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GPS Receiver Autonomous Integrity Monitoring Based on Hierarchical Particle Filter

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Abstract

Reliability is an essential factor for GPS navigation system. Therefore, an integrity monitoring is considered one of the most important parts for a navigation system. GPS receiver autonomous integrity monitoring (RAIM) technique can detect and isolate fault satellite. Based on particle filter, a novel RAIM method was proposed to detect two-satellite faults of the GPS signal by using hierarchical particle filter based probability test. The particle filter is popular filtering methods to estimate states of a general dynamic system. It can deal with any system nonlinear and any noise distributions. Because GNSS measurement noise does not follow the Gaussian distribution perfectly, the particle filter can estimate the posterior distribution more accurately. In order to detect fault, the consistency test statistics is established through cumulative log-likelihood ratio (LLR) between the main and auxiliary particle filters (PFs).Specifically, an approach combining PF with the hierarchical filter is used in the process of two-satellite faults. Through GPS real measurement and the application of the RAIM method, the performance of the proposed GPS two-satellite faults detection algorithm was illustrated. Some simulation and experiment results are given to evaluate integrity monitoring performance of the algorithm. Validated by the real experimental data, the results show that the proposed algorithm can successfully detect and isolate the faulty satellite in the case of non-Gaussian measurement noise.

***Keywords**: Global positioning system (GPS), Receiver autonomous integrity monitoring (RAIM), Hierarchical Particle filter, Fault detection and isolation*

1. Introduction

Integrity of global navigation satellite system (GNSS) is important for safety-critical applications, such as aircraft and missile applications. With the development of GNSS and the increasing requirements for satellite navigation and positioning performance, the integrity monitoring is an inseparable part of GNSS. Integrity monitoring can be able to detect and exclude faults satellite that could cause risks to the accuracy and reliability of GNSS positioning, so that GNSS receivers can operate continuously without any degradation in performance[1]. Because it needs a long time for satellite fault monitoring to alarm through 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. At present, with multiple GNSSs development, there is a need for RAIM to identify multiple outliers. Multiple outliers are more frequent due to the additional affects of non line of sight multipath[2-3]. Therefore, the RAIM needs to be able to detect and exclude multiple biases. It is difficult to detect simultaneous multiple faults using conventional snapshot RAIM algorithms, and therefore various filter algorithms have been studied for reducing the measurement noise level so that GNSS receiver can estimate its position more accurately and reliably[4]. However, for example, Kalman filter presumes that the measurement error follows a Gaussian distribution, the performance can degrade if this assumption is not correct. Because GNSS measurement error does not follow a Gaussian distribution perfectly[5], Kalman filter will use an inaccurate error model that may cause performance degradation. Particle filters have been researched over

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the last few years as an alternative for solving nonlinear/non-Gaussian problems. And, the particle filter for fault detection has been widely used [6-7].

Based on the particle filter, the two-satellite faults detection and isolation algorithm was designed. The new integrity monitoring algorithm for RAIM using hierarchical particle filter was proposed. The proposed algorithm estimates a distribution of a measurement residual from the posterior density and detects large residuals to satisfy a false alarm rate. With a non-Gaussian measurement error, the algorithm can estimate the distribution of the state more accurately. The work focused on the effect of a non-Gaussian error distribution of the GPS measurement on the integrity monitoring. The paper is organized as follows. First, a theory of a particle filter is briefly reviewed. Then the general scheme of the approach followed by a hierarchical particle filtering based log likelihood ratio (LLR) approach to fault detection and isolation (FDI) are presented. And the consistency test statistics is derived and established. The next section is a description of the system and measurement equation of GPS receiver. Finally, the GPS receiver autonomous integrity monitoring and its usefulness are presented with numerical simulation and experiment.

2. Particle Filter Algorithm

In this section, the principle of PF algorithm will be given. Particle filter is a method based on sequential monte carlo method and sequential importance sampling (SIS). It has a good filtering effect for non-linear and non-Gaussian system state estimation problem by obtaining sampling from the probability density function (PDF) in the state space. These sampling are called particles. Each of the particles has an assigned weight, and the state variable's distribution can then be approximated by a discrete distribution that depends on each of the particles. The probability assigned to each particle is proportional to the weight. These particles are random samples from the priori PDF. With the increasing of number of particles, a good approximation to the required PDF is effectively provided. Through the system state equation and measurement equation, the collection of sampling for approximating random Bayesian estimation of nonlinear system can be predicted and updated. Gordon, first proposed an algorithm of PF. The algorithm is known as the SIR (sampling importance resampling) [8-9]. At present, the particle filter has been widely used in location tracking, robot localization, signal estimation and detection, speech recognition and enhancement, dynamic fault detection system and satellite navigation[10-11], and so on. Let's consider the PF dynamic state space model below.

$$x_k = f\left(x_{k-1}, v_{k-1}\right)$$
$$z_k = h\left(x_k, n_k\right)$$

Where x_k is a state vector, z_k is an output measurement vector. $f(\cdot,\cdot)$ and $h(\cdot,\cdot)$ are state transition function and measurement function respectively. v_k is the process noise vector independent of current state, and n_k is a measurement noise vector independent of states and system noise.

The basic principle of particle filter algorithm is that, first, based on the priori conditional distribution of system state vector, the state space generates a group of random samples, and these samples are called particles. Then, based on the measurements constantly, the weight of each particle and the distribution position of each particle are adjusted. And the priori conditional distribution is modified. The algorithm is a recursive filtering algorithm, commonly used to handle non-Gaussian and nonlinear system state and parameter estimation.

The basic flow of particle filter algorithm can be described as the following steps.

(1).Initialized

According to the priori probability distribution $p(x_0)$, the initial particles $\{x_0(i)\}_{i=1}^{N_s}$ from the pdf $(x_{k-1}|Z_{k-1})$ are generated, and the weight of the particles is $1/N_S$.

(2).Prediction

Using these particles to generate new samples $(x^i_{k/k-1}, \mathrm{i}=1,...,\mathrm{N})$,which is approximated the predicted PDF $p(x_k|Z_{k-1})$.

Where, $$x^i_{k/k-1} = f\left(x^i{}_{k-1}, v^i{}_{k-1}\right)$$

(3). Update

After the measurement z_k attained, the weight of each particle at time k instant is updated. The weights are given by the following equation.

$$w^i_k = w^i_{k-1} p(z_k \left| x^i_{k|k-1}\right.) = w^i_{k-1} p(z_k - h(x^i_{k|k-1}))$$

Where, $i = 1,2,3,\cdots,N$ .The weights are normalized by.

$$w^i_k = w^i_k \bigg/ \sum_{i=1}^{N} w^i_k$$

(4). Resampling

From a set of particles $(x^i_{k/k-1}, w^i_k)$, according to the value of the importance resampling, a new set of particles $(\tilde{x}^i_{k/k-1}, \mathrm{i}=1,...,\mathrm{N})$ can be gotten.

(5). Estimation

The set of particles can be used to approximate the posterior PDF, that is $p(x_k|Z_k)$ and the estimated value is as follows.

$$\hat{x}_k \approx \sum_{i=1}^{N_s} w^i_k \tilde{x}^i_{k/k-1}$$

Then, k=k+1, go to step (2).

3. Hierarchical Particle Filter for Two-Satellite Faults Detection

The problem of fault detection (FD) consists of making the decision on the presence or absence of faults for GPS monitored system, and the problem of fault isolation (FI) consists of deciding the present faulty mode among a number of possible modes. In this paper, a fault detection and isolation (FDI) method is designed for GPS integrity monitoring using hierarchical PF algorithm to detect the consistency of GPS system measurements, and then make the consistency of the test statistic. Finally, the consistency of changes caused by fault compares with the detection threshold to determine the moment of fault and fault satellite. In the algorithm, calculating each time the accumulated LLR function, according to the characteristic of the accumulated LLR function, the characteristic is that under normal circumstances the function curve is smooth with time. When the data fluctuates, it will produce a negative drift before the change and after the change it will produces a positive drift[12]. So the fault detection is to decide a model shift or detecting a jump from the normal model.

GPS receiver state equation can be expressed using a linear function.

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

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

GPS measurement equation can be expressed using the following function.

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

Where ρ^i is the pseudorange between the GPS receiver with the coordinate $(\mathrm{r}_x, \mathrm{r}_y, \mathrm{r}_z)$ and the satellite i with its coordinate $(\mathrm{s}_x, \mathrm{s}_y, \mathrm{s}_z)$, and c stands for light speed. $\Delta\delta$ is the time offset. E^i is the ephemeris error. ε is the code measurement noise. And , R^i stands for the distance between the satellite i and the GPS receiver.

$$R^i = \sqrt{(\mathrm{r}_x - \mathrm{s}_x^i)^2 + (\mathrm{r}_x - \mathrm{s}_y^i)^2 + (\mathrm{r}_x - \mathrm{s}_z^i)^2}$$

The measurements are selected as follows. The coordinates of satellite $i(\mathrm{s}_x, \mathrm{s}_y, \mathrm{s}_z)$, the pseudorange ρ^i and the offset $\Delta\delta$ at each instant time, which all can be extracted from the measured data from GPS receiver[13].

3.1. Test Statistics Establishment

Statistics for problem of simple null hypothesis $H_0 : \theta = \theta_0$ to alternative hypothesis is,

$$\lambda(\mathrm{X}) = \frac{\prod_{i=1}^{n} p(\mathrm{X}_i; \hat{\theta})}{\prod_{i=1}^{n} p(\mathrm{X}_i; \theta_0)}$$

So when the null hypothesis H_0 is valid, the log-likelihood ratio statistic $2\ln\lambda(\mathrm{X})$ is asymptotic convergence in $\chi^2(\mathrm{k})$. The LLR test statistic $s^q(y)$ is asymptotic convergence in χ^2 and the cumulate log-likelihood ratio statistic $S_j^k(q)$ is asymptotic convergence in χ^2 .

When GPS monitoring system is working properly and no pseudo-range failure, malfunction alarm is false alarm. Given false alarm probability as follows,

$$P_{FA} = (1 - P(\chi^2 | r))(\tau | n - 4)$$

The derivation of probability formula,

$$P_r(\lambda(\mathrm{X}) < \tau^2) = \int_0^{\tau^2} f\,\chi^2_{(n-4)}(x)dx = 1 - P_{FA}$$

When given false alarm probability P_{FA}, the test statistic threshold $\tau \sim \chi^2_{1-P_{FA}}(\mathrm{n}-4)$ can be determined by the above formula.

Decision function for FD is defined as the following equation.

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

Where U is a window size of the most recent past observations and τ is a threshold. Select the window size is generally based on system real requirement[14].

If the decision function exceeds the threshold $\beta_k > \tau$, it means that failures have been occurred and alarm will be issued. The fault isolation is then achieved by determining the index g of the faulty subset of measurements which is given by.

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

Where, g is the fault satellite number, and t_a is alarm time.

3.2. Hierarchical Particle Filter for Fault Detection

This particle filter combining with LLR is used to detect and isolate satellite faults, namely, through PF generating the state estimates, the LLR at each time is calculated. Among the window time, the cumulative LLR is gotten. The consistency is checked. Then the satellite faults are detected and isolated. Therefore, the MAIN PF and auxiliary PF particle normalized weights are calculated in every moment, which is easy to do for PF algorithm. Accumulated LLR can be gotten for consistency test to detect whether there is fault satellite. To explain the approach based on PF, assuming the current satellite number used for position, velocity and timing (PVT) solution $s=6$, and one of them has a satellite fault. In order to detect and isolate satellite fault, we need $Q=s+1$ PF, one as the MAIN PF, remaining as an auxiliary PF. The MAIN PF calculates all satellites measurements to get system state estimation. Other s auxiliary PF calculates the removal of the satellite measurements state estimation in turn for consistency check.

If we have six measurements, that is $y=[y_1, y_2, y_3, y_4, y_5, y_6]^T$, then we use seven number of PFs. As shown in Figure 1, the MAIN PF processes all the 6 measurements to generate the best state estimate $\hat{x}^M$ and its PDF $p^M(y)$. While the auxiliary PFs process six out of seven measurements to provide the state estimates $\hat{x}^q$ $(q=A,B,\cdots,F)$ and their PDF $p^q(y)$ for consistency testing using LLR test statistics. If a satellite being tracked fault, one of the auxiliary PF remains uncontaminated and so at least one of the consistency tests is expected to signal an alarm.

The fundamental schemes of RAIM are the same, whether multiple-satellite faults or a single-satellite fault using hierarchical PF based on LLR is achieved to FDI. Thus, given the standard deviation of the pseudo-range errors and false alarm probability, the detection thresholds are the same for both situations. The RAIM method to detect two-satellite faults of the GPS is adapted by using hierarchical particle filter based probability test.

1) First, after calculating system state estimation with all N measurements, the corresponding state estimation with remaining N-1 measurements is calculated. Then LLR consistency checking is evaluated, if it exceeds the detection threshold, fault alarm is set, or no fault.

2) If there is a fault, the corresponding state estimation with remaining N-2 measurements is calculated. Then LLR consistency checking is evaluated, if it exceeds the detection threshold, second fault alarm is set, or no fault. The flow diagram is shown as Figure 3.

3) Using the method, after two iterations, the detection of two-satellite faults can be implemented. According to the principle of the method, it can also detect multi- satellite faults.

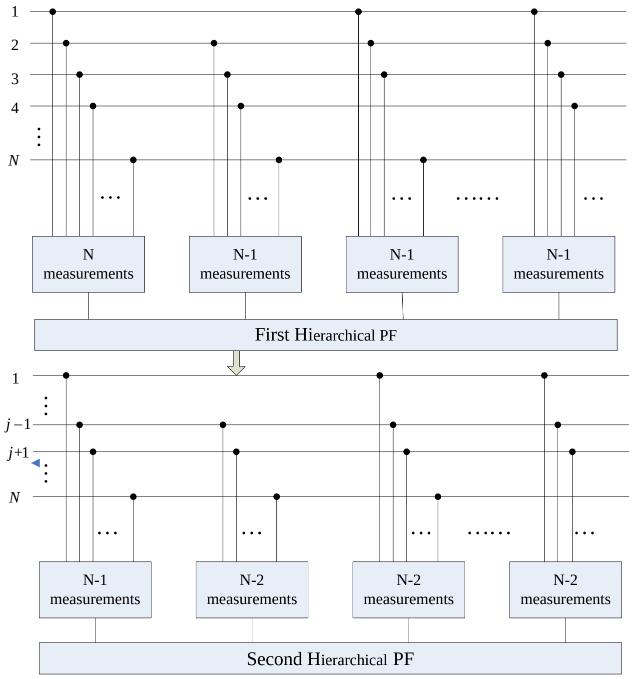

Figure 1. Implementation Diagram Based on Hierarchical PF for Two-Satellite Fault Detection

3.3. Hierarchical Particle Filter Algorithm Flow for GPS RAIM

The FDI algorithm for GPS integrity monitoring which is based on hierarchical PF can be summarized as follows.

(1) According to the coordinates (r_x, r_y, r_z) of the receiver, generate the initial set of N particles $\{x_0^A(i); i=1,2,...,N\}$ for main PF from the prior probability density function $p(x_0)$, and the auxiliary PFs particle $\{x_0^q(i); i=1,2,...,N\}$, $x_0^q(i)=x_0^A(i)$ for $i=1,2,...,N$. The main PF processes all N measurements, while the auxiliaries process subset of measurements (N-1 measurements).

(2) First hierarchical PF. Repeating the following steps for each time instant k.

1). State prediction. The particles of $\{x_0^A(i); i=1,2,...,N\}$ and $\{x_0^q(i); i=1,2,...,N\}$ are used in the system state equation to obtain the particles of the predicted values $x_{k/k-1}^A(i)$ and $x_{k/k-1}^q(i)$.

2). Calculate the particles weight. Taking the predicted values of the particles $x_{k/k-1}^A(i)$, $x_{k/k-1}^q(i)$ and the satellite position coordinates (s_x^i, s_y^i, s_z^i) and the time error into the system measurement equation to obtain the predicted satellite pseudorange value $\hat{\rho}^i$.Taking the $\hat{\rho}^i$ and the pseudorange measurement value ρ^i into the weight calculation formula and the normalized particle weights $\tilde{\omega}_k^A(i)$ and $\tilde{\omega}_k^q(i)$ are obtained.

3).Likelihood calculation. LLR $S_j^k(q)$ is computed by equation as follows.

$$S_j^k(q)=\sum_{r=j}^{k}\ln\frac{\frac{1}{N}\sum_{i=1}^{N}\tilde{w}_r^q(i)}{\frac{1}{N}\sum_{i=1}^{N}\tilde{w}_r^A(i)}$$

4).Decision function. Decision function for FD is defined as the following equation.

$$\beta_k = \max_{k-U+1\le j\le k} \max_{1\le d\le D} S_j^k(q)$$

Where , U is a window size of the recent observations. The window size is generally based on system real requirement.

5) Fault detection.

If $\beta_k > \tau$ (the decision threshold value is τ , the fault alarm time is set to $t_a = t$ and jump to step 6), if $\beta_k < \tau$ then no fault, go to step 7).

6).Fault isolation. The fault isolation is then achieved by determining the index g of the faulty subset of measurements which is given by:

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

Where, g is the fault satellite number, t_a is alarm time.

7). Status update. The particles of particle filter are updated.

(3) Second hierarchical PF. After removing the largest subset of accumulated LLR Q satellites, the other satellites carry out the test again with the remaining measurement values. Then the second satellite fault from the remaining satellites is detected and isolated.

4. Experiment Testing and Results Analysis

In this section, the numerical simulations on GPS positioning were performed. And the FDI performance of the proposed method for GPS integrity monitoring was evaluated. Two-satellite faults detection and isolation were simulated with the hierarchical PF. The experimental raw measurement data are collected by GPS receiver N220 (positioning accuracy is 2.5 meters (RMS)), the measurement data including the position information of satellites and the pseudoranges were generated for each epoch for 418 epochs. The user's position outputs at a frequency of 1Hz. During the period of this collected data, there are six satellites used for PVT solution, the number of GPS satellites is 3, 15, 18, 19, 21, 26 respectively, and the corresponding pseudorange value can be expressed as $Y = (y_1, y_2, y_3, y_4, y_5, y_6)$. At the same time, another RCB-4H receiver produced by the ublox company is used to monitor whether the satellite is working normally. In order to simulate the fault satellite, the biases were intentionally injects into the pseudorange of two satellites. Here, the 50m bias was added to No.19 and No.26 satellites at time 90 ~ 120(k=90 ~ 120). In the simulated experiment, the particle number is chosen as N=100, the calculated decision function of window length is selected as U=30, the simulated experimental data measurement noise obeys Gaussian kernel Laplace distribution. Some results of applying the proposed FDI algorithm for GPS integrity monitoring were shown as follows.

4.1. Experiment Results under Normal Condition

Figure 2 and 3 show the results of applying the proposed FDI algorithm for GPS integrity monitoring under nominal conditions.

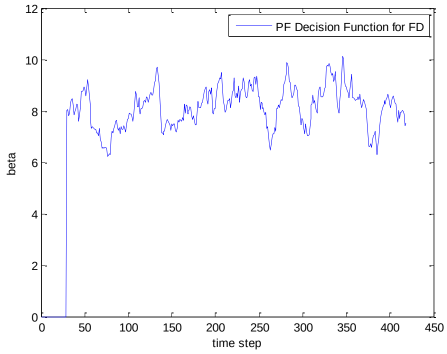

Figure 2. Decision Statistic For Fault Decision

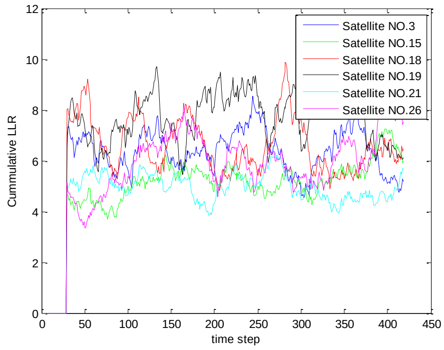

Figure 3.Cumulative LLR for Fault Isolation Under Normal Condition Under Normal Condition

Figure 2 shows the decision function for fault detection under normal condition. Figure 3 shows the cumulative LLR of PF algorithm under normal condition. The decision threshold value is chosen as τ =10. Figure 2 shows that the decision function β_k is steady under 10. Figure 3 shows although there are fluctuations of the auxiliary PF and PF accumulative LLR function curve, but its value is not more than 10.

4.2. Fault Testing Results under Two-Satellite Faults Condition

In order to conduct fault testing, the bias was added into the pseudoranges measurements. And the detection of anomalies with the proposed FDI method for GPS integrity monitoring was tested. Firstly, by inserting errors into nominal GPS data. In this work, the pseudorange measurements of satellites No.19 and No.26 were modified. Then these modified pseudorange measurements were put back into the FDI system for hierarchical filter. The results of first hierarchical PF are shown as Figure 4 and Figure 5.

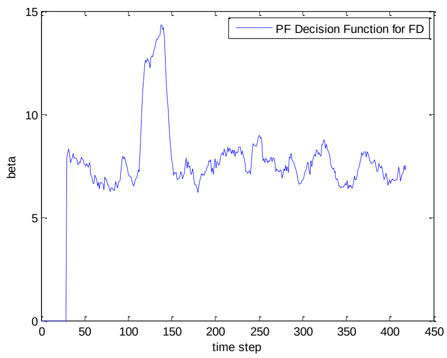

Figure 4. Decision Function for Fault Decision for First Hierarchical PF under Two-Satellite Faults Condition Isolation

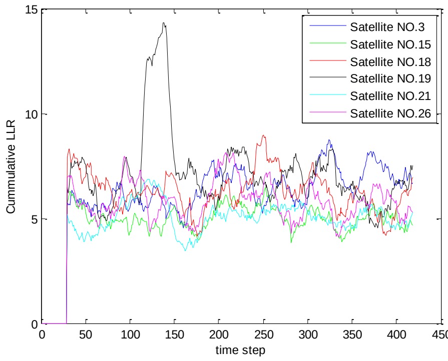

Figure 5. Cumulative LLR For FaultFor First Hierarchical PF under Two-Satellite Faults Condition

Figure 4 and Figure 5 shows the experimental results of the hierarchical particle filter for GPS RAIM under the first hierarchical PF under two-satellite faults conditions. From Figure 4 and Figure 5, it can be seen that the decision function β_k appeared a significant jump at k=95 that has over the detection threshold. According to the principle of fault detection of the above described, it can be judged that the first satellite No.19 exists fault. When calculating the PVT (position velocity and time) using the data, among the measurement data of the first hierarchical PF, the satellite No.19 should be abandoned. Therefore, it guarantees the reliability of GPS positioning. Then the second hierarchical

PF continues to detect the other fault satellite. The results of second hierarchical PF are shown as Figure 6 and Figure 7.

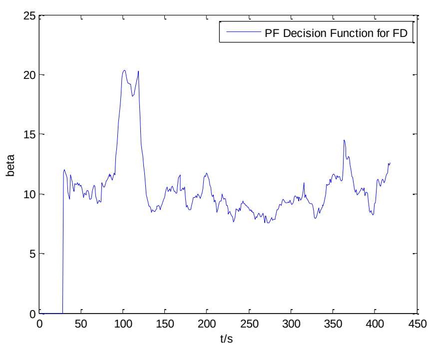

Figure 6. Decision Function for Fault Decision Isolation Second Hierarchical PF under Failure Condition

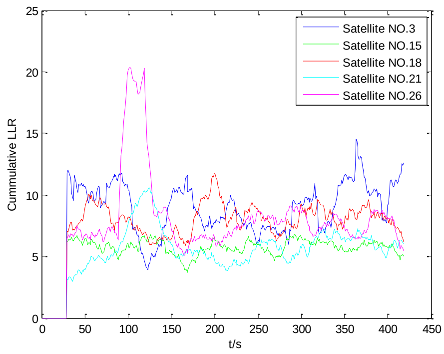

Figure 7. Cumulative LLR for Fault for Second Hierarchical PF for Under Failure Condition

Figure 6 and Figure 7 shows the experimental results of the hierarchical particle filter for GPS RAIM under the second of two-satellite faults conditions. From Figure 6 and Figure 7, it can be seen that the decision function β_k appeared a significant jump at k=95 that has over the detection threshold. According to the principle of fault detection of the above described, it can be judged that the satellite No.26 exists fault. When calculating the PVT using the satellite data, the satellite No.26 should be abandoned. So far, two-satellite faults are both abandoned. And the purpose of two-satellite fault detection for GPS integrity monitoring is achieved. The method based on hierarchical PF for GPS RAIM is feasible and effective.

5. Conclusions

A new FDI method for GPS integrity monitoring by using the hierarchical particle filter was proposed. The proposed method makes it possible to detect two-satellite faults for GPS receiver. The hierarchical PF is executed in turn for detecting and isolating two-satellite faults. The test statistics is established .The likelihood function is established and tested by integrating state estimate from both the main PF and auxiliary PFs. Furthermore, the LLR test is used to detect fault, which compares the consistency of the measurement between the main PF and auxiliary PFs. The evaluation of FDI is conducted through simulation using the real GPS measurement data. The measured data from GPS receiver are deliberately contaminated with the bias. Based on the simulation result, the proposed approach demonstrated that it can successfully detect GPS measurement fault under non-Gaussian measurement noise, and particularly showed its outstanding performance in the aspects of processing multi-satellite faults. The proposed RAIM algorithm has certain reference value for BeiDou navigation receiver autonomous integrity monitoring.

Acknowledgments

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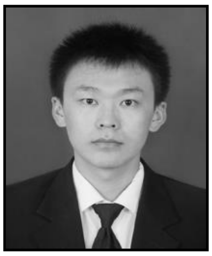

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