphi_n)$.

The coefficient θ_1 is determined based on the value r_1 of AFC(1) [8]:

$$r_1 = \frac{\theta_1}{1 + \theta_1^2} \tag{3}$$

Once the value of θ_1 is known, the coefficients $\varphi_i, i = 1, 2, \dots, \infty$. In practice, the order of the AR(∞) model is typically truncated to the fifth order for computational feasibility [7].

2.2. Development of the SWAKF algorithm

Based on equation (2), the state-space model can be formulated, where the state vector is defined as follows: $\mathbf{x}_k = [x_1, x_2, x_3, x_4, x_5, x_6]^T = [y_k, y_{k-1}, y_{k-2}, y_{k-3}, y_{k-4}, c]^T$

The state-space equation is expressed as follows:

$$\mathbf{x}_k = F \mathbf{x}_{k-1} + G \varepsilon_k \tag{4}$$

where

$$\mathbf{x}_{k-1} = [y_{k-1}, y_{k-2}, y_{k-3}, y_{k-4}, y_{k-5}, c]^T$$

$$F = \begin{bmatrix} \varphi_1 & \varphi_2 & \varphi_3 & \varphi_4 & \varphi_5 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$G = \text{diag}([1 \ 0 \ 0 \ 0 \ 0 \ 0])$$

ε_k - White noise.

In this case, the sensor output at time step k is used as the measurement input to the Kalman filter, and the state vector includes the filtered estimates of the measured values as described in (2), along with a constant c . By linearizing the system, this approach employs the Optimal Kalman Filter (OKF). However, unlike existing methods, the measurement equation of the filter accounts

for low-frequency noise components with non-zero mean present in the measurement signal, which are identified using the Sage sliding window technique [9] and subsequently removed during the filter's state update phase. Consequently, the measurement covariance matrix R_k can also be estimated in real-time, enhancing the accuracy of the filter's output parameter estimation. Based on this, the proposed method is referred to as the SWAKF. In the proposed filter, the expected value of the noise in the measurement equation is non-zero; therefore, the measurement equation takes the following form:

$$\mathbf{z}_k = \mathbf{H} * \mathbf{x}_k + v_k \quad (5)$$

where $\mathbf{z}_k = y_k$; $\mathbf{H} = [1 \ 0 \ 0 \ 0 \ 0 \ 0]$;

$$v_k = r_k + w_k \quad (6)$$

where r_k – Zero-bias drift at time step k ; w_k – White noise of the measured signal.

Process covariance matrix: $\mathbf{Q}_{6 \times 6} = \text{diag}([\sigma^2 \ \sigma^2 \ \sigma^2 \ \sigma^2 \ \sigma^2 \ 0])$, where σ – Angle Random Walk (ARW) is determined based on the Allan variance. Measurement covariance matrix $\mathbf{R}_{1 \times 1}$ is updated at each step of the filter. From equations (5) and (6), we obtain:

$$\begin{cases} r_k = M[v_k] = M[\mathbf{z}_k - \mathbf{H}\mathbf{x}_k - w_k] \\ R_k = \text{cov}(w_k, w_k) = M[(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k - r_k)(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k - r_k)^T] \end{cases} \rightarrow \begin{cases} r_k = M[\mathbf{z}_k - \mathbf{H}\mathbf{x}_k], \text{ due to } M[w_k] = 0 \\ R_k = \text{cov}(w_k, w_k) = M[(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k - r_k)(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k - r_k)^T] \end{cases} \quad (7)$$

where $M[\cdot]$ denotes the expectation operator; $\text{cov}(\cdot)$ represents the covariance function.

It should be noted that equation (7) cannot be directly applied in filtering since the true state \mathbf{x}_k is unobservable. Since the bias instability r_k is a form of low-frequency noise, the proposed approach considers a sliding window of N measurement steps, assuming that r_k remains constant or varies insignificantly within the window. Under this assumption, by replacing the true state \mathbf{x}_k with its filtered estimate $\hat{\mathbf{x}}_k$ and applying averaging within each window, the optimal estimate $\hat{\mathbf{r}}_k$ can be obtained, which in turn allows real-time determination of the covariance matrix \hat{R}_k . Consequently, the optimal estimate is given by:

$$\begin{cases} \hat{\mathbf{r}}_k = \frac{1}{N} \sum_{j=1}^N (\mathbf{z}_{k-j} - \mathbf{H}\hat{\mathbf{x}}_{k-j}) \\ \hat{R}_k = \frac{1}{N} \sum_{j=1}^N (\mathbf{z}_{k-j} - \mathbf{H}\hat{\mathbf{x}}_{k-j} - \hat{\mathbf{r}}_k)(\mathbf{z}_{k-j} - \mathbf{H}\hat{\mathbf{x}}_{k-j} - \hat{\mathbf{r}}_k)^T \end{cases} \quad (8)$$

The algorithm flowchart of the SWAKF is illustrated in figure 3. It is important to note that the estimation of $\hat{\mathbf{r}}_k, \hat{R}_k$ begins only after the filter reaches a stable state, which is assumed to occur after N_{start} steps from initialization. In the diagram, N_{window} denotes the size of the Sage sliding window, and N_{start} represents the step index at which the filter is considered stable. In this way, $\hat{\mathbf{r}}_k, \hat{R}_k$ are updated at each filter step, thereby improving the accuracy of the filter's output signal.

3. EXPERIMENTS AND DISCUSSION

3.1. Experimental results evaluating the effectiveness of the proposed method in reducing the output noise of FOG

To verify the effectiveness of the proposed method, the authors conducted a series of experiments using the IMU500 measurement unit mounted on a KPIA-5 turntable, which allows variation of both pitch and azimuth angles (figure 4). Based on the analysis of the graphs in figure 1 and equations (2) and (3), the coefficients of the AR(5) model for the output noise of the FOG

were determined, as shown in table 2. The suitability of the AR model for modeling FOG output noise was validated by: consistency between the statistical characteristics of the simulated and original sensor signals; Allan variance plots; Power spectral density analysis; Autocorrelation functions. Following equations (4) and (5), the state and measurement equations for the SWAKF filter applied to the FOG were then constructed. The effectiveness of the proposed method is evaluated by comparing two key parameters of the FOG output noise before and after filtering: bias instability and white noise intensity. This evaluation is conducted using Allan variance analysis, output signal plots, and statistical result tables. For comparison, the authors applied two filtering approaches to reduce the output noise of the FOG signal: the conventional method using the OKF, and the proposed method using the SWAKF.

Figure 5 illustrates the FOG signals before and after applying different filtering methods, along with the corresponding Allan variance. Based on the Allan variance curves, the characteristics of the output noise components in the FOG signals, both before and after filtering, were identified and are summarized in table 3.

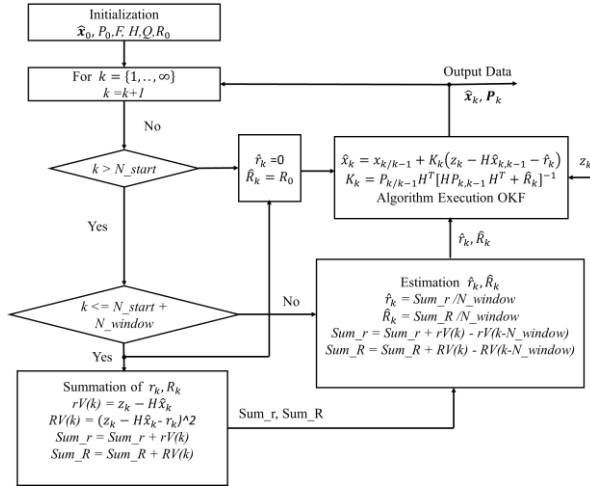


Figure 3. SWAKF algorithm flowchart.

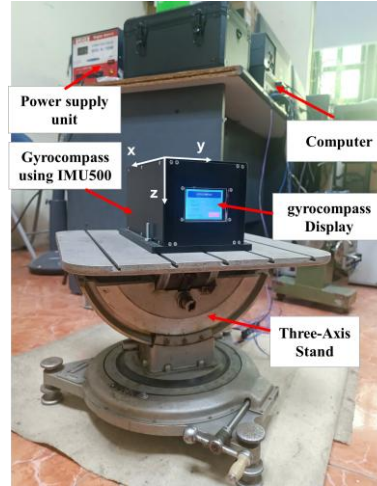


Figure 4. Experimental setup with IMU500 mounted on KITA-5 turntable.

Table 2. Coefficients of the mathematical model for the FOG signal in the IMU500.

Coefficient	φ_1	φ_2	φ_3	φ_4	φ_5
Value	0.0576	-0.0033	0.00019	-0.000011	$6.34 \cdot 10^{-7}$

Table 3. Comparison of allan variance characteristics before and after applying filters.

Method	ARW (Deg/ \sqrt{h})	Bias instability (Deg/h)
Input Signal	0.8523	0.0781
Output signal after OKF	0.0086	0.003
Output signal after SWAKF	0.0048	1.05E-04

The data presented in table 3 demonstrate the effectiveness of the filtering methods in reducing the stochastic noise components in the FOG signal. Specifically, the application of the OKF and the proposed SWAKF resulted in a reduction of Angular Random Walk (ARW) by 98.9% and 99.4%, respectively. Furthermore, the bias instability was reduced by 96.1% using OKF and by 99.8% with the SWAKF method. These results clearly indicate that the SWAKF approach outperforms the conventional OKF in reducing stochastic noise in the FOG signal, especially in the suppression of bias instability, a critical factor affecting the accuracy of azimuth estimation in gyrocompass systems.

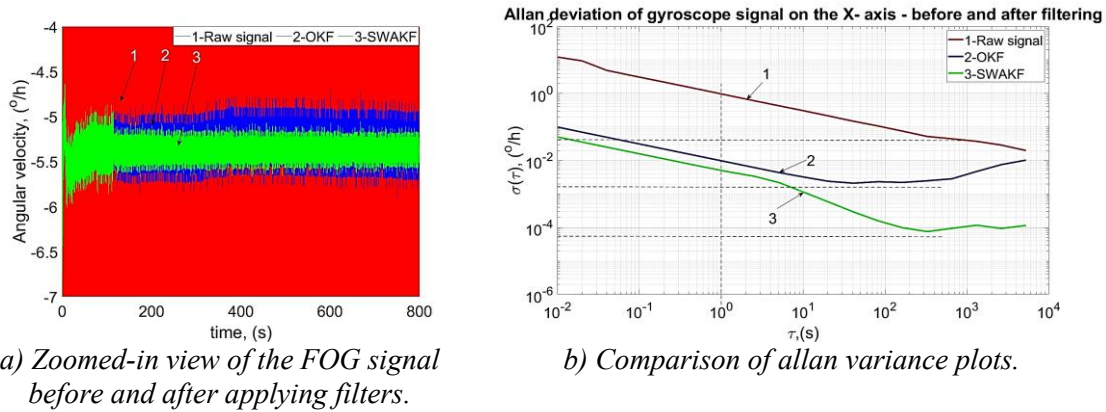


Figure 5. Characteristics of the FOG signal before and after applying filters.

3.2. Experimental results evaluating the effectiveness of the proposed method in reducing initial alignment time in gyrocompass mode

The initial alignment time in gyrocompass mode depends on the bias instability of the FOG. This bias instability varies with the sampling duration used for averaging. The evaluation of bias instability was carried out as follows: Based on a 20-minute data acquisition session (corresponding to the minimum point of the Allan variance curve), 500 separate datasets were generated for each averaging duration of 1, 2, 3, 4, 5, 6, 7, 8, and 9 minutes. The mean value of each dataset was then calculated. By comparing these means to a reference value (defined as the mean of the full 20-minute dataset), the bias instability for each averaging duration was determined. The reference system used to evaluate the effectiveness of the proposed method is the strapdown inertial navigation system SINS500K, developed by Optolink, which incorporates the IMU500 unit. According to the technical specifications provided by the manufacturer, the initialization time of the SINS500K in static mode is 10 minutes [10]. The proposed method is considered effective if it can reduce the required initial alignment time to below 10 minutes while maintaining the required level of bias instability. The relationship between the bias instability of the FOG signal's mean value and the sampling duration is illustrated in figure 6.

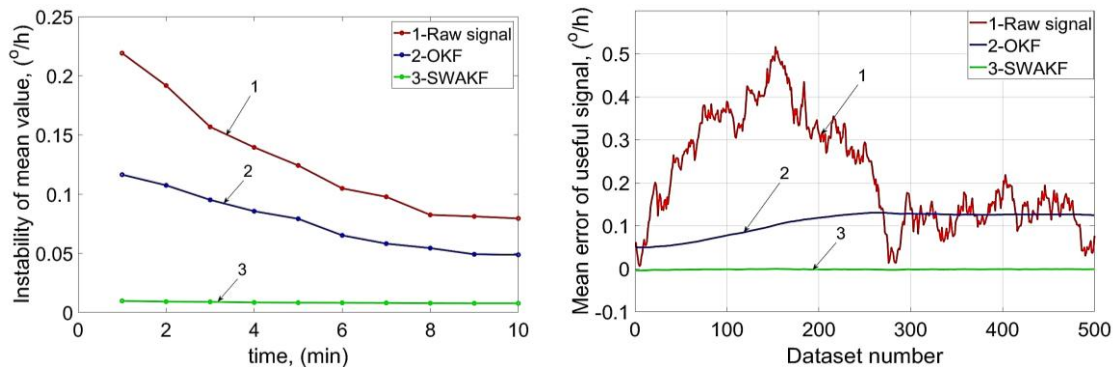


Figure 6. Graph Evaluating the bias instability of the mean FOG signal.

Based on the graphs in figure 6, it is evident that the longer the data collection period for averaging, the lower the bias instability of the mean FOG signal. Specifically, for a 10-minute dataset, the bias instability of the raw FOG data's mean value reaches 0.0795 °/h. To achieve this level of instability, using the OKF method requires only 4 minutes of data collection, while the

proposed SWAKF method requires only 1 minute (excluding the time needed to reach filter convergence). According to the output signal graphs of the filters (figure 5a), the stabilization time for both OKF and SWAKF filters is determined to be 2 minutes. Therefore, the total time required from IMU500 startup until achieving a bias instability of 0.0795 °/h is 3 minutes when using the proposed algorithm. These results demonstrate the effectiveness of the proposed method in significantly reducing random noise.

3.3. Experimental results on azimuth angle determination error of the gyrocompass

In automatic mode, the initial azimuth angle is determined by the following formula [1]:

$$\psi_0 = \text{acos} \frac{W_x - U \sin \theta_0 \sin \varphi}{U \cos \theta_0 \cos \varphi} \tag{9}$$

Where: ψ_0 is the initial azimuth angle, W_x is the FOG signal along the x-axis of the gyrocompass, measuring the projection of Earth's angular velocity, U is the Earth's rotation rate, φ is the latitude at the gyrocompass installation location, θ_0 is the pitch angle determined by the accelerometer in the IMU500. Since there was no reference device available for calibration, the authors used a turntable (figure 4) to evaluate the azimuth angle error of the gyrocompass. First, the turntable was leveled to a horizontal plane with an accuracy of 1 arcminute. The reference azimuth angle was taken from the turntable's angular position. Using the turntable's scale, the table was rotated through 36 positions, each separated by 10°, to complete a full 360° azimuth rotation. Sensor signals from the gyrocompass were collected at each position, and the azimuth angle was calculated using three methods: Averaging the raw sensor signals without any noise filtering; Filtering sensor data with the OKF before calculating the azimuth; Filtering sensor data with the proposed SWAKF before calculating the azimuth. The Earth's rotation rate was 15.0412 °/h, and the test location latitude was 21.0278°, corresponding to the laboratory in the Institute of Missile. After determining the azimuth angles at each position, the angular deviations to the reference position at 0° were compared with the expected reference deviations (i.e., 10°, 20°, ..., 350°) to calculate the azimuth determination error. The error results are illustrated in figure 7.

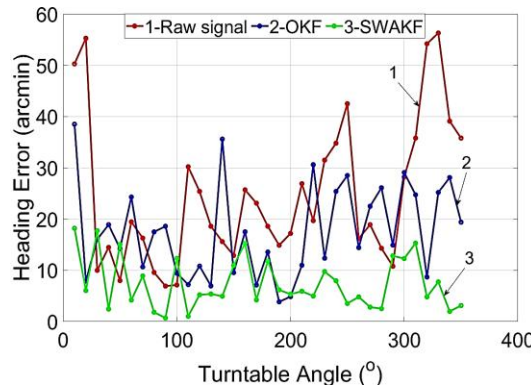


Figure 7. Azimuth determination error before and after applying different filtering.

The results indicate that, when using a 3-minute data collection window after powering on the IMU500, the maximum azimuth angle error reached: 38.6 arcminutes when using the OKF, and 18.2 arcminutes when applying the proposed SWAKF method. These findings demonstrate that the SWAKF significantly improves azimuth determination accuracy compared to the conventional OKF approach. Furthermore, compared to the error obtained using raw FOG data, which resulted in a maximum azimuth error of 56.3 arcminutes, the SWAKF reduced the error to 18.2 arcminutes. This represents a substantial improvement and confirms that the proposed method achieves higher accuracy than the azimuth error specification provided by the manufacturer (heading accuracy = 19.29 arcminutes [10]) for the gyrocompass mode.

4. CONCLUSIONS

Based on the theoretical foundation and the experimental results presented above, it can be concluded that the proposed SWAKF method demonstrates superior performance in random noise reduction compared to traditional approaches. Specifically, through the processing of experimental data from the FOG in the IMU500, the results show that the time required for initial azimuth determination was reduced from 10 minutes (as specified by the manufacturer [10]) to only 3 minutes. These results can be widely applied to improve the performance and accuracy of SINS. In the next phase of research, the authors will continue to investigate the feasibility of gyrocompass initialization in dynamic conditions using FOG.

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REFERENCES

- [1]. В. В. Матвеев, В. Я. Распопов, “Основы построения бесплатформенных инерциальных навигационных систем,” СПб: РИЦ РФ ОАО «Концерн «ЦНИИ «Электроприбор», с. 159-161, (2009).
- [2]. Shipeng Han, Zhen Meng, Olatunji Omisore, Toluwanimi Akinyemi, Yuepeng Yan, “Random Error Reduction Algorithms for MEMS Inertial Sensor Accuracy Improvement,” A Review. *Micromachines*, vol. 11, iss. 11, pp. 1021-1057, (2020). doi: 10.3390/mi11111021.
- [3]. N. T. Yen, A. M. Boronakhin, R. V. Shalymov, D. Y. Larionov, N. Q. Khanh, “Comparison of Adaptive Kalman Filters for Suppressing Random Noise of Optical Gyroscopes in Inertial Navigation,” *IEEE Seminar on Signal Processing*, (2023), doi: 10.1109/IEEECONF60473.2023.10366085, pp. 87-91.
- [4]. Lei Huang., “Auto Regressive Moving Average (ARMA) Modeling Method for Gyro Random Noise Using a Robust Kalman Filter,” *Sensors*, vol. 15, iss. 10, pp. 25277–25286, (2015). doi:10.3390/s151025277.
- [5]. Pengfei Wang, Guangchun Li, Yanbin Gao, “A Compensation Method for Gyroscope Random Drift Based on Unscented Kalman Filter and Support Vector Regression Optimized by Adaptive Beetle Antennae Search Algorithm,” *Applied Intelligence*, vol. 53, pp. 4350–4365, (2022). doi: 10.1007/s10489-022-03734-7.
- [6]. Sun J., Xu X., Liu Y., Zhang T., Li Y., “FOG Random Drift Signal Denoising Based on the Improved AR Model and Modified Sage-Husa Adaptive Kalman Filter,” *Sensors*. Vol. 16, no. 7. pp. 1–19, (2016), doi: 10.3390/s16071073
- [7]. Артамонов Н. В., Ивин Е. А., Курбацкий А. Н., Фантащини Д., “Введение в анализ временных рядов,” учебное пособие для вузов: Московский государственный университет имени М. В. Ломоносова, Московская школа экономики, Кафедра эконометрики и математических методов экономики. – Вологда : ВолНИЦ РАН, с. 18-25, (2021).
- [8]. Robert Nau, “ARIMA models for time series forecasting,” (2022). Available at: <https://people.duke.edu/~rnau/411arim3.htm>.
- [9]. Shesheng Gao, Wenhui Wei, Yongmin Zhong, Subic A., “Sage Windowing and Random Weighting Adaptive Filtering Method for Kinematic Model Error,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 51, no. 2, pp. 1488–1500, (2015). doi: 10.1109/TAES.2015.130656.
- [10]. Научно-производственная Компания "Оптолинк",
“http://www.optolink.ru/en/products/strapdown_inertial_navigation_systems.”

TÓM TẮT

Phương pháp giảm nhiễu ngẫu nhiên con quay sợi quang nâng cao hiệu quả cho gyrocompass

Bài báo này trình bày một phương pháp giảm nhiễu ngẫu nhiên và độ bất ổn định độ trôi điểm 0 trong tín hiệu của con quay sợi quang trên cơ sở thuật toán kết hợp mô hình toán tử hồi quy với bộ lọc Kalman thích nghi và sử dụng cửa sổ trượt Sage. Kết quả của bài báo giúp rút ngắn được thời gian khởi động của gyrocompass mà vẫn bảo đảm độ chính xác của các tham số định hướng ban đầu, đặc biệt là góc phương vị ban đầu. Trên cơ sở đó nâng cao hiệu quả cho gyrocompass trong hệ thống dẫn đường quán tính không đế, đặc biệt trong các trường hợp cần khởi động nhanh.

Từ khoá: Gyrocompass; Con quay sợi quang (Fiber Optic Gyroscope – FOG); Cảm biến quán tính; Hệ thống dẫn đường quán tính không đế; Bộ lọc Kalman thích nghi.