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Fault Detection and Isolation for GPS RAIM Based on Genetic Resampling Particle Filter Approach

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Abstract

An integrity monitoring system is an inseparable part of global positioning system (GPS). According to the measurement noise feature of GPS receiver and the degeneracy phenomenon and alleviating the sample impoverishment problem in particle filter (PF). An approach to fault detection and isolation (FDI) for GPS receiver autonomous integrity monitoring (RAIM) based on genetic resampling particle filter is proposed. The genetic algorithm (GA) is melted into the re-sampling process of the basic particle filter to solve the particles degeneracy and impoverishment problem. A main GA-aided particle filter (GPF) is used to process all the measurements to produce the optimal state estimate, several auxiliary GPFs are used to process subsets of measurements to produce the state estimate as detection references. By setting up the log-likelihood ratio (LLR) test to check the consistency of test statistics. The particles in GPF are assorted by weights, in order to reduce the computation complexity of the algorithm, only the lower weight particles participate in genetic operations. By collecting the GPS data from the GPS reciver, the feasibility and effectiveness of the RAIM approach is verified, and comparing with extended Kalman filter (EKF) and PF algorithm. The results show that the approach in the case of non-Gaussian measurement noise can estimate the state accurately, also can successfully detect fault satellite, therefore, improve the reliability of GPS positioning.

Keywords*: global positioning system (GPS), receiver autonomous integrity monitoring (RAIM), particle filter, genetic algorithm, extended Kalman filter*

1. Introduction

With the development of the global navigation satellite system (GNSS) and the grows of user performance requirements for GNSS service, for safety-critical applications of global navigation satellite system (GNSS), such as aircraft and missile navigation systems, it is important to be able to detect and exclude faults that could cause risks to the accuracy and integrity, so that the navigation system can operate continuously without any degradation in performance [1, 2]. Because it needs a long time for satellite fault monitoring to alarm through controlling the satellite navigation system itself, usually within 15 minutes to a few hours, that can't meet the demand of air navigation. As a result, to monitor the satellite fault rapidly, namely the receiver autonomous integrity monitoring (RAIM) has been researched a lot [3, 4].

In recent years, various failure detectiong methods have been discussed to improve the accuracy and reliability of the systems.The snapshots algorithm has been widely used at present. This kind of algorithm mainly has Parity space (Parity) method, the sum of least Squares of the Error (SSE) method, and the largest interval method, etc [5, 6]. Kalman filtering algorithm is by using historical measure to improve the performance, Kalman filter-based fault detection approach has been used [7]. For most systems are usually nonlinear and system noise are generally non-Gaussian, GNSS measurement error does not follow a Gaussian distribution perfectly. Kalman filter is difficult to obtain the optimal state estimation. Particle filter algorithm is suitable to any non-linear, non-Gaussian systems, therefore, the particle filter for fault detection has been widely used [8]. But basic particle filter exists the degeneracy phenomenon and alleviating the sample impoverishment problem. In order to solve these problem, in the paprer, genetic algorithm is melted into ordinary particle filtering algorithm by genetic manipulation to improve the quality of particles, combined with the log-likelihood ratio (LLR) test method. By checking the consistency of the test statistic, fault satellite is detected.

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2. Genetic Algorithm Aided Particle Filter

Particle filter is a filter method based on Monte Carlo simulation and recursive Bayesian estimation. Since Gordon proposed the sequential importance resampling (SIR) particle filter algorithm based on sequential Monte Carlo method, particle filter algorithm becomes a hotspot of nonlinear non-Gaussian system state estimation problem, being widely used in fault diagnosis, signal processing, navigation and other research areas [9-11].

The core idea of the particle filter is to use finite random samples (these samples referred to as "particles") and their weight to approximate the posterior probability distribution of state variables, thereby obtain the estimate of the state. Resampling particle filter can inhibit the degeneracy of weights, but also make the resampled particles no longer independent. Genetic algorithm is a search optimization algorithm based on natural selection and genetic mechanisms.It includes selection, crossover and mutation operations. In order to obtain the optimal solution or satisfactory solution, the process terminates until it meets certain performance indicators [12-15]. The genetic of particles is manipulated in the real domain, the codec of genetic manipulation is avoided. The advantage of the introduction of genetic algorithms lies in: It can improve the efficiency of particles, greatly reduces the required number of particles to approximate the maximum posterior probability distribution. Secondly, genetic algorithm can effectively increase the diversity of particle, and effectively solve the particle degradation phenomena, thus improving the accuracy of state estimation. Considering the dynamic state space model below:

$$\boldsymbol{X}_k = \boldsymbol{f}_k(\boldsymbol{X}_{k-1}, \boldsymbol{v}_{k-1})$$
$$\boldsymbol{Z}_k = \boldsymbol{h}_k(\boldsymbol{X}_k, \boldsymbol{n}_k)$$

Where x_k is a state vector, z_k is an output measurement vector, $f(.,.)$ and $h(.,.)$ are state transition function and measurement function respectively. v_{k-1} is a process noise vector independent of current state, and n_k is a measurement noise vector independent of states and the system noise.

The detailed steps of the GPF applied are as follows:

Step 1: Initialization. Sample a set of random particles $\{x_0^i\}_{i=1}^{N_s}$ from the probability density function (pdf) $p(x_0)$. The weight of each particle is set by $1/N_s$.

Step 2: Update the weights of particles. Calculating and updating the particle weights according to the weight calculate formula. Calculating the weight and normalized formula are as follows:

$$\omega_k^i = \omega_{k-1}^i \frac{p(z_k | x_k^i) p(x_k^i | x_{k-1}^i)}{q(x_k^i | x_{0:k-1}^i, z_{0:k})}, \quad i = 1,2,\cdots,N_s \tag{1}$$

$$\bar{\omega}_k^i = \omega_k^i \Big/ \sum_{i=1}^{N_s} \omega_k^i \tag{2}$$

Step 3: Asort the particles by weights.The threshold of particle weight classification at time k can be calculated by:

$$A = sort\left(\bar{\omega}_k^1, \bar{\omega}_k^2, \cdots, \bar{\omega}_k^{N_s}\right) \tag{3}$$

$$\omega_{thr}(k) = A(round(N_s/3)) \tag{4}$$

If the weight of particle x_k^i is less than the threshold $\bar{\omega}_k^i < \omega_{thr}(k)$, the particle will be classified as low-weight particle classification $\{x_k^l\}_{l=1}^{N_L}$ .Otherwise, the particle will be put into high-weight particle classification $\{x_k^h\}_{h=1}^{N_H}$, where $N_L + N_H = N_s$.

Step 4: Genetic manipulation. Conduct genetic manipulation on particle set of low-weight classification. Specific steps are as follows:

a) Crossover. Select two random samples $(x_k^m, x_k^n)_{m,n=1}^{N_s}$ from the low-weight particle set $\left\{x_k^l\right\}_{l=1}^{N_L}$ according to the rules as follows:

$$\tilde{x}_k^m = \alpha x_k^m + (1-\alpha) x_k^n + \eta \tag{5}$$

$$\tilde{x}_k^n = \alpha x_k^n + (1-\alpha) x_k^m + \eta \tag{6}$$

Where $\eta \sim N(0,\Sigma)$ and $\alpha \sim U(0,1)$. The guideline of crossover is:

If $p(z_k \left| \tilde{x}_k^m) > \max\{p(z_k \right| x_k^m), p(z_k \left| x_k^n)\}\right.$, particle $\tilde{x}_k^m$ accepted. Otherwise, accept the particle with a probability of $p(z_k \left| \tilde{x}_k^m) \middle/ \max\{p(z_k \right| x_k^m), p(z_k \left| x_k^n)\}\right.$. Accept or abandon particle $\tilde{x}_k^n$ in the same way.

b) Mutation. Select one random sample $(x_k^j)_{j=1}^{N_s}$ from the low-weight particle set $\left\{x_k^l\right\}_{l=1}^{N_L}$ according to the rules as follows:

$$\tilde{x}_k^j = x_k^j + \eta \text{ , } \eta \sim N(0,\Sigma)$$

The guideline of mutation is as follows:

If $p(z_k \left| \tilde{x}_k^j) > p(z_k \right| x_k^j)$, particle $\tilde{x}_k^j$ accepted. Otherwise, accept the particle with a probability of $p(z_k \left| \tilde{x}_k^j) \middle/ p(z_k \right| x_k^j)$.

Through the crossover and mutation operation described above, getting a new set of low-weight particles $\left\{\tilde{x}_k^l\right\}_{l=1}^{N_L}$, then mergeing it with high-weight particle set $\left\{x_k^h\right\}_{h=1}^{N_H}$ obtained in step 3, therefore obtaining a new particle set $\left\{\tilde{x}_k^{i'}, \bar{\omega}_k^{i'}\right\}_{i'=1}^{N_s}$.

Step 4: Resampling from new particle set $\left\{\tilde{x}_k^{i'}, \bar{\omega}_k^{i'}\right\}_{i'=1}^{N_s}$, we will obtain a new resampled particle set $\left\{\tilde{x}_k^{i'}, \bar{\omega}_k^{i'}\right\}_{i'=1}^{N_s}$, $\sum_{i=1}^{N_s} \bar{\omega}_k^{i'} = 1$.

Step 5: Prediction. Calculate the state estimation by $\hat{x}_k = \sum_{i=1}^{N_s} \bar{\omega}_k^i \tilde{x}_k^i$, and predicte the unknown status x_{k+1}^i by using the state equation f as $x_{k+1}^i = f(\tilde{x}_k^i, v_k)$, $i = 1, 2, \cdots, N_s$.

Step 6: Turn to step 2 when $k = k + 1$.

3. GPF Algorithm for RAIM

RAIM include two functions: detection of satellite whether there is a fault, Identify a faulty satellite, and the navigation calculating process will be removed.

Fault detection and isolation model based on GPF algorithm for receiver autonomous integrity monitoring system is as follows:

System state equation:

$$X_k = F_{k-1} X_{k-1} + w_{k-1} \tag{7}$$

Where, $X = [r_x, r_y, r_z, \Delta\delta]$, $\Delta\delta$ is the error of receiver time with respect to satellite time, F is the transfer matrix, which is characteristic matrix in the stationary state, w is the process noise.

Measurement equation:

$$\rho^i(k) = R^i(k) + c\Delta\delta^i + T^i(k) + E^i(k) + \varepsilon^i(k) \tag{8}$$

Where, ρ^i is the pseudorange between receiver (r_x, r_y, r_z) and satellite i (s_x^i, s_y^i, s_z^i), c stands for lightspeed, $\Delta\delta$ is the time compensation, E^i is the ephemeris error, ε is the code observation noise. And, $R^i = \sqrt{(r_x - s_x^i)^2 + (r_y - s_y^i)^2 + (r_z - s_z^i)^2}$ stands for the true distance between the satellite i and the receiver [16].

Measurement selected includes: coordinates of satellite i (s_x^i, s_y^i, s_z^i), pseudorange ρ^i, the compensation $\Delta\delta$ at each time.

The flow diagram of implementing the satellite fault detection and isolation method based on LLR test and GPF algorithm shows in Figure 1.

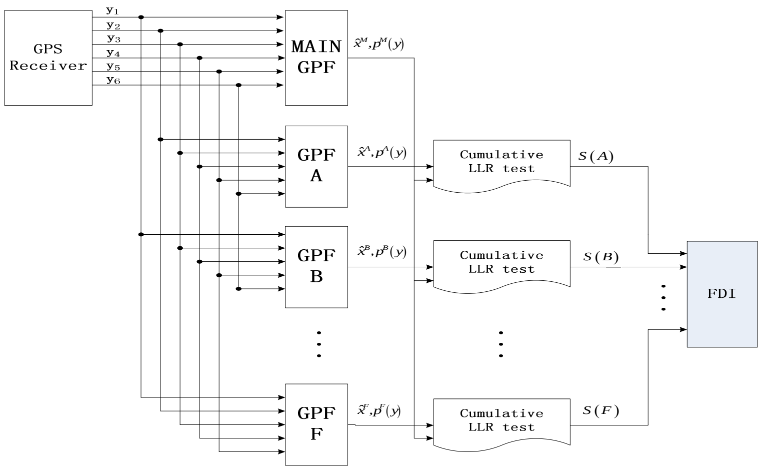

Figure 1. FDI Approach Based on LLR Test and GPF Algorithm

From each input measured value of PFs, it can be seen that when a positioning satellite fails, one of auxiliary PFs will not contain the measured values from the fault satellite, so the consistency test can be detected.

3.1. Logarithmic Likelihood Ratio Test Statistic

The LLR test can be defined as the ratio of each auxiliary PFs and main PF's probability density function[17], and can be expressed as:

$$s^q(y) = \ln \frac{p^q(y)}{p^A(y)} \tag{9}$$

The accumulate LLR of measurements from y_j to y_k can be expressed as:

$$S_j^k(q) = \sum_{i=j}^{k} ln \frac{p^q(y_i | Y_{i-1})}{p^A(y_i | Y_{i-1})} \tag{10}$$

Because the system state estimation likelihood function can be approximated by the normalized weights of particles, so the formula $p^q\left(y_i \middle| Y_{i-1}\right)$ and $p^A\left(y_i \middle| Y_{i-1}\right)$ above can be expressed as:

$$p^q\left(y_i \middle| Y_{i-1}\right) \approx \frac{1}{N}\sum_{m=1}^{N}\tilde{w}_i^q(m) \tag{11}$$

$$p^A\left(y_i \middle| Y_{i-1}\right) \approx \frac{1}{N}\sum_{m=1}^{N}\tilde{w}_i^A(m) \tag{12}$$

3.2. RAIM Based on Genetic Particle Filter

The accumulated LLR function of each time by Equation (10) can be obtained, then based on the accumulated LLR function's feature that under normal circumstances, as time increases, the curve is a smooth function. When the data changes, there will be a negative drift before the change, and a positive drift after the change.When the change is reflected in the curve of function S_j^k , it is a fluctuation quite different from the other time. With this feature any faults of system can be detected [18, 19].

Decision function for FD is:

$$\beta_k = \max_{k-U+1\le j\le k}\ \max_{1\le d\le D} S_j^k\left(d\right) > \tau \tag{13}$$

Where, U is the window function that contains the each observations before current time, the window size is selected based on experience. τ is the decision threshold.

When $\beta_k > \tau$, it means the system has detected a fault, it should set alarm and set the current time as t_a. Then, fault isolation can be conducted by using the following formula to determine faulty satellite ID: obtain the index g of the faulty subset.

$$g = \arg\max_{1\le d\le D} S_{t_a}^k \quad \left(k > t_a\right) \tag{14}$$

In which the parameter g stands for the index of faulty subset of measurements.

The detailed algorithm processes can be expressed by:

Step 1. Generate the initial particles from the prior pdf $p(x_0)$ around the receiver's coordinate for main PF and auxiliary PFs. The particles are:

Main PF: $\{x_0^A(i), i = 1,2,\cdots,N_s\}$

Auxiliary PFs: $\{x_0^q(i), i = 1,2,\cdots,N_s\}$

And $x_0^q(i) = x_o^A(i)$.

Step 2. State prediction. Put $\{x_0^A(i), i = 1,2,\cdots,N_s\}$ and $\{x_0^q(i), i = 1,2,\cdots,N_s\}$ into the system state Equation (7) respectively, the predicted values of particle $x_{k|k-1}^A(i)$ and $x_{k|k-1}^q(i)$ can be obtained.

Step 3. Calculate particle weights. Put particle predicted values $x_{k|k-1}^A(i)$, $x_{k|k-1}^q(i)$, the position coordinates (s_x^i, s_y^i, s_z^i) of satellite i and the time error $\Delta\tau$ into system measurement equation, obtain the predicted pseudorange value ρ^{*^i} of satellite i . The normalized particle weights $\tilde{\omega}_k^A(i)$ and $\tilde{\omega}_k^q(i)$ can be calculated by putting the pseudorange prediction value ρ^{*^i} and pseudorange measurement value ρ^i into weight calculation formula.

Step 4. Calculate the LLR. Calculating the log-likelihood ratio by Equation (15).

$$S_j^k(q)=\sum_{r=j}^{k}\ln\left(\frac{1}{N_s}\sum_{i=1}^{N_s}\tilde{\omega}_r^q(i)\Big/\frac{1}{N_s}\sum_{i=1}^{N_s}\tilde{\omega}_r^A(i)\right) \quad (15)$$

Step 5. Calculate the decision function by $\beta_k=\max_{k-U+1\le j\le k}\max_{1\le q\le Q}S_j^k(q)$.

Step 6. Fault detection. Decision threshold is τ.
If $\beta_k>\tau$, fault alarm sets at time $t_a=t$ and skip to step 6;
If $\beta_k\le\tau$, there is no fault, go to step 7.

Step 7. Fault isolation. Comparing the q cumulative LLRs $S_{t_a}^k(q)$ for $k>t_a$, the faulty satellite g will be the one that makes accumulated LLR maximum.

Step 8. Status updates. Update particles of particle filter by resampling.

4. Experiment Results and Analysis

Using N220 GPS receiver, the GPS data was collected.The observation data includes position information and the pseudorange values of the satellite for PVT solution, and the data is collected for 418 seconds. In the meantime, there are six satellites for PVT solution.The pseudorange measured value can be expressed as $y=(y_1,y,y_3,y_4,y_5,y_6)$. In order to verify whether the proposed FDI algorithm is able to detect and isolate the fault satellite, intentionally, the pseudorange bias was added to the pseudorange measurements of satellite 19.

In the experiment, EKF, PF and GPF algorithm are employed to process the collected experimental data, in order to compare the performance of three algorithms when used in RAIM algorithm. Figure 2 shows the decision function for fault detection under normal condition. Figure 3 shows the cumulative LLR of EKF, PF and GPF algorithm under normal condition.

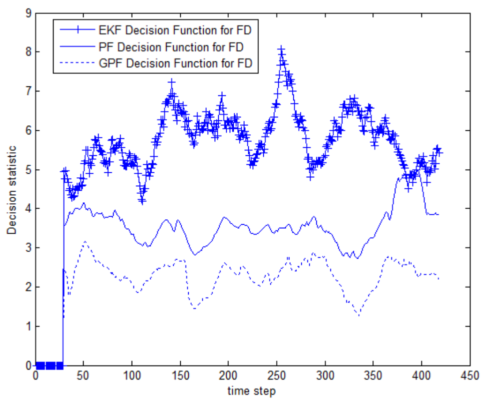

Figure 2. Decision Statistic for Fault Detection under Normal Condition

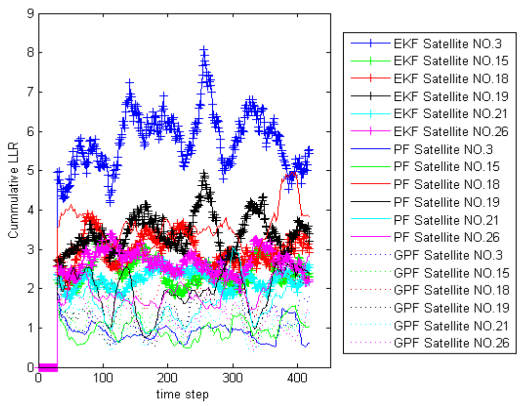

Figure 3. Cumulative LLR for Fault Isolation under Normal Condition

It can be seen in Figure 2 that GPF-based FDI's decision function value at each time is less than the EKF-based FDI's and PF-based FDI's decision function value, which shows that for the selected alarm threshold, using GPF algorithm FDI system is less likely to reach the alarm threshold when the failure did not occur, which is to say, the system false alarm probability of FDI system using GPF algorithm is less than the FDI method using EKF algorithm and PF algorithm. Figure 3 shows the cumulative LLR curves of each auxiliary EKF-based FDI, auxiliary PF-based FDI and auxiliary GPF-based FDI. With regard to the cumulative LLR function curve of the same satellite, EKF-based FDI and PF-based FDI's cumulative LLR have a greater fluctuation range than the cumulative LLR of FDI based on GPF, indicating that GPF algorithm can estimate the system state more precisely than EKF algorithm and PF algorithm.

Figure 4 and Figure 5 shows the experiment results under failure conditions. Figure 4 shows the decision statistic curves of FDI based on EKF, PF and GPF for fault decision, and Figure 5 shows the cumulative LLR curves of each auxiliary filter for fault isolation.

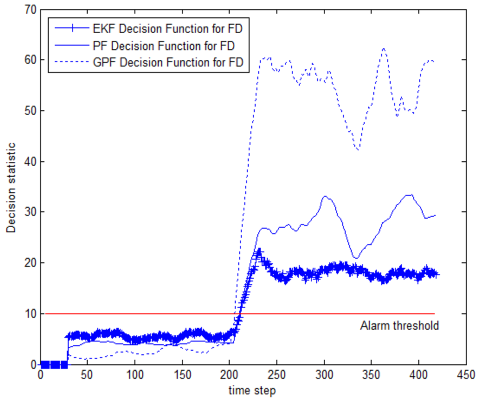

Figure 4. Decision Statistic for Fault Decision under Failure Condition

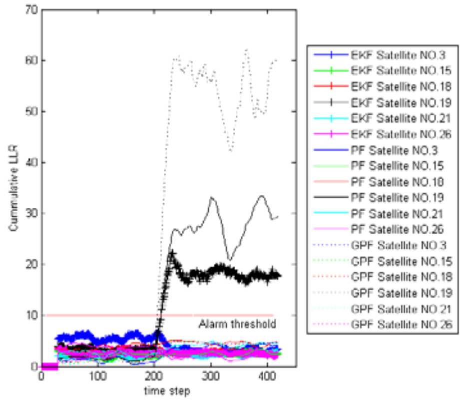

Figure 5. Cumulative LLR for Fault Isolation under Failure Condition

The pseudorange measurements of satellite No.19 from time $k=200$ to time $k=418$ has been modified by adding constant errors. As can be seen from Figure 4 and Figure 5, when the fault occurs, the decision statistic β_k of three FDI systems all jump cross the alarm threshold significantly. This means they all set alarm after the onset of a fault. The FDI algorithm using GPF sets alarm at the time $k=205$, the FDI using EKF and FDI using PF sets alarm at the time $k=210$. In Figure 5, the cumulative LLR value $S_{t_a}^k(D)$ of satellite No.19 has the greatest value among other LLRs, according to the fault detection principle above, the pseudorange data of satellite No.19 does't exist in auxiliary PF D, so satellite No.19 can be determined to be the fault satellite. Fault isolation can be correctly accomplished by discarding the 19th satellite's observation data for position velocity and time solution. Figure 4 and Figure 5 shows that all three FDI systems can successfully detect and isolate the faulty satellite. Under nominal condition, but RAIM algorithm based on GPF has a smallest probability of setting false alarm than EKF and PF. The detection and isolation performance of GPF-based RAIM algorithm is better than PF-based RAIM algorithm and EKF-based RAIM algorithm.

Table 1. Performance Comparison of Different Algorithms

Algorithm	Number of Particles	Average Number of Effective Particles	RMSE
EKF	—	—	15.63751
PF	100	17.8779	7.45375
	300	36.6847	6.85361
GPF	100	28.7612	6.98691
	300	59.6315	6.57852

Where, The average number of effective particles and RMSE can be calculated by:

$$N_{eff} = 1 \Big/ \sum_{k=1}^{N_s} (\omega_i^{(k)})^2 \quad (16)$$

$$RMSE = \sqrt{\frac{1}{N_s} \sum_{k=1}^{N_s} (x_i - \hat{x}_i^k)^2} \quad (17)$$

As shown in Table 1, when the number of particles selected as $N_s = 100$, RMSE of GPF is 6.98691, RMSE of PF is 7.45375, and RMSE of EKF is 15.63751, which indicates that GPF has the optimal accuracy of state estimation. The average number of effective particles of GPF is 28.7612, which is more than PF, indicates GPF do better in suppressing sample degradation. When the number of particles chosen as $N_s = 300$, RMSE of GPF and PF both reduced, the average number of effective particles of GPF and PF both increased, means under the same conditions, the more particles, the more accurate of the estimation.

4. Conclusion

The approach of fault detection and isolation (FDI) for GPS receiver autonomous integrity monitoring (RAIM) based on genetic algorithm-assisted particle filter (GPF) algorithm and the log-likelihood ratio (LLR) test method was proposed. Compared with PF and EKF estimation, the accuracy of improved particle filter estimation is improved by applying selection, crossover and mutation of genetic algorithm into the basic particle filter. The quality of particles after resampling is improved. The RAIM algorithm proposed are compared with PF-based and EKF-based RAIM algorithm and verified by measured data collected from the GPS receiver experiment platform, the simulation results show that in environment of non-Gaussian measurement noise, the FDI approach using GPF is superior to PF-based FDI and EKF-based FDI. Applying GPF algorithm in FDI for RAIM also reduce the false alarm rate of fault detection, shorten the time of setting alarms. The genetic algorithm-assisted particle filter (GPF) algorithm improves the state estimation accuracy, improves the reliability of fault detection. It is feasible and effective to combine GPF algorithm with log-likelihood ratio test methd for GPS receiver autonomous integrity monitoring (RAIM) in non-Gaussian measurement noise environment, and the detection and isolation performance of GPF-based RAIM method is better than EKF-based RAIM approach and PF-based RAIM approach. The GPF-based RAIM algorithm proposed in this paper has a certain significance value for the study of Beidou second-generation navigation receiver autonomous integrity monitoring.

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