

Abnormal Performance Monitoring Algorithm for Dual Single-Axis RINSs Redundant System in the Reference Information Absence[†]

Yuanhan Wang^{1,2} , Zhonghong Liang^{1,2}, Pengcheng Mu^{1,2}, Ming Tian^{1,2}, Zhikun Liao^{1,2,*}  and Lin Wang^{1,2,*} 

¹ College of Advanced Interdisciplinary Studies, National University of Defense Technology, Changsha 410073, China; wyuanhan@nudt.edu.cn (Y.W.); liangzhonghong@nudt.edu.cn (Z.L.); mupengcheng@nudt.edu.cn (P.M.); tianming13@nudt.edu.cn (M.T.)

² Nanhu Laser Laboratory, National University of Defense Technology, Changsha 410073, China;

* Correspondence: liaozhikun12@nudt.edu.cn (Z.L.); wanglin11@nudt.edu.cn (L.W.)

[†] Presented at the European Navigation Conference 2025 (ENC 2025), Wrocław, Poland, 21–23 May 2025.

Abstract

Rotational inertial navigation systems (RINSs) are often employed in long-endurance navigation due to their high-precision characteristics. A redundant configuration is often adopted in practice to cope with potential faults. To effectively monitor the dual single-axis RINSs redundant system, this paper proposes a novel real-time fault monitoring algorithm that integrates adaptive filtering with parameter estimation. The adaptive fault monitoring filter based on the state transformation error model with attitude observations increases the sensitivity of the filter to potential faults. Based on analysis of the filter estimation, a robust fault diagnosis criterion is proposed. Furthermore, the drift variation fitting mechanism is further proposed to address the challenge in monitoring faults of azimuth gyros. Experiments conclusively demonstrate the proficiency of the proposed method in achieving precise and swift fault monitoring.

Keywords: redundant configuration; rotational inertial navigation system; reference absence; abnormal monitoring

1. Introduction

The inertial navigation system (INS) is highly autonomous and can provide comprehensive real-time navigation information [1]. Robust anti-jamming capability and exceptional concealment performance collectively ensure its adaptability to complex operational mission requirements. However, the integration-based operational principle causes system errors to accumulate over time. To mitigate the effects of the constant and slow changing drifts, and further improve navigation accuracy, the rotational inertial navigation system (RINS) has been developed by rotating a strap-down INS around one or more axes periodically and demonstrates wide applications, particularly in marine navigation [2].

Conventionally, INS is often combined with other navigation methods, such as GNSS, in practical applications [3]. In recent years, driven by the demand for navigation system reliability, multi-INS configurations have gradually become a prominent research focus [4]. These configurations, when combined with information fusion techniques, enable significant improvements in positioning [5] and attitude estimation accuracy [6]. Furthermore, the integration of multi-INSs with other navigation sensors is documented in [7,8]. Here, we do not go deeper, as these are not the main focus of this paper. It should be emphasized



Academic Editor: Tomasz Hadaś

Published: 25 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

that this paradigm shift can achieve fault tolerance and continuous operation during GNSS outages or single-system degradation scenarios.

Several studies have been conducted on the abnormal performance monitoring of redundant INSs. Li et al. introduced an adaptive low-pass filter into the general likelihood ratio test to reduce the disturbance of sensor noises on fault detection and addressed the challenge of detecting low-amplitude faults in redundant inertial measurement units [9]. Dai et al. proposed a sequential weighted generalized likelihood ratio test method based on the principal component parity vector, effectively improving the sensitivity of fault detection while reducing the false alarm rate [10]. Eslam et al. proposed a bank of auxiliary Kalman filters and an optimal dual-objective function combined with the differential evolution algorithm to achieve a comprehensive fault diagnosis [11]. Nevertheless, these abnormal performance monitoring methods are applied in scenarios characterized by sufficient redundancy, entailing the installation of three or more sets of INSs. Actually, when there are only two INSs, the complexity and challenge of abnormal performance monitoring increase significantly due to the lack of additional redundancy. There is also a dearth of relevant research. Wu et al. proposed an online monitoring method of inertial sensor biases for fault detection in redundant single-axis RINSs [12]. However, it requires the rotational axis to be orthogonal. For the fault diagnosis of two single-axis RINSs in homogeneous configurations, we previously conducted a preliminary study [13]. However, the results suffer from the problem of time-consuming azimuth gyro fault diagnosis.

This paper presents a novel abnormal performance monitoring algorithm to improve the rapidity of fault diagnosis. The algorithm introduces the state transformation error model and attitude observation to construct a residual-normalized strong tracking filter as a monitoring filter. Then, a statistical method is employed to evaluate filter estimations with robust threshold-based diagnosis criteria. Furthermore, the challenging issue of fault localization for azimuth gyros is addressed by the drift variation fitting mechanism.

2. Problem Definition and Model Establishment

2.1. Problem Definition

The research on the abnormal performance monitoring of inertial sensors is carried out through two homogeneous single-axis RINSs, i.e., RINS 1 and RINS 2, and the redundant configuration is presented in Figure 1. Each RINS mainly includes an inertial measurement unit (IMU) and a single-axis turntable. The IMU mainly composed of three ring laser gyros (x -gyro, y -gyro, and z -gyro) and three quartz accelerometers (x -acc, y -acc, and z -acc) is installed on the turntable, which could be forced to rotate along its azimuth axis using a four-position rotation scheme under motor control [14].

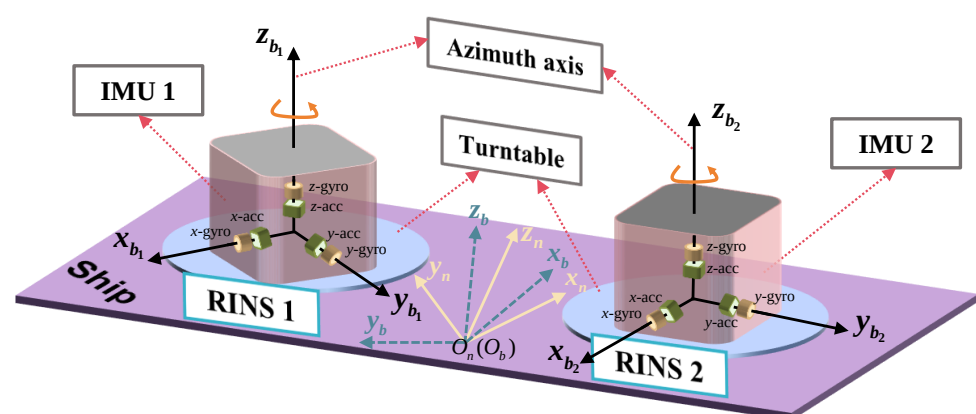


Figure 1. Dual single-axis RINS redundant configuration.

The coordinate frames are also involved in Figure 1. The navigation frame (n -frame) is selected as an east–north–upward (ENU) coordinate system, defined by x_n, y_n, z_n . The body frame (b -frame) of the ship is defined by x_b, y_b, z_b with the directions pointing to right, forward, and up, respectively. The b_m -frame serves as the sensor frame of IMU m ($m = 1, 2$), defined by $x_{b_m}, y_{b_m}, z_{b_m}$, and the directions of these axes are coincident with the sensitive axes of respective inertial sensors.

The faults studied are artificially introduced into the raw data, categorized into intermittent and persistent faults, which are modeled as follows:

$$\theta(k) = \begin{cases} \theta(k-1) + \Delta_\theta \delta(k-\tau) & \text{Persistent fault} \\ \theta(k-1) + \Delta_\theta \delta(k-\tau) - \Delta_\theta \delta(k-\tau-\tau^*) & \text{Intermittent fault} \end{cases} \quad (1)$$

where $\delta(k)$ is a Dirac function, and Δ_θ , also known as fault value, is a pre-determined constant in the experiment. On this basis, Equation (1) describes two types of faults: a persistent fault with a starting time at τ and an amplitude of Δ_θ , and an intermittent fault with an amplitude of Δ_θ occurring from τ to $\tau + \tau^* - 1$.

2.2. Joint Error State Model Based on State Transformation

The state transformation error model is adopted to describe the error propagation characteristics [15]. Based on this, the joint error state equations with the difference of attitude error, velocity error, and position error between two RINSs as the joint error states can be obtained as follows:

$$\dot{\boldsymbol{\phi}}_{12}^n = \boldsymbol{\phi}_{12}^n \times \boldsymbol{\omega}_{in}^n + \delta \boldsymbol{\omega}_{in12}^n - \mathbf{C}_b^n \mathbf{C}_{b_1}^b \delta \boldsymbol{\omega}_{ib_1}^{b_1} + \mathbf{C}_b^n \mathbf{C}_{b_2}^b \delta \boldsymbol{\omega}_{ib_2}^{b_2} \quad (2)$$

$$\begin{aligned} \delta \dot{\mathbf{v}}_{\phi_{12}}^n = & -[\mathbf{g}^n + (\mathbf{v}^n \times \boldsymbol{\omega}_{ie}^n)] \times \boldsymbol{\phi}_{12}^n - (2\boldsymbol{\omega}_{ie}^n + \boldsymbol{\omega}_{en}^n) \times \delta \mathbf{v}_{\phi_{12}}^n + \mathbf{C}_{b_1}^n \delta \mathbf{f}^{b_1} - \mathbf{C}_{b_2}^n \delta \mathbf{f}^{b_2} \\ & + (\tilde{\mathbf{v}}_1^n \times) \mathbf{C}_{b_1}^n \delta \boldsymbol{\omega}_{ib_1}^{b_1} - (\tilde{\mathbf{v}}_2^n \times) \mathbf{C}_{b_2}^n \delta \boldsymbol{\omega}_{ib_2}^{b_2} + \mathbf{v}^n \times \delta \boldsymbol{\omega}_{ie12}^n \end{aligned} \quad (3)$$

$$\delta \dot{\mathbf{p}}_{12}^n = \mathbf{F}_{pv}(\mathbf{v}^n \times) \boldsymbol{\phi}_{12}^n + \mathbf{F}_{pv} \delta \mathbf{v}_{\phi_{12}}^n + \mathbf{F}_{pp} \delta \mathbf{p}_{12}^n \quad (4)$$

with

$$\mathbf{F}_{pp} = \begin{bmatrix} 0 & 0 & -\frac{v_N}{(R_N+h)^2} \\ \frac{v_E \tan L}{(R_E+h) \cos L} & 0 & -\frac{v_E}{(R_E+h)^2 \cos L} \\ 0 & 0 & 0 \end{bmatrix}, \mathbf{F}_{pv} = \begin{bmatrix} 0 & \frac{1}{R_N+h} & 0 \\ \frac{\sec L}{R_E+h} & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

where the subscript ' $(\cdot)_{12}$ ' indicates the difference between the error states of RINS 1 and RINS 2; $\boldsymbol{\phi}_{12}^n = [\phi_{E12}^n \ \phi_{N12}^n \ \phi_{U12}^n]^T$ and $\delta \mathbf{v}_{\phi_{12}}^n = [\delta v_{\phi_{E12}}^n \ \delta v_{\phi_{N12}}^n \ \delta v_{\phi_{U12}}^n]^T$ represent the difference of attitude and rigorous velocity errors; $\boldsymbol{\omega}_{in}^n$ denotes the angular rate of the n -frame relative to the inertial frame (i -frame); $\delta \boldsymbol{\omega}_{in12}^n$ denotes the difference of the navigation frame angular rate errors; $\delta \boldsymbol{\omega}_{ib_m}^{b_m} = \boldsymbol{\varepsilon}^{b_m} + \mathbf{w}_{\varepsilon^{b_m}}$ denotes the gyro triad error vector modeled as the sum of constant drift $\boldsymbol{\varepsilon}^{b_m} = [\varepsilon_{x_m} \ \varepsilon_{y_m} \ \varepsilon_{z_m}]^T$ and gyro noise $\mathbf{w}_{\varepsilon^{b_m}}$; $\mathbf{v}^n$ is the true velocity; $\boldsymbol{\omega}_{ie}^n$ is the earth rotation rate in the n -frame; $\boldsymbol{\omega}_{en}^n$ is the transport rate of the n -frame relative to the earth frame (e -frame); $\delta \mathbf{f}^{b_m} = \nabla^{b_m} + \mathbf{w}_{\nabla^{b_m}}$ is the accelerometer triad error vector modeled as the sum of constant bias $\nabla^{b_m} = [\nabla_{x_m} \ \nabla_{y_m} \ \nabla_{z_m}]^T$ and process noise $\mathbf{w}_{\nabla^{b_m}}$; $\delta \boldsymbol{\omega}_{ie12}^n$ denotes the difference of the earth rotation rate errors; the subscripts ' E ', ' N ', and ' U ' refer to the component of a vector along each axis of the n -frame; ' x ', ' y ', and ' z ' represent the component of a vector along each axis of the b -frame; and $\delta \mathbf{p}_{12}^n = [\delta L_{12} \ \delta \lambda_{12} \ \delta h_{12}]^T$ represents the difference of the latitude, longitude and height errors. Furthermore, the differential equations for gyro drifts and accelerometer bias are as follows:

$$\dot{\boldsymbol{\varepsilon}}^{b_1} = \mathbf{0}, \dot{\boldsymbol{\varepsilon}}^{b_2} = \mathbf{0}, \dot{\nabla}^{b_1} = \mathbf{0}, \dot{\nabla}^{b_2} = \mathbf{0} \quad (5)$$

The azimuth axes of the two RINSs coincide in the n -frame and exhibit no relative attitude changes, leading to the non-separable estimation of azimuth gyros drifts. Therefore, the joint error state is denoted as

$$\mathbf{X} = [\phi_{E12}^n \quad \phi_{N12}^n \quad \phi_{U12}^n \quad \delta v_{\phi_{E12}}^n \quad \delta v_{\phi_{N12}}^n \quad \delta L_{12} \quad \delta \lambda_{12} \quad \varepsilon_{x1} \quad \varepsilon_{y1} \quad \varepsilon_{x2} \quad \varepsilon_{y2} \quad \varepsilon_{z1} - \varepsilon_{z2} \quad \nabla_{x1} \quad \nabla_{y1} \quad \nabla_{x2} \quad \nabla_{y2}]^T \quad (6)$$

Considering a fixed relative geometric relationship between two RINSs, attitude error differences, velocity error differences, and position error differences are chosen as observations as described in Equation (7):

$$\mathbf{Z} = [\phi_{E12}^n \quad \phi_{N12}^n \quad \phi_{U12}^n \quad \delta v_{E12}^n \quad \delta v_{N12}^n \quad \delta L_{12} \quad \delta \lambda_{12}]^T \quad (7)$$

3. Abnormal Performance Monitoring Algorithm

3.1. Residual-Normalized Strong Tracking Filter for Performance Monitoring

The strong tracking filter (STF) with exceptional ability to track both states and parameters exhibits high compatibility and effectiveness in model-based fault monitoring methods. The fault information contained in its innovation is important for state estimation and fault monitoring. However, the attitude, velocity, and position outputs differ by orders of magnitude, further leading to differences in their innovation by orders of magnitude in a steady state. This information asymmetry caused by numerical differences in the innovation can affect the speed and accuracy of fault monitoring [16]. Therefore, a residual-normalized strong tracking filter is employed as the monitoring filter unit in the proposed method, and its specific principle is elaborated as follows:

$$\mathbf{P}_{k/k-1} = \lambda_k \Phi_{k/k-1} \mathbf{P}_{k-1} \Phi_{k/k-1}^T + \Gamma_{k-1} \mathbf{Q}_{k-1} \Gamma_{k-1}^T \quad (8)$$

with

$$\lambda_k = \max\left(\frac{\text{Tr}(\mathbf{N}_k)}{\text{Tr}(\mathbf{M}_k)}, 1\right), \quad \mathbf{N}_k = \hat{\mathbf{C}}_k - \mathbf{H}_k \mathbf{Q}_{k-1} \mathbf{H}_k^T - l_k \mathbf{R}_k, \quad \mathbf{M}_k = \mathbf{H}_k \Phi_{k/k-1} \mathbf{P}_{k-1} \Phi_{k/k-1}^T \mathbf{H}_k^T$$

$$\hat{\mathbf{C}}_k = \begin{cases} \eta^{-1} \tilde{\mathbf{Z}}_{k/k-1} \cdot (\eta^{-1} \tilde{\mathbf{Z}}_{k/k-1})^T, & k = 0; \\ \frac{\rho \hat{\mathbf{C}}_{k-1} + \eta^{-1} \tilde{\mathbf{Z}}_{k/k-1} \cdot (\eta^{-1} \tilde{\mathbf{Z}}_{k/k-1})^T}{1 + \rho}, & \text{else} \end{cases}$$

where λ_k is the suboptimal fading factor introduced in the computation formula of one-step prediction error covariance $\mathbf{P}_{k/k-1}$, $\mathbf{Q}_k$ is the covariance matrix of the process noise $\mathbf{w}_k$, $\mathbf{R}_k$ is the covariance matrix of the observation noise $\mathbf{v}_k$, $\tilde{\mathbf{Z}}_{k/k-1}$ is innovation, $\hat{\mathbf{C}}_k$ denotes the innovation covariance, $\mathbf{P}_k$ denotes the error covariance, the value range of attenuating factor ρ is usually $0.95 \leq \rho \leq 0.995$, $l_k (l_k \geq 1)$ is a weakening factor, generally selected based on experience, and the diagonal matrix η can be predetermined based on prior knowledge about the system output. More formally, a set of system output values $z_{01}, z_{02}, \dots, z_{0m}$ is acquired by leveraging prior knowledge. Then, each normalized parameter η_i in the matrix η can be calculated according to Equation (9):

$$\eta_i = z_{0i} \sqrt{\frac{m}{z_{01}^2 + \dots + z_{0m}^2}} \quad i = 1, 2, \dots, m \quad (9)$$

where m equals the dimension of the observation vector $\mathbf{Z}$.

3.2. Monitoring Criteria Based on Statistical Method

Considering the fact that sensor faults can be reflected in the corresponding biases, a strategy that applies the modified Bayesian (MB) algorithm [17] in parallel to evaluate

the individual parameters of the monitoring filter outputs is adopted to achieve precise fault localization. For the i -th component $\hat{X}_k(i)$ (where $i = 8, 9, \dots, 16$) of the filter outputs, which represents either an estimation of gyro drift or accelerometer bias, the process using the MB algorithm to analyze the variance of its estimations can be determined by Equations (10)–(13):

$$\mu_k(i) = \frac{1}{N} \sum_{j=1}^N \hat{X}_{k-j}(i) \quad (10)$$

$$\sigma_{k_I}^2(i) = \frac{1}{N-1} \sum_{j=1}^N [\hat{X}_{k-j}(i) - \mu_{X^0}(i)]^2 \quad (11)$$

$$\sigma_{k_{II}}^2(i) = \frac{1}{N-1} \sum_{j=1}^N [\hat{X}_{k-j}(i) - \mu_k(i)]^2 \quad (12)$$

$$d_k(i) = \frac{\sigma_{k_I}^2(i)}{\sigma_{X^0}^2(i)} - \ln \frac{\sigma_{k_{II}}^2(i)}{\sigma_{X^0}^2(i)} - 1 \quad (13)$$

where N is the length of the preselected data window, $\mu_{X^0}(i)$ and $\sigma_{X^0}^2(i)$ denote the mean and variance of the i -th component in the fault-free case, respectively, d_k represents a set of calculated parameters used to locate faults.

Given the extremely low probability of multiple sensor malfunctions occurring simultaneously during actual operation, the robustness monitoring criterion based on the fault of up to one sensor is shown as Table 1, where M is the duration of a fault confirmation stage used to reduce the false alarm rate, β is a predefined set of thresholds determined by system performance.

Table 1. Robustness monitoring criterion.

Input:	calculated parameters d_k
Step 1:	If $d_k(i) > \beta(i) \quad \forall k \in \{\hat{\tau} - M + 1, \hat{\tau} - M + 2, \dots, \hat{\tau}\}$ Turn to Step 2 else Output: There is no fault.
Step 2:	$\bar{i} = \arg \max_{8 \leq i \leq 16} \left(\sum_{k=\hat{\tau}-M+1}^{\hat{\tau}} d_k(i) \right)$ Output: Sensor $\bar{i}$ fails at time $\hat{\tau}$.

3.3. Abnormal Performance Monitoring for Azimuth Gyros

The aforementioned approach heavily relies on the constructed filter, which is inherently limited to estimating the difference between azimuth gyro drifts. Consequently, when an azimuth gyro fails, it becomes challenging to pinpoint the exact location of the fault. To address this intricate issue, a novel method for estimating azimuth gyro drift variations is introduced, in case systems are damped by the log. When analyzing navigation information within a few hours, the effects caused by Foucault oscillation and 24 h oscillation can be reasonably overlooked, and the errors in the east, north, and vertical channels can be analyzed independently [18]. Assuming that the variation of azimuth gyro drift at time τ is ε_Δ , this drift variation is eventually reflected in the forced solution of $\Delta v_N(t)$:

$$\Delta v_N(t) = R \varepsilon_\Delta \omega_{ie} \cos L \left(t - \tau - \frac{1}{\omega_s} \sin \omega_s(t - \tau) \right) \quad (14)$$

where $\omega_s = \sqrt{g/R}$ represents the Schuler frequency, R is the radius of the earth, and g is the gravity value.

The marine RINS is usually damped by the ship-equipped log to suppress Schuler oscillation, enabling the precise fitting and identification of fault-induced Schuler oscillation parameters through the least squares method as shown in Equation (15). At this point, fault diagnosis can be achieved by comparing the fitted values of the two systems, respectively:

$$\hat{\varepsilon}_{\Delta} = \arg \min_{\varepsilon_{\Delta}} \|A\varepsilon_{\Delta} - \mathbf{y}\|_2^2 \quad (15)$$

with

$$\begin{aligned} \mathbf{A} &= [A_1 \ A_2 \ \dots \ A_j \ \dots \ A_n]^T \\ A_j &= R\omega_{ie} \cos L \left(j\Delta t - \frac{1}{\omega_s} \sin \omega_s(j\Delta t) \right) \\ \mathbf{y} &= [\Delta v_N(\tau + \Delta t) \ \Delta v_N(\tau + 2\Delta t) \ \dots \ v_N(\tau + n\Delta t)]^T \end{aligned}$$

where $j = 1, 2, \dots, n$, n is the total number of data used, and Δt is the time interval. Significantly greater fitting value indicates that the system fails.

4. Monitoring Assessment

Experiments were conducted with two single-axis RINSs under a stationary base. Each IMU mainly consists of three ring laser gyros and three quartz accelerometers, and the specifications are listed in Table 2. Based on the reset period in long-endurance marine navigation, a thorough analysis of the navigation process spanning a total of 24 h is conducted. The raw RINS data are collected off-line at the frequency of 100 Hz for analysis.

Table 2. Inertial sensor parameters.

Characteristics	Values
Sampling frequency	100 Hz
Gyro drift stability	<0.003 °/h
Gyro angular random walk	<0.001 °/√h
Accelerometer bias stability	<20 µg
Power spectral density of accelerometer noise	<20 µg/√Hz
Error of optical encoder	3''

To analyze the impact of adding attitude observations on fault monitoring, we consider a scenario where the azimuth gyro of RINS 1 malfunctions. Figure 2 provides a comparative analysis of the estimation curves of the difference between azimuth gyro drifts generated by the filter under two distinct observation conditions: velocity and position observations (VPs), and additionally, attitude, velocity and position observations (AVPs). When a persistent fault with $\Delta_{\theta} = 0.05$ °/h occurs in the azimuth gyro at the $\tau = 8$ h, the comparative results presented in Figure 2a reveal that both the AVP and VP observation-based estimations eventually converge to a value close to the preset fault value. However, it is evident that the convergence speed is notably slower for a filter with VP observations. When intermittent faults respectively occur at $\tau_1 = 8$ h, $\tau_2 = 12$ h, $\tau_3 = 16$ h with durations of $\tau_1^* = 0.35$ h, $\tau_2^* = 0.7$ h, and $\tau_3^* = 1$ h, and consistent fault values of $\Delta_{\theta} = 0.1$ °/h, Figure 2b shows that the outputs of the filter under VP observations deviate significantly from the actual fault condition due to the inherent limitation of its convergence speed. In contrast, when AVP observations are employed, the filter outputs remain consistent with the actual fault conditions and exhibit excellent performance.

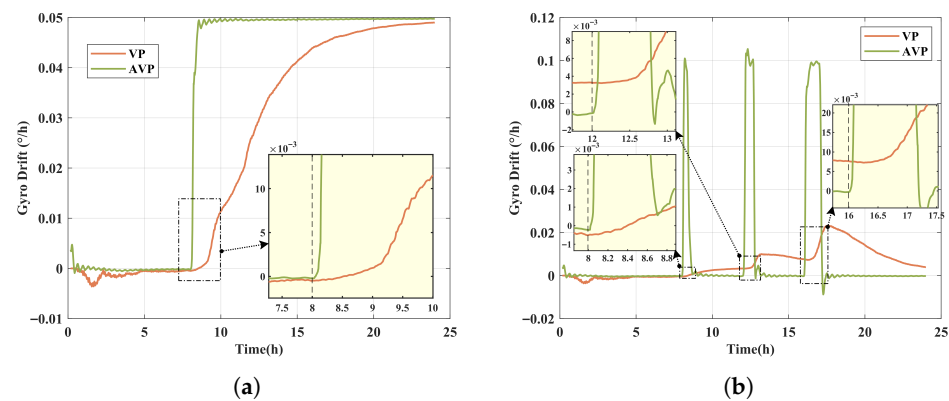


Figure 2. Comparison of monitoring filter outputs under different observations. (a) Persistent fault. (b) Intermittent fault.

Considering the scenario where only one sensor fails, both intermittent and persistent faults are designed to occur on a certain inertial sensor. Given the similarity in the analytical processes for RINS1 and RINS2, we shall solely focus on the scenario where a fault occurs in RINS1. Firstly, under the scenario of gyro faults, the testing scheme is designed as follows: intermittent faults with consistent fault values of $\Delta_\theta = 0.1^\circ/\text{h}$ are applied independently to the x -gyro, y -gyro, and z -gyro during the 8th to 9th hour of navigation, and starting from the 14th hour, persistent faults with the same value as the previous faults are subsequently injected into these gyros. Figure 3 comprehensively shows the filter estimation results and final monitoring results. Based on the filter estimation results, a set of parameters are calculated through the MB algorithm and evaluated by robustness monitoring criteria. According to the established monitoring criterion, the monitoring results are recorded in real time, where ‘1’ indicates that the corresponding sensor has a fault, and ‘0’ indicates that there is no fault. Specifically, Figure 3a,b illustrate the results where horizontal gyro faults occur, while Figure 3c presents the results pertaining to azimuth gyro faults. The time marked by the black dashed line in figures represents the moment when the actual fault occurred or disappeared. As illustrated diagrammatically in Figure 3, all faults have been diagnosed quickly and accurately. It is noteworthy that the distinction of azimuth gyro faults in the monitoring results is insufficient, making it difficult to distinguish whether the fault occurred in the azimuth gyro of RINS 1 or RINS 2. Hence, upon detecting the azimuth gyro fault, further analysis of the north velocity from the two RINS is conducted. For the preset fault scenarios and specific fault types, Table 3 records the starting time of the further step $\hat{\tau}$, along with the fitting values for the azimuth gyro drift variations of two RINSs after the fitting step. The fitting result for azimuth gyro drift of the faulty sensor is significantly greater than that of the non-faulty sensor, enabling the realization of fault monitoring for azimuth gyros.

Table 3. Fitting results of azimuth gyro faults.

	$\hat{\tau}$ (h)	ε_{z_1} ($^\circ/\text{h}$)	ε_{z_2} ($^\circ/\text{h}$)
Intermittent fault	8.15	0.0846	0.0059
Persistent fault	14.16	0.0938	0.0063

Similarly, in the scenario of accelerometer faults, two types of faults are also assumed to occur successively on a single inertial sensor, specifically, intermittent faults occurring between the 8th and 9th hour with a fault value of $\Delta_\theta = 500 \mu\text{g}$ and persistent faults starting from the 16th hour with a fault value of $\Delta_\theta = 500 \mu\text{g}$ as well. Figure 4 exhibits the

filter outputs and visualized results of fault diagnosis during various accelerometer faults. The monitoring results depicted in each subplot conclusively demonstrate that both types of faults can be rapidly and accurately diagnosed, and the system is capable of promptly responding as it transitions from a faulty state back to a fault-free condition.

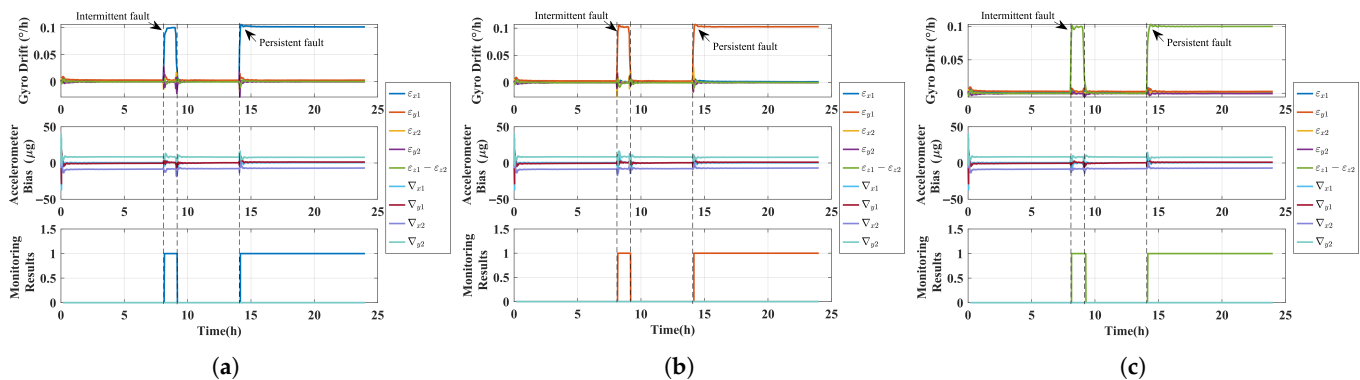


Figure 3. Experiment results in case of gyro faults. (a) x -gyro of RINS 1. (b) y -gyro of RINS 1. (c) z -gyro of RINS 1.

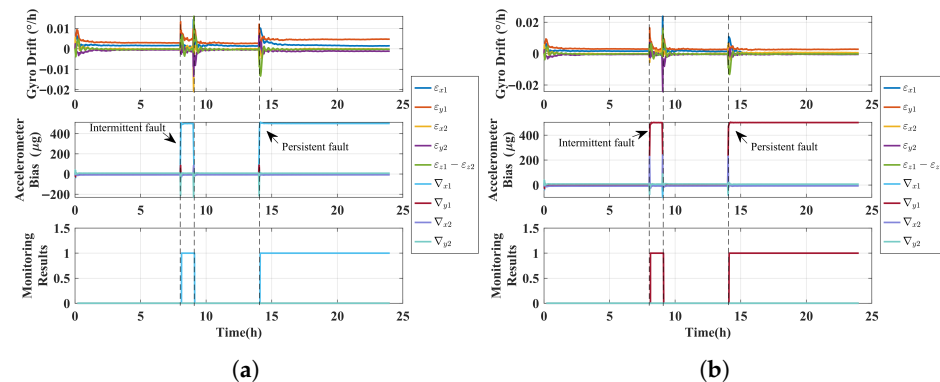


Figure 4. Experiment results in case of accelerometer faults. (a) x -acc of RINS 1. (b) y -acc of RINS 1.

5. Discussion

This paper proposes a real-time fault monitoring algorithm for two single-axis RINS redundant configuration. Based on the state transformation error model, the fault monitoring filter is constructed using the residual-normalized STF technique. By incorporating the relative attitude, velocity, and position between two RINSs as observations, the filter achieves greater sensitivity to faults, with a notable enhancement in detecting azimuth gyro malfunctions. However, due to the inseparable estimation of azimuth gyro drifts, the method only dependent on filter outputs and parameter estimations is insufficient for accurately pinpointing the location of azimuth gyro faults. To address this challenge, a proposed approach for monitoring azimuth gyro faults involves deriving azimuth gyro drift variations through fitting the north velocity based on the gyrocompass effect. Experiments are conducted to verify the effectiveness and efficiency of the proposed method. All faults have been diagnosed quickly and accurately.

Author Contributions: Conceptualization, Y.W. and L.W.; methodology, Y.W.; software, Y.W.; validation, Y.W., Z.L. (Zhonghong Liang) and P.M.; formal analysis, Y.W.; investigation, Y.W.; resources, L.W. and Z.L. (Zhikun Liao); data curation, Y.W. and Z.L. (Zhonghong Liang); writing—original draft preparation, Y.W.; writing—review and editing, L.W., Z.L. (Zhikun Liao) and M.T.; visualization, Y.W.; supervision, L.W. and Z.L. (Zhikun Liao); project administration, L.W. and Z.L. (Zhikun Liao);

funding acquisition, L.W. and Z.L. (Zhikun Liao). All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Independent Science Innovation Foundation of the National University of Defense Technology under Grant 23-ZZCX-JDZ-18 and in part by Science and Technology Program of Hunan Province under Grant 2022RC1198.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. El-Sheimy, N.; Youssef, A. Inertial sensors technologies for navigation applications: State of the art and future trends. *Satell. Navig.* **2020**, *1*, 2. [\[CrossRef\]](#)
2. Wang, L.; Wu, W.; Wei, G.; Pan, X.; Lian, J. Navigation information fusion in a redundant marine rotational inertial navigation system configuration. *J. Navig.* **2018**, *71*, 1531–1552. [\[CrossRef\]](#)
3. Boguspayev, N.; Akhmedov, D.; Raskaliyev, A.; Kim, A.; Sukhenko, A. A comprehensive review of GNSS/INS integration techniques for land and air vehicle applications. *Appl. Sci.* **2023**, *13*, 4819. [\[CrossRef\]](#)
4. Liang, Z.; Wang, Y.; Guo, H.; Luo, H.; Wei, G.; Liao, Z.; Wang, L. Collaborative calibration method for redundant dual-axis RINSS based on geometric constraint in GNSS-denied environments. *IEEE Trans. Ind. Inform.* **2025**, *21*, 2461–2470. [\[CrossRef\]](#)
5. Si, L.; Wang, Z.; Wei, D.; Gu, J.; Zhang, P. Fusion positioning of mobile equipment in underground coal mine based on redundant IMUs and UWB. *IEEE Trans. Ind. Inform.* **2023**, *20*, 5946–5958. [\[CrossRef\]](#)
6. Wang, M.; Wang, L.; Han, H. Research on improving heading and attitudes accuracy by online calibration of errors based on multi-RINSS joint rotation modulation. *IEEE Sens. J.* **2022**, *22*, 4503–4513. [\[CrossRef\]](#)
7. Eckenhoff, K.; Geneva, P.; Huang, G. Sensor-failure-resilient multi-imu visual-inertial navigation. In Proceedings of the 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 20–24 May 2019; pp. 3542–3548.
8. Yang, S.; Zhang, X.; Li, A.; Zhang, X.; Xu, B. Integrity monitoring for decentralized redundant IMUs/GNSS integrated navigation system with correlated measurements. *Meas. Sci. Technol.* **2024**, *35*, 086311. [\[CrossRef\]](#)
9. Li, Z.; Cheng, Y.; Wu, X.; Zhang, Y.; Wang, H. ALPF-GLRT based fault detection method for small faults applied to redundant IMUs. *Meas. Sci. Technol.* **2021**, *32*, 125101. [\[CrossRef\]](#)
10. Dai, Y.; Lai, J.; Zhang, Q.; Li, Z.; Shen, Y. An improved fault detection and isolation method for airborne inertial navigation system/attitude and heading reference system redundant system. *Aerospace* **2023**, *10*, 1024. [\[CrossRef\]](#)
11. Mounier, E.; Karaim, M.; Korenberg, M.; Noureldin, A. Multi-IMU system for robust inertial navigation: Kalman filters and differential evolution-based fault detection and isolation. *IEEE Sens. J.* **2025**, *25*, 9998–10014. [\[CrossRef\]](#)
12. Wu, Q.; Li, K. An inertial device biases on-line monitoring method in the applications of two rotational inertial navigation systems redundant configuration. *Mech. Syst. Signal Process.* **2019**, *120*, 133–149. [\[CrossRef\]](#)
13. Wang, Y.; Liang, Z.; Guo, H.; Yu, X.; Liao, Z.; Wang, L. Collaborative fault detection and diagnosis method for dual single-axis RINSS configuration in GNSS-denied environment. *Measurement* **2025**, *240*, 115620. [\[CrossRef\]](#)
14. Tucker, T.; Levinson, E. The AN/WSN-7B marine gyrocompass/navigator. In Proceedings of the 2000 National Technical Meeting of the Institute of Navigation, Pacific Hotel Disneyland, Anaheim, CA, USA, 26–28 January 2000; pp. 348–357.
15. Scherzinger, B.M.; Reid, D.B. Modified strapdown inertial navigator error models. In Proceedings of the 1994 IEEE Position, Location and Navigation Symposium-PLANS'94, Las Vegas, NV, USA, 11–15 April 1994; pp. 426–430.
16. Wei, D.; Li, S.; Fu, Q. A new initial alignment scheme for dual-axis rotational inertial navigation system. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 8503010. [\[CrossRef\]](#)
17. Chen, Z.; Zheng, C.; Lin, T.; Yang, Q. Multifault diagnosis of Li-ion battery pack based on hybrid system. *IEEE Trans. Transp. Electr.* **2021**, *8*, 1769–1784. [\[CrossRef\]](#)
18. Zhou, Z.; Liang, X.; Shi, Z.; Wang, G.; Lang, J.; Liu, L. An improved comprehensive calibration method for ship strapdown inertial navigation system. *Ocean. Eng.* **2023**, *269*, 113567. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.