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A Novel Approach for Fault Detection in Integrated Navigation Systems

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ABSTRACT Detecting subsystem faults quickly is critical to the accuracy and reliability of integrated navigation systems. This paper, therefore, proposes an effective approach based on the novel test statistic to detect faults. Machine learning is introduced to estimate the innovation and its variance of local filter. The estimates combined with the actual ones are used to construct the test statistic, which is then proved to obey chi-square distribution. Thus fault detection can be realized by chi-square test. However, the special structure of the test statistic makes it sensitive to faults, even to the gradual faults. The experimental results demonstrate that the approach can detect faults quickly. Especially for gradual fault detection, the proposed test statistic has a marked superiority compared with the traditional test statistic of residual chi-square test.

INDEX TERMS Fault detection, integrated navigation system, test statistic, chi-square test, Kalman filter.

I. INTRODUCTION

Navigation systems, which provide position, velocity and attitude information, are widely used in various vehicles. As single navigation system or sensor has relatively poor reliability and accuracy, integrated navigation systems are widely applied in vehicles with a high demand of reliability, such as autonomous underwater vehicles, aircrafts and rockets [1]–[7]. Each subsystem of the integrated navigation system provides its measurements to the information fusion center. If one of the subsystems has a failure, incorrect measurements will contaminate the whole navigation system by information fusion and feedback [8], [9]. In some severe cases, false navigation information may cause the loss of vehicle, even property damages and human casualties. Therefore, it is the effective and fast fault detection that plays a pivotal role in the reliability and safety of integrated navigation systems.

Existing fault detection methods can be classified into two broad categories: non model-based and model-based. Non model-based fault detection methods depend on knowledge or observed data. Knowledge based methods are intelligent, which rely on expertise or training results. Bu *et al.* [10] combined particle filter estimated state residuals with fuzzy inference system (FIS) decision system to detect anomaly of the navigation sensor. However, the fixed rules in FIS restrict the detection capability for unknown faults. To improve on this, neural network [11], [12], support vector machine [13] and other machine learning tools are applied to train the model of fault detection. Data-based methods, which are essentially data-driven, analyze the observed data directly by using wavelet transform [14], [15], auto regressive moving average [16] and so on. In this way, characteristic values such as amplitude, frequency and variance of measurement signals are extracted to detect faults.

Model-based methods, among which chi-square is the most famous [17], [18], depend on the analytical model of system. This kind of fault detection methods for integrated navigation systems are usually designed on the basis of Kalman filter (KF). Residual chi-square test [19] constructs the statistic of filtering residuals and then compares them with probability statistical distributions. The performance of the detection mostly rests with the residuary sensitivity relative to faults. But in early occurrence phase of gradual failures, residual chi-square test uses corrupted measurements for fault detection, leading to an insensitivity to gradual faults. Thereby some improved methods [20]–[24] are proposed. The chi-square test with two state propagators [20], [21]

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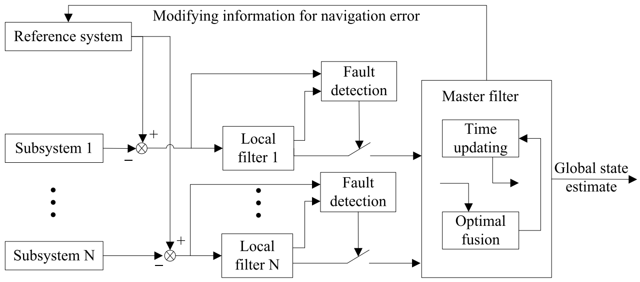

FIGURE 1. **The structure of fault-tolerant integrated navigation system.**

is designed for quick fault detection. The two state propagators which are alternately reset by filtering results take turns as the reference system for fault detection. From a distinct perspective, some researchers aim to construct completely new detection test statistics [22]–[24]. Joerger and Pervan [22] built the KF-based test statistic by adding the current-time residual contribution to a previously computed weighted norm of past-time residuals. In [23], the normalized residual and the sum of absolute residual are adopted as the determinants of fault detection. These studies explore faster and more efficient fault detection algorithms.

In this paper, a fast fault detection approach is proposed to enhance the fault-tolerance and reliability of integrated navigation systems. The approach is realized by establishing a sensitive test statistic which obeys chi-square distribution. The proposed approach is beneficial because of the following aspects:

1) It can quickly detect subsystem faults for integrated navigation systems, even gradual faults which are difficult to be detected by general approaches.
2) It can be realized by the means of any machine learning algorithms, allowing users to choose freely their own familiar algorithms.
3) It does not require the expertise of fault model, so that unknown faults can be dealt with.

This approach aims to increase the sensitivity of test statistics to faults. Specifically, the approach applies machine learning algorithms into the estimation of the filter innovation online. The estimates and the actual ones are used to construct the test statistic. The differential structure of the test statistic makes its value with a sharp increase when there occurs a fault, although the amplitude of the fault is relatively small. Therefore, this approach provides an alternative test statistic for fault detection in integrated navigation systems.

The rest of this article is organized as follows. Section II describes the fault-tolerant navigation system. Section III presents the fast fault detection approach and its implementation in integrated navigation systems. Section IV gives field experiments along with specific analyses to evaluate the proposed approach. Finally, Section V concludes the study.

II. FAULT-TOLERANT NAVIGATION SYSTEM

The fault-tolerant structure of integrated navigation system is presented in Fig. 1. In order to enhance the fault-tolerant capacity of system, non-feedback federal filter [25] is adopted to realize information fusion in integrated navigation systems. Strapdown inertial navigation system (SINS) composed by inertial measurement unit (IMU) and a computer is usually functioned as a reference system because of its autonomy and independence. IMU consists of gyroscopes and accelerometers. SINS continually provides position, velocity and attitude information of vehicles, without needing external signals. Subsystems of integrated navigation systems, which can be the odometer, magnetic compass, global position system (GPS), terrain-aided navigation system, Doppler velocity sonar and so on, offer different navigation information. The measurement differences between reference system and subsystems are passed to local filters as input information. In this paper, local filter is realized by conventional KF. Fault detection module is set for each local filter branch. On account of its high reliability, reference system is normally assumed to be fault-free. Therefore, fault detection result of local filter n indicates whether subsystem n fails or not. If a fault is detected, the fault filter branch will be cut off to avoid cross-contamination. Consequently, accurate state estimates of local filters are delivered to master filter. Then global state estimate, which is output by information fusion of local state estimates, is delivered to correct the errors of reference system.

The integrated navigation system is described at discrete time k by a process equation and a measurement equation.

$$X_k = \Phi_{k,k-1} X_{k-1} + w_k \tag{1}$$
$$Z_k = H_k X_k + v_k \tag{2}$$

where X_k is the state vector at time k. $\Phi_{k,k-1}$ is the state transition matrix from time k-1 to k. wk is the process noise vector. Z_k is the measurement vector at time k. H_k is the measurement matrix. v_k is the measurement noise vector. w_k and v_k are assumed to be a zero mean white noise sequence with covariance Q_k and R_k, respectively. Taking SINS/GPS/Odometer integrated navigation system as example, the position measurement differences between GPS and SINS serve as the measurement information of local filter 1. The velocity measurement differences between odometer and SINS serve as the measurement information of local filter 2.

Set East-North-Up geographic coordinate as the navigation frame, Right-Front-Up frame as the body frame. The state vector X_k of the integrated navigation system is defined by fifteen error variables, detailed as

$$X_k = [\phi_e\ \phi_n\ \phi_u\ \delta V_e \delta V_n\ \delta V_u\ \delta L\ \delta\lambda\ \delta h\ \varepsilon_x\ \varepsilon_y\ \varepsilon_z\ \nabla_x\ \nabla_y\ \nabla_z]^T \tag{3}$$

where ϕ_e, ϕ_n, ϕ_u are attitude errors. δV_e, δV_n, δV_u are velocity errors. δL, $\delta\lambda$, δh are position errors. ε_x, ε_y, ε_z are gyroscope drifts. ∇_x, ∇_y, ∇_z are accelerometer biases.

III. FAULT DETECTION APPROACH

This section introduced the proposed approach in detail, including specific implementations and relevant proofs.

A. TEST STATISTIC FOR FAULT DETECTION

The innovations of local filters are closely related to the measurements of the corresponding navigation subsystems. Therefore, the innovations are treated as the significant variables for fault detection. Here a new variable η_k is defined, named as double innovation

$$\eta_k = r_k - \hat{r}_k \tag{4}$$

where r_k is the innovation of local filter. $\hat{r}_k$ is an unbiased estimate of r_k. η_k will be proved to be a Gaussian white noise with zero mean when the system is fault-free.

In this paper local filters are implemented by KF algorithm. The innovation of local filter is expressed as

$$\begin{aligned} r_k &= Z_k - \hat{Z}_{k,k-1} \\ &= H_k(X_k - \hat{X}_{k,k-1}) + v_k \end{aligned} \tag{5}$$

where $\hat{X}_{k,k-1} = \Phi_{k,k-1}\hat{X}_{k-1}$ is an unbiased estimate of X_k. Then the expectation of innovation is

$$\begin{aligned} E(r_k) &= E\{H_k(X_k - \hat{X}_{k,k-1}) + v_k\} \\ &= H_k E(X_k - \hat{X}_{k,k-1}) + E(v_k) = 0 \end{aligned} \tag{6}$$

The correlation matrix of innovation is

$$\begin{aligned} &E(r_k r_{k-i}^T) \\ &= E\{(H_k\tilde{X}_{k,k-1} + v_k)\cdot(H_{k-i}\tilde{X}_{k-i,k-i-1} + v_{k-i})^T\} \\ &= H_k E(\tilde{X}_{k,k-1}\tilde{X}_{k-i,k-i-1}^T)H_{k-i}^T + H_k E(\tilde{X}_{k,k-1}v_{k-i}^T) \\ &\quad + E(v_k\tilde{X}_{k-i,k-i-1}^T)H_{k-i}^T + E(v_k v_{k-i}^T) \\ &= H_k E(\tilde{X}_{k,k-1}\tilde{X}_{k-i,k-i-1}^T)H_{k-i}^T + H_k E(\tilde{X}_{k,k-1}v_{k-i}^T) \end{aligned} \tag{7}$$

where $i \neq 0$.

The one step prediction error of KF is

$$\begin{aligned} \tilde{X}_{k,k-1} &= X_k - \hat{X}_{k,k-1} \\ &= \Phi_{k,k-1}X_{k-1} + w_{k-1} - \Phi_{k,k-1}\hat{X}_{k-1} \\ &= \Phi_{k,k-1}(X_{k-1} - \hat{X}_{k-1}) + w_{k-1} \end{aligned} \tag{8}$$

The state estimate of KF is

$$\hat{X}_k = \hat{X}_{k,k-1} + K_k(Z_k - H_k\hat{X}_{k,k-1}) \tag{9}$$

where K_k is the gain matrix of KF. Then

$$\begin{aligned} X_k - \hat{X}_k &= X_k - \hat{X}_{k,k-1} - K_k(Z_k - H_k\hat{X}_{k,k-1}) \\ &= \tilde{X}_{k,k-1} - K_k(H_kX_k + v_k - H_k\hat{X}_{k,k-1}) \\ &= (I - K_kH_k)\tilde{X}_{k,k-1} - K_kv_k \end{aligned} \tag{10}$$

Substituting the recursion formula of Eq. (10) into Eq. (8) yields

$$\begin{aligned} \tilde{X}_{k,k-1} = \Phi_{k,k-1}(I - K_{k-1}H_{k-1})\tilde{X}_{k-1,k-2} \\ - \Phi_{k,k-1}K_{k-1}v_{k-1} + w_{k-1} \end{aligned} \tag{11}$$

Backstep

$$\begin{aligned} \tilde{X}_{k-1,k-2} = \Phi_{k-1,k-2}(I - K_{k-2}H_{k-2})\tilde{X}_{k-2,k-3} \\ - \Phi_{k-1,k-2}K_{k-2}v_{k-2} + w_{k-2} \end{aligned} \tag{12}$$

According to the above reasoning, a recurrence formula can be obtained

$$\begin{aligned} \tilde{X}_{k-i+1,k-i} = \Phi_{k-i+1,k-i}(I - K_{k-i}H_{k-i})\tilde{X}_{k-i,k-i-1} \\ - \Phi_{k-i+1,k-i}K_{k-i}v_{k-i} + w_{k-i} \end{aligned} \tag{13}$$

Substituting the recurrence formulas into Eq. (11), the one step prediction error $\tilde{X}_{k,k-1}$ can be expressed by $\tilde{X}_{k-i,k-i-1}$, v_{k-i} and w_{k-i}

$$\begin{aligned} &\tilde{X}_{k,k-1} \\ &= [\prod_{j=1}^{i}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})]\tilde{X}_{k-i,k-i-1} \\ &\quad - \sum_{j=1}^{i}[\prod_{l=1}^{j-1}\Phi_{k-l+1,k-l}(I - K_{k-l}H_{k-l})]\Phi_{k-j+1,k-j}K_{k-j}v_{k-j} \\ &\quad + \sum_{j=1}^{i}[\prod_{l=1}^{j-1}\Phi_{k-l+1,k-l}(I - K_{k-l}H_{k-l})]w_{k-j} \end{aligned} \tag{14}$$

v_{k-j} and w_{k-j} $(j = 1,2,\ldots i)$ are uncorrelated with $\tilde{X}_{k-i,k-i-1}^T$. The expectations of w_k and v_k are zero. Multiply Eq. (14) by $\tilde{X}_{k-i,k-i-1}^T$, and then calculate the expectation

$$\begin{aligned} &E(\tilde{X}_{k,k-1}\tilde{X}_{k-i,k-i-1}^T) \\ &= [\prod_{j=1}^{i}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})]P_{k-i,k-i-1} \end{aligned} \tag{15}$$

where $P_{k-i,k-i-1}$ is the covariance matrix of $\tilde{X}_{k-i,k-i-1}$.

Multiplying Eq. (14) by v_{k-i}^T yields

$$\begin{aligned} &E(\tilde{X}_{k,k-1}v_{k-i}^T) \\ &= -[\prod_{j=1}^{i-1}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})]\Phi_{k-i+1,k-i}K_{k-i}R_{k-i} \end{aligned} \tag{16}$$

Substituting Eq. (15) and Eq. (16) into Eq. (7) yields

$$\begin{aligned} &E(r_k r_{k-i}^T) \\ &= H_k[\prod_{j=1}^{i}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})]P_{k-i,k-i-1}H_{k-i}^T \\ &\quad - H_k[\prod_{j=1}^{i-1}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})]\Phi_{k-i+1,k-i}K_{k-i}R_{k-i} \\ &= H_k[\prod_{j=1}^{i-1}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})][\Phi_{k-i+1,k-i}(I \\ &\quad - K_{k-i}H_{k-i})]P_{k-i,k-i-1}H_{k-i}^T \\ &\quad - H_k[\prod_{j=1}^{i-1}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})]\Phi_{k-i+1,k-i}K_{k-i}R_{k-i} \\ &= H_k[\prod_{j=1}^{i-1}\Phi_{k-j+1,k-j}(I - K_{k-j}H_{k-j})]\Phi_{k-i+1,k-i} \\ &\quad \cdot[P_{k-i,k-i-1}H_{k-i}^T - K_{k-i}(H_{k-i}P_{k-i,k-i-1}H_{k-i}^T + R_{k-i})] \end{aligned} \tag{17}$$

The gain matrix of KF is

$$K_k = P_{k,k-1}H_k^T[H_kP_{k,k-1}H_k^T + R_k]^{-1} \quad (18)$$

Then

$$K_{k-i} = P_{k-i,k-i-1}H_{k-i}^T[H_{k-i}P_{k-i,k-i-1}H_{k-i}^T + R_{k-i}]^{-1} \quad (19)$$

Assume the measurement matrix is constant, that is $H_k = H_{k-i}$. Substituting Eq. (19) into Eq. (17) yields

$$E(r_k r_{k-i}^T) = 0 \quad (20)$$

If $i = 0$, the variance of innovation $D(r_k)$ can be gained based on $r_k = H_k\tilde{X}_{k,k-1} + v_k$.

$$\begin{aligned} D(r_k) &= E(r_k r_k^T) \\ &= H_k E(\tilde{X}_{k,k-1}\tilde{X}_{k,k-1}^T)H_k^T + E(v_k v_k^T) \\ &= H_k P_{k,k-1} H_k^T + R_k \end{aligned} \quad (21)$$

where $P_{k,k-1}$ is the covariance matrix of $\tilde{X}_{k,k-1}$.

According to Eq. (20) and Eq. (21), the innovation r_k is an orthogonal white noise sequence. The relationships between the innovation r_k and the random variables v_k, $\tilde{X}_{k,k-1}$ are linear. Therefore, the distribution of innovation is the same as the random variables, which obeys Gaussian distribution. Hence the innovation r_k is a Gaussian white noise sequence with zero mean while the system has no faults.

As $\hat{r}_k$ is the unbiased estimate of r_k, the expectation of η_k is

$$E(\eta_k) = E(r_k - \hat{r}_k) = 0 \quad (22)$$

The correlation matrix of η_k is

$$\begin{aligned} E(\eta_k \eta_{k-i}^T) &= E\{(r_k - \hat{r}_k)(r_{k-i} - \hat{r}_{k-i})^T\} \\ &= E(r_k r_{k-i}^T) + E(\hat{r}_k \hat{r}_{k-i}^T) - E(r_k \hat{r}_{k-i}^T) \\ &\quad - E(\hat{r}_k r_{k-i}^T) \end{aligned} \quad (23)$$

where $i \neq 0$. While the system works well, $E(r_k) = 0$ and $E(\hat{r}_k) = 0$. r_k and $\hat{r}_k$ are independent with each other, then

$$E(r_k \hat{r}_{k-i}^T) = E(r_k)E(\hat{r}_{k-i}^T) = 0 \quad (24)$$

$$E(\hat{r}_k r_{k-i}^T) = E(\hat{r}_k)E(r_{k-i}^T) = 0 \quad (25)$$

Based on Ep. (20) and the definition of $\hat{r}_k$,

$$E(\hat{r}_k \hat{r}_{k-i}^T) = 0 \quad (26)$$

Substituting Ep. (20), Ep. (24), Ep. (25) and Ep. (26) into Ep. (23) yields

$$E(\eta_k \eta_{k-i}^T) = 0 \quad (27)$$

If $i = 0$, the variance of double innovation $D(\eta_k)$ is

$$\begin{aligned} D(\eta_k) &= E(\eta_k \eta_k^T) = E(r_k r_k^T) + E(\hat{r}_k \hat{r}_k^T) \\ &= D(r_k) + D(\hat{r}_k) \end{aligned} \quad (28)$$

According to Eq. (27) and Eq. (28), the double innovation η_k is an orthogonal white noise sequence. As a linear combination of innovation r_k and its unbiased estimate $\hat{r}_k$, η_k is a Gaussian white noise sequence with zero mean when the system works well. If there is a fault in the system, the innovation r_k will be modified wrongly by the KF gain matrix which is contaminated by the false measurements. At this moment, r_k and η_k are not white noise process. The mean of η_k is no longer zero. Hence, make binary hypothesis about η_k as

$$\begin{aligned} H_0 &= \text{Fault-free } E(\eta_k) = 0, \quad E(\eta_k \eta_k^T) = D(\eta_k) \\ H_1 &= \text{Fault } E(\eta_k) = \theta, \quad E[(\eta_k - \theta)(\eta_k - \theta)^T] = D(\eta_k) \end{aligned}$$

The conditional probability density functions of η_k are expressed as

$$P(\eta_k/H_0) = \frac{1}{\sqrt{2\pi}\,|D(\eta_k)|^{1/2}} e^{-\frac{1}{2}\eta_k^T D^{-1}(\eta_k)\eta_k} \quad (29)$$

$$P(\eta_k/H_1) = \frac{1}{\sqrt{2\pi}\,|D(\eta_k)|^{1/2}} e^{-\frac{1}{2}(\eta_k-\theta)^T D^{-1}(\eta_k)(\eta_k-\theta)} \quad (30)$$

The log likelihood rate of $P(\eta_k/H_0)$ and $P(\eta_k/H_1)$ can be calculated as

$$\begin{aligned} \Lambda_k = \ln\frac{P(\eta_k/H_1)}{P(\eta_k/H_0)} &= \frac{1}{2}[\eta_k^T D^{-1}(\eta_k)\eta_k \\ &\quad -(\eta_k - \theta)^T D^{-1}(\eta_k)(\eta_k - \theta)] \end{aligned} \quad (31)$$

Λ_k reaches its maximum when equals η_k. Make use of the maximum Λ_k to construct the test statistic. Thus the test statistic for fault detection in integrated navigation systems can be defined as

$$\begin{aligned} \lambda_k &= \eta_k^T \cdot D^{-1}(\eta_k) \cdot \eta_k \\ &= (r_k - \hat{r}_k)^T \cdot [D(r_k) + D(\hat{r}_k)]^{-1} \cdot (r_k - \hat{r}_k) \end{aligned} \quad (32)$$

As η_k is a random variable in Gaussian distribution, λ_k obeys chi-square distribution, noted as $\lambda_k \sim \chi^2(m)$. m is the dimension of Z_k. When there is a fault, the test statistic λ_k increases. The decision rule can be expressed by

$$\begin{cases} \lambda_k > T_D & \text{Fault} \\ \lambda_k \le T_D & \text{Nofault} \end{cases} \quad (33)$$

where T_D is the threshold. If the threshold value is too large, the probability of missed detection will increase. On the contrary, if the threshold value is too small, the probability of false alarm will increase. Therefore, the probability of false alarm and the probability of missed detection must be measured simultaneously when determining the detection threshold.

In other words, the fault detection is still realized by chi-square test. Nevertheless, the special structure of the test statistic λ_k makes it sensitive to faults, owing to the different disposal of innovations.

B. IMPLEMENTATION IN NAVIGATION SYSTEMS

Test statistic is constructed by double innovation η_k shown in Eq. (4). The unbiased estimates of innovation $\hat{r}_k$ can be obtained by machine learning [26]–[29], such as Gaussian process regression (GPR) [30], support vector regression

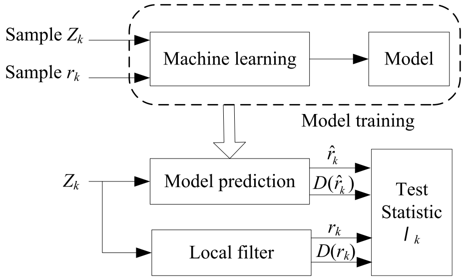

FIGURE 2. The test statistic for fault detection in navigation systems.

FIGURE 3. Experimental setup.

(SVR), neural network (NN) and so on. Users can freely choose their familiar way of algorithm to realize the fast fault detection. The construction of the test statistic in integrated navigation systems is shown in Fig. 2.

As the innovations are associated with the measurements, machine learning is introduced to establish the relationship between them. The model is trained with sample data, in particular: measurements and their corresponding innovations. It is worth mentioning that the training samples are collected from the fault-free navigation system. Taking the real-time measurements as inputs, the trained model gives the unbiased estimate of innovation along with its variance. The predicted innovations and the actual ones of local filters are adopted to construct the test statistic for the fast fault detection.

IV. EXPERMENTS AND RESULTS

The proposed fault detection approach is applied to SINS/GPS/odometer integrated navigation system. The experimental setup is shown in Fig. 3. The reference navigation trajectory is provided by the system consisted of a navigation-grade IMU and a GPS receiver. The reference navigation result is used to validate the proposed approach and to examine the system performance during the period of the subsystem faults which are intentionally introduced. The test navigation system for evaluating the proposed approach is composed of a low-cost IMU, an odometer and a GPS receiver. Specifically, gyroscope bias error is 0.03°/h, gyroscope random walk error $0.005°/\sqrt{h}$, accelerometer bias error 0.2mg, accelerometer random walk error $50\mu g/\sqrt{\text{Hz}}$, GPS receiver position precision 10m and odometer measured velocity precision 0.01m/s.

TABLE 1. Designed faults.

Fault mode	Time interval (s)	Fault value
Abrupt	250~270	420m
Gradual	600~700	2.8m/s

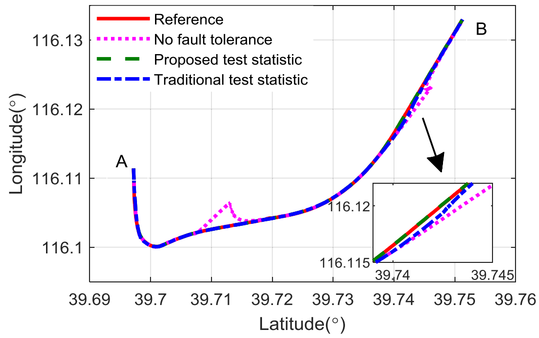

FIGURE 4. Trajectories.

To verify the proposed fast fault detection approach towards abrupt faults as well as gradual faults, fault information is set artificially by adding abrupt and gradual variables into the measurements of GPS. The fault information is only added to GPS outcomes of the test navigation system. The reference navigation system maintains fault-free. Artificial fault information for GPS is set up as Table 1.

As is described in Section III, the novel test statistic is the key to the proposed fault detection approach. In the experiments, the unbiased estimates of innovation used to construct the test statistic are provided by the trained GPR model. To compare with the proposed approach, traditional test statistic as is described in Eq. (34) is also applied to the navigation experiments.

$$t_k = r_k^T \cdot D^{-1}(r_k) \cdot r_k \tag{34}$$

where r_k is the innovation of local filter. $D(r_k)$ is the variance of innovation r_k. Fault-tolerant processing of the experimental system is performed as is described in Section II. Once a fault is detected, the incorrect local filtering information will be no longer transferred to the master filter, which realizes fault isolation.

The field experiments with a total test time of 15 minutes are carried out in Beijing. The navigation trajectories of different treatments are shown in Fig. 4. The test vehicle drives from point A to point B. During the period of failures (whether abrupt fault or gradual fault), the navigation trajectory of the system with no fault tolerance obviously deviates from the reference trajectory, which is caused by use of the wrong GPS measurements to information fusion. The other two approaches have no distinct deviation of trajectory during the occurrence of abrupt fault, which shows the effectiveness of the proposed and traditional test statistics to abrupt fault. During the occurrence of gradual fault, clearer trajectories can be seen in the partial enlargement of Fig.4.

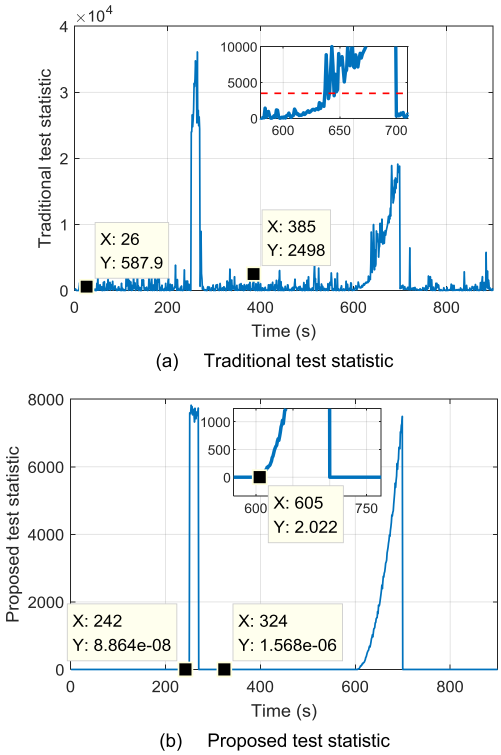

FIGURE 5. Test statistics.

The navigation trajectory of the system using the proposed test statistic is almost consistent with the reference trajectory. The system utilizing the traditional test statistic has less positional error compared with the system of no fault tolerance. Nevertheless, its performance is worse than the system using the proposed test statistic. To further reveal the reason of this phenomenon, the test statistics are concretely shown in Fig. 5.

During the fault-free period, the values of the traditional test statistic and the proposed test statistic are in the order of $10^2 \sim 10^3$ and $10^{-8} \sim 10^{-6}$ respectively. While fault occurs, the values increase to 10^4 and 10^3 respectively. Therefore, compared with the traditional test statistic, the proposed test statistic has a more significant increase during the fault period. This mutation is beneficial to fault detection. When the abrupt fault happens, the two test statistics all instantly increase at 250^{th} second. Thus the abrupt fault can be detected timely. The navigation trajectories of the system taking the two test statistics all almost have no deviation from the reference trajectory during $250^{th} \sim 270^{th}$ second as is shown in Fig. 4.

Different from the abrupt fault, test statistics are relatively small at the initial period of gradual fault, which is due to the small fault amplitude at that time. The test statistics increase with the increase of the fault amplitude. Once the test statistic is larger than the threshold, the fault will be detected. Contrast Fig. 5(a) and Fig. 5(b), the proposed test statistic increases more rapidly than the traditional test statistic starting at 600^{th} second. Therefore, the system with the proposed test statistic can do the fault-tolerant processing more timely. Taking both false alarm rate and omission rate into account, the fault detection thresholds of the system with traditional and proposed test statistics are assigned the value of 3500 and 1 respectively. In this case, the system with two different test statistics detects the gradual fault at 641^{th} and 605^{th} second respectively. The detection delay time of the system using proposed test statistic is significantly less than that of the traditional test statistic. The superiority of the proposed test statistic depends on the huge difference between its values during the fault-free and fault period. The difference is attributed to the special construction of the proposed test statistic.

The detailed comparison of detection results is shown in Table 2. The results are consistent with the above curves and analysis. The less duration time of false alarm and missed detection further proves the superiority of the proposed test statistic.

The position errors and velocity errors of the system with two different test statistics are shown in Fig. 6 and Fig. 7 respectively. During $250^{th} \sim 270^{th}$ second, the abrupt fault has been detected in time whichever application approach is.

TABLE 2. Detection results.

Duration(s)	Traditional test statistic	Proposed test statistic
False alarm	7	0
Missed detection	40	4

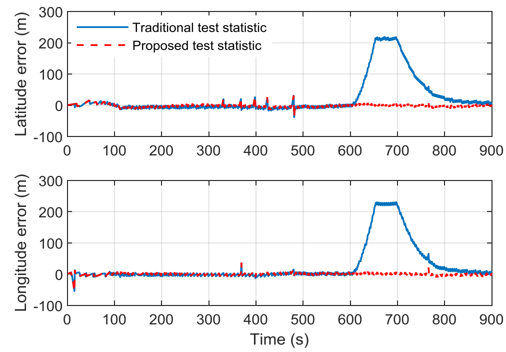

FIGURE 6. Position errors.

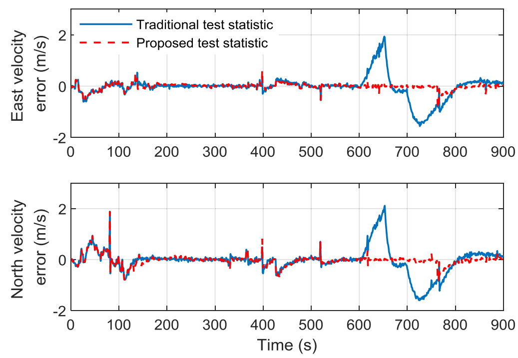

FIGURE 7. Velocity errors.

TABLE 3. Error statistics of position and velocity.

		Traditional test statistic	Proposed test statistic
Latitude error (m)	Mean	24.060	-1.697
	STD	59.740	5.901
Longitude error (m)	Mean	26.350	0.180
	STD	61.870	4.980
East velocity error (m/s)	Mean	-0.035	-0.015
	STD	0.446	0.129
North velocity error (m/s)	Mean	-0.038	-0.035
	STD	0.504	0.210

Through the fault-tolerant processing, the system switched to SINS/Odometer integrated navigation. Despite the loss of position auxiliary information, there are not significant increase in navigation errors because of the velocity auxiliary information provided by the odometer. However, the errors of the system with traditional test statistic increase evidently beginning at 600^{th} second. The maximum position error and velocity error reach 230.9m and 2.1m/s respectively, which are attributed to the detection delay of the traditional test statistic to the gradual fault. During the missed detection period, the incorrect measurements of GPS are adopted to realize information fusion. Thus the errors accumulate rapidly. The faulty local filter branch will be cut off until the gradual fault is detected. After that, the velocity errors reduce gradually with the assistance of the odometer. The position errors commence to decrease with the disappearance of the gradual fault. Different from the traditional test statistic, the system with the proposed test statistic detects the gradual fault relatively timely. The position errors and the velocity errors of the system have no significant increase during the gradual fault period. The experimental results prove that the proposed test statistic has a fast detection speed for gradual faults. Table 3 lists the navigation error statistics. This is a further evidence that the proposed test statistic has outperformed the traditional test statistic.

V. CONCLUSION

In order to ensure the reliability of integrated navigation systems, fault detection for subsystems is imperative. Therefore, the fault-tolerant structure of integrated navigation system is designed. The KF-based approach introduced in the paper applies machine learning to the construction of a novel test statistic. The prediction model is trained with measurements and corresponding innovations. The test statistic is then constructed by the predicted innovations and the actual ones. The mathematical distribution of the test statistic is also proved to be chi-square distribution. The performance of the approach is verified by comparative experiments based on SINS/GPS/Odometer integrated navigation system. The results show that the proposed test statistic is sensitive not only to abrupt faults but also to gradual faults.

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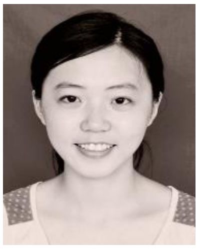

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