GPS Receiver Autonomous Integrity Monitoring Algorithm Based on Improved Particle Filter

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***Abstract*—Reliability of a navigation system is one of great importance for navigation purposes. Therefore, an integrity monitoring system is an inseparable part of aviation navigation system. Failures or faults due to malfunctions in the systems should be detected and repaired to keep the integrity of the system intact. According to the characteristic of GPS (Global Positioning System) receiver noise distribution and particle degeneracy and sample impoverishment problem in particle filter, an improved particle filter algorithm based on genetic algorithm for detecting satellite failures is proposed. The combination of the re-sampling method based on genetic algorithm and basic particle filter is used for GPS receiver autonomous integrity monitoring (RAIM). Dealing with the low weight particles on the basis of the genetic operation, genetic algorithm is used to classify the particles. It brings the selection, crossover and mutation operation in genetic algorithm into the basis particle filter .The method for detecting satellite failures which affect only subsets of system measurement. In addition to a main particle filter, which processes all the measurements to give the optimal state estimate, a bank of auxiliary particle filters is also used, which process subsets of the measurements to provide the state estimates which serve as failure detection references. The consistency of test statistics for detection and isolation of satellite fault is established. The failure detection is undertaken by checking the system state logarithmic likelihood ratio (LLR). The RAIM algorithm combined the genetic particle filter and the likelihood method is illustrated in detail. Experimental results based on GPS real raw data demonstrate that the algorithm under the condition of non-Gaussian measurement noise can improve the accuracy of state estimation, effectively detect and isolate fault satellite, improve the performance of the fault detection. Experimental results demonstrate that the proposed approach is available and effective for GPS RAIM.**

***Index Terms*—global positioning system(GPS); receiver autonomous integrity monitoring(RAIM);genetic algorithm (GA);particle filter; fault detection**

I. Introduction

With the development of the global navigation satellite system (GNSS) and the increase 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[1-3]. 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[4]. As a result, to monitor the satellite fault rapidly in the client part, namely the Receiver Autonomous Integrity Monitoring (RAIM) has been researched a lot.

Currently, RAIM algorithm includes two categories: one is to the snapshots algorithm using the current amount of pseudorange observation, the other is the RAIM algorithm based on kalman filter. The snapshots algorithm does not need external support equipment, and it has the advantage of fast speed and implement easily, and it 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. Kalman filtering algorithm is by using historical measure to improve the performance, and it has a strong dependence to the a priori error characteristic, but the actual error characteristics is difficult to accurately forecast. Moreover, this algorithm requires measurement noise obey Gaussian distribution, and the noise is very difficult to strictly obey Gaussian distribution in the actual measurement, at this point, the performance of the algorithm will downgrade much [5-7].

Various filtering methods have been studied for reducing the measurement noise level or integrating a GNSS with other sensors so that the navigation system can estimate its position more accurately and reliably. Because filters reduce the noise level of measurements using previous information, they can provide a better integrity monitoring performance than snapshot algorithms can. However, since most filters, such as Kalman filters, presume that the measurement error and disturbance follow a Gaussian distribution, their performance can degrade if this assumption is not correct. Because GNSS measurement error does not follow a Gaussian distribution perfectly[8], the kalman filter approach has to use an inaccurate error model that may cause performance degradation.

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To address this problem, a new integrity monitoring algorithm using particle filters (PF) is proposed. Particle filters can deal with nonlinear/non-Gaussian dynamic systems as well as linear/Gaussian systems[9-10]. The basic particle filtering methods, such as Sequential Importance Sampling (Sequential Importance Sampling) method has a problem of particle degradation, as a result, solving this problem mainly relies on two key factors: choosing the importance density function and resampling strategy. Although the resampling strategy can solve the problem of particle degradation, but at the same time will bring the sample depletion problem, that is the power value of particle is selected for many times, and it will contain many repeated sampling results, thus diversity of particles will be lost. The combination of the re-sampling method based on genetic algorithm and basic particle filter is used in GPS receiver autonomous integrity monitoring (RAIM).The proposed algorithm estimates a distribution of a measurement residual from the posterior density and detects exceedingly large residuals to satisfy a false alarm rate. This algorithm can detect faults based on an accurate estimation of the posterior distribution, and it can detect and exclude faults almost simultaneously, so that the system can exclude a fault measurement easily. With a non-Gaussian measurement error, a genetic particle filter can estimate the distribution of the state more accurately than a basic particle filter can, and therefore it has a better integrity monitoring performance. In addition, if the system is also highly nonlinear, then the performance will also be better.

The paper is organized as follows. First, a theory of a particle filter is briefly reviewed. Then the genetic algorithm is described in detail. And the genetic algorithm is combined with the particle filter. The general scheme of the approach followed by a genetic particle filtering based on log likelihood ratio (LLR) approach to FDI is presented. The next section is a description of the system and measurement equation of GPS system. Finally, based on the real GPS raw data, the GPS autonomous integrity monitoring system and its usefulness are presented with the numerical simulations.

II. Fault Detection Based on Particle Filter

Fault detection refers to detect the existence of the monitored system fault, fault isolation refers to identify the source of fault or failure of the system when a failure occurs. Particle filter algorithm is a kind of algorithm based on sequential monte carlo and the sequential importance sampling (SIS) filter. PF is a modern Bayesian methods based on numerically approximating posterior distributions of interest. Particle filters are suited for nonlinear state-space models and non-Gaussian noise. Through the probability density distribution function from the system, the samples is generated, and through the system state equation and measurement equation, forecast the sampling set and update to approximate random Bayesian estimation of nonlinear system. Since Gordon proposed sequential importance resampling particle filter algorithm based on monte carlo method, the particle filtering has become one of the hot research topics in the state estimation problem of nonlinear system and non-gaussian noise. And now it is widely used in navigation, automatic control, target tracking, and so on, and successfully applied to the dynamic system failure detection problems[11-14].

The principle of detecting the fault based on particle filter algorithm is applicable to any nonlinear and non-gaussian system. It has no any limitation with the system process noise and measurement noise, and it’s easy to get the optimal state estimation. The error of the particle filter is closely related to model mismatch, and with the increase of model mismatch, the particle filter error will increase rapidly[15]. Based on this conclusion, the particle filter is applied in fault detection. Meanwhile, RAIM algorithm itself evaluates the consistency of the state of the system.

A. *Basic Particle Filter Algorithm*

Particle filters can deal with nonlinear/non-Gaussian dynamic systems as well as linear/Gaussian systems. The sequential importance sampling (SIS) algorithm is a Monte Carlo (MC) method that forms the basis for most sequential MC filters developed over the past decades[16]. This sequential MC (SMC) approach is known variously as bootstrap filtering[17], the condensation algorithm, particle filtering , interacting particle approximations[18]. It is a technique for implementing a recursive Bayesian filter by MC simulations. The key idea is to represent the required posterior density function by a set of random samples with associated weights and to compute estimates based on these samples and weights. As the number of samples becomes very large, this MC characterization becomes an equivalent representation to the usual functional description of the posterior probability density function (PDF), and the SIS filter approaches the optimal Bayesian estimate.

This section briefly introduces the basic SIR algorithm to provide a background to our proposed integrity monitoring algorithm. In order to develop the details of the particle filter algorithm, first, let’s consider 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 expectation and the variance of the states are obtained from the posterior probability density function (PDF), which is expressed using a mass function of random samples and associated weights, as shown in equation (1). The random samples are known as particles.

$$\widehat{p}(x_k \mid z_{1:k}) = \sum_{i=1}^{Ns} \tilde{\omega}_k^{(i)} \delta(x_k - x_k^{(i)}) \qquad (1)$$

Where $z_{1:k} = \{z_i, i = 1,\dots,k\}$. The particles are derived from the prior distribution, and the associated weights are calculated using equations (2) and (3).

$$\tilde{\omega}_k^{(i)} = \omega_k^{(i)} / \sum_{j=1}^{Ns} \omega_k^{(j)} \tag{2}$$

$$\omega_k^{(i)} = \omega_{k-1}^{(i)} \frac{p(z_k \mid x_k^{(i)}) p(x_k^{(i)} \mid x_{k-1}^{(i)})}{q(x_k^{(i)} \mid x_{k-1}^{(i)}, z_k)} \tag{3}$$

The conditional probabilities $p(x_k^{(i)} \mid x_{k-1}^{(i)})$ and $p(z_k \mid x_k^{(i)})$ which are known as the transition prior density and likelihood density, respectively, are determined by the system definition. The importance density $q(x_k^{(i)} \mid x_{k-1}^{(i)}, z_k)$ which is not defined by the problem, is a design parameter chosen by the designer. A popular choice of the importance density in the SIS algorithms is the transition prior density.

$$q(x_k^{(i)} \mid x_{k-1}^{(i)}, z_k) = p(x_k^{(i)} \mid x_{k-1}^{(i)}) \tag{4}$$

This method is very simple and easy to implement.

However, it has a degeneracy problem which can be mitigated by using a resampling (or selection) procedure. This algorithm is called the SIR filter. The SIS algorithm thus consists of recursive propagation of the weights and support points as each measurement is received sequentially.

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, these samples called particles. Then based on the measurement value adjust constantly the particle weight and position of the particle distribution, modified initial priori conditional distribution. The algorithm is a recursive filtering algorithm, commonly used to handle non-gaussian and nonlinear systems state and parameter estimation. The huge computational burden is the bottleneck of particle filter algorithm.

Basic particle filter algorithm can be described by the following steps:

(1)Initialized

According to the priori probability $p(x_0)$, the initial particles $\{x_0^i\}_{i=1}^{N_s}$ are obtained, the weight value of the particles is $1/N_S$.

(2) For k=1,2,…performing the following steps;

① State prediction

Priori particles extracted based on the state equation of system at time k.

$$\{\mathbf{x}_{k|k-1}(i) : i = 1,2,\cdots,N\} \sim p(\mathbf{x}_k \mid \mathbf{x}_{k-1}) 。$$

② Update

Update particle weights at time k:

$$w_k^i = w_{k-1}^i p(z_k \left| x_k^i \right.) = w_{k-1}^i p_{e_k}(z_k - h(x_k^i))$$

where,i=1,2,3... N_s .The weight values are normalized:

$$\tilde{w}_k^i = w_k^i \Big/ \sum_{i=1}^{N_S} w_k^i, \sum_{i=1}^{N_S} \tilde{w}_k^i = 1$$

(3)Resampling

From the set of particles（$\mathbf{X}^i_{k|k-1}, \tilde{w}_k^i$）, according to the values of the importance resampling , getting a new set of particles（$\hat{\mathbf{X}}^i_{k|k-1}, i = 1,\cdots,N$）.

(4) Estimate. State estimation

Calculating the system state estimation value at current time: $\hat{x}_k \approx \sum_{i=1}^{N_s} \tilde{w}_k^i \hat{\mathbf{X}}^i_{k|k-1}$

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

B. Degeneracy Problem of Basic Particle Filter

A common problem with the SIS particle filter is the degeneracy phenomenon. It is thus impossible to avoid a degeneracy phenomenon. Practically, after a few iterations of the algorithm, all but one of the normalized importance weights are very close to zero, and a large computational burden is devoted to updating trajectories whose contribution to the final estimate is almost zero. After a few iterations, all but one particle will have negligible weight. It has been shown that the variance of the importance weights can only increase over time, and thus, it is impossible to avoid the degeneracy phenomenon. This degeneracy implies that a large computational effort is devoted to updating particles whose contribution to the approximation is almost zero. A suitable measure of degeneracy of the algorithm is the effective sample size N_{eff} .

$$N_{eff} = \frac{N_s}{\sum_{i=1}^{N_s} (w^{*i}_k)^2}$$

Where $w^{*i}_k = p(x_k^i, z_{1:k}) / q(x_k^i \left| x_{k-1}^i, z_k \right.)$ is referred to as the true weight. This can not be evaluated exactly, but an estimate $\widehat{N}_{eff}$ of N_{eff} can be obtained by the following equation.

$$\widehat{N}_{eff} = \frac{1}{\sum_{i=1}^{N_s} (w_k^i)^2}$$

Where w_k^i is the normalized weight. Notice that $\widehat{N}_{eff} \le N_s$, and small N_{eff} indicates severe degeneracy. Clearly, the degeneracy problem is an undesirable effect in particle filters. The brute force approach to reducing its effect is to use very large particles. This is often impractical, therefore, there are two methods for the degeneracy phenomenon: good choice of importance density and using of resampling. The latter is described as follows.

Resampling particle filter can suppress weight degradation, but it introduces other practical problems, for example, the resampling particle no longer independent. Moreover, it limits the opportunity to parallelize since all the particles must be combined. And the particles that have high weights are statistically selected many times. This leads to a loss of diversity among the particles as the resultant sample will contain many repeated points. This problem, which is known as sample impoverishment, is severe in the case of small process noise.

As a theoretical basis of evolutionary thought, the genetic mechanism to solve the problem of particle degradation problems provides an important guiding ideology, and it has obvious advantages of inheritance choice. As a result, using genetic algorithm operation such as crossover, mutation and reproduction to produce new samples, it can abandon the resampling simple trade-off shortcomings, and at the same time, it meets the demand of satisfying the requirements of sample diversity [19-20]. A generic particle filter is then as described as follows.

C.Particle Filter Based on Genetic Algorithm Resampling

Genetic algorithm is search optimization algorithm of simulating biological evolution on the computer based on natural selection and genetic mechanism. Because the genetic algorithm reflects a kind of evolutionary thought, it has the certain reference value to solve the problem of degradation of particle filter[21]. Compared with genetic algorithm, the particle filter algorithm has an initial sample collection, and a collection of each individual represents a possible solution of the system, these individuals change with the state transition equation and has the high fitness individuals to reproduce. The Particle Filter GAPF (Genetic Algorithm based Particle Filter)of Genetic Algorithm and resample are to introduce the selection, crossover and mutation operation in Genetic Algorithm into the basic Particle Filter Algorithm instead of the traditional resampling method. In this paper, the particle evolution operation does not need for encoding and decoding operation, but directly operate within the scope of the real number. Genetic resampling process is the genetic mechanism of execution, which is for each particle status with weights, the crossover and mutation operation is done as following:

(1) Crossover operation

Two particles are randomly selected from the particle concentration $(x_k^m, x_k^n)_{m,n=1}^{N_s}$, According to the following equations for crossover operation.

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

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

If $p(z_k|\widetilde{x}_k^m) > \max\{p(z_k|x_k^m), p(z_k|x_k^n)\}$, then take the particles $\widetilde{x}_k^m$, or take the particles with the probability is $p(z_k|\widetilde{x}_k^m) / \max\{p(z_k|x_k^m), p(z_k|x_k^n)\}$. It is the same way to take or abandon particles $\widetilde{x}_k^n$ with $\widetilde{x}_k^m$.

(2) Mutation operation

One particle $(x_k^j)_{j=1}^{Ns}$ from particles sets is randomly selected and the variation operation is done according to $\tilde{x}_k^j = x_k^j + \eta$, $\eta \sim N(0,\Sigma)$.

The mutation principle is:

If $p(z_k|\tilde{x}_k^j) > p(z_k|x_k^j)$,select the particles $\tilde{x}_k^j$, or select the particles with the probability $p(z_k|\tilde{x}_k^j) / p(z_k|x_k^j)$ .According to the crossover and mutation operation above, the new particles sets $\left\{\tilde{x}_k^i, \overline{w}_k^i\right\}_{i=1}^{Ns}$ will be got, and then get state estimation by the following expression.

$$\hat{x}_k = \sum_{i=1}^{N_s} \overline{\omega}_k^i \widetilde{x}_k^i$$

The advantage of introducing the genetic algorithm is to improve the efficiency of the use of the particle and to make the number of particles decreased, which is needed by posterior probability distribution when approximating to the system state variables. On the other hand, due to the genetic algorithm can effectively increase the diversity of the particle, restrain effectively the sample impoverishment.

III RAIM BASED ON GENETIC ALGORITHM PARTICLE FILTER AND LIKELIHOOD RATIO

GNSS-based navigation systems must have an integrity monitoring system that contains two main functions: 1) detection and exclusion of satellite faults and 2) estimation of the uncertainty of the position solutions. The system calculates decision variables and compares these to thresholds that have been set to satisfy the integrity requirements for the desired operation. If any decision variable exceeds the threshold, then the system concludes that the corresponding measurement has a fault, and excludes the detected fault.

RAIM include two functions: detection of satellite whether there is a fault, identify a faulty satellite, and the navigation calculating process will be removed[22]. Through the establishment of likelihood ratio test statistic consistency inspection, and test statistics calculated using the measured values, it can approximately describe the fault as much as possible. Detection threshold is the threshold of the fault test statistics of the judgment system, the threshold could be obtained according to the requirements of the false alarm rate detection.

A. GPS Observation Equation

The GPS dynamic system model is as follows:

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

Where, $X_k = [r_x, r_y, r_z, \Delta\delta]^T$ is three dimensional position and GPS-receiver clock offset, and F is a transition matrix which is an identity matrix in the static case[23].

The GPS signal consists of a clock signal and a navigation message that is amplitude modulated. Each satellite sends the clock signal in two different bands, L1 and L2. The GPS receiver receives the signal corrupted by noise and other sources of error. The raw measurements of the code and carrier phase pseudoranges are presented as follows[24].

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

where:

ρ : code pseudoranges（m）

i : satellite number

R : distance between the receiver and satellite position(m)

c : speed of light（$m\ s$）

$\Delta\delta$: combined clock offsets of the receiver and satellite

clock with respect to GPS time（s）

E : effect of ephemeris error（m）

I : ionospheric delay（m）

T : trophospheric delay（m）

ε : code observation noise（m）

The data of satellite coordinates $(s_x{}^i, s_y{}^i, s_z{}^i)$, pseudo-range ρ^i and time error $\Delta\delta$ is got from the GPS receiver.

The problem of fault detection consists of making the decision on the presence or absence of faults in the monitored system. An FDI system for GPS integrity monitoring is designed. The main failures to be detected affect only a subset of the system measurements. A reference system unaffected by failures is required for the FD which monitors the state estimate of a PF[25].

Assuming the number of the satellites used for calculating is m = 6, and a satellite is failure, so take 5 (that is m -1) from all of the observations, which forms a new observation subsets $C_6^5\,(C_m^{m-1})$.

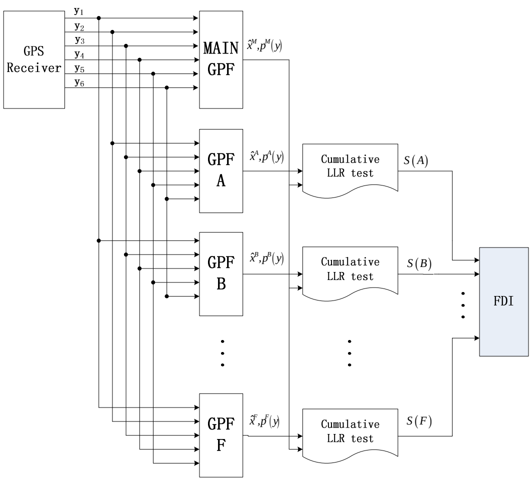

Figure 1. Failure detection principle diagram based on genetic particle filter algorithm

where y1,y2,y3,y4,y5,y6 are the current measurement values, including the pseudorange between the satellite and receiver obtained by computing and the visible satellite coordinates got from satellite navigation message. Particle filter $GAPF\ \ J(J = B,C,D,E,F,G)$ is the input for subsets of the measuring values. $\{\hat{x}^J, p^J(y), J = B,C,D,E,F,G\}$ is by measuring a subset given after the corresponding particle filter state estimation and the likelihood probability density.

$$y^M(k) = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix} \quad y^A(k) = \begin{bmatrix} y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix} \quad y^B(k) = \begin{bmatrix} y_1 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix}$$

$$y^C(k) = \begin{bmatrix} y_1 \\ y_2 \\ y_4 \\ y_5 \\ y_6 \end{bmatrix} \quad y^D(k) = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_5 \\ y_6 \end{bmatrix} \quad y^E(k) = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_6 \end{bmatrix}$$

$$y^F(k) = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix}$$

From each input measured value of PFs we can know, when a positioning satellite fails, one of six auxiliary PFs will not contain the measured values send from the faulty satellites, and then we can detect faulty satellite through consistency test.

B. Logarithmic Likelihood Ratio Test Statistic

The log-likelihood ratio is defined as a function of a random variable y as follows.

$$s(y) = ln\frac{p_{\alpha 1}(y)}{p_{\alpha 0}(y)} \tag{5}$$

The LLR test is defined as the probability density function of the auxiliary GAPF and main GAPF ratio, the LLR can be computed as follows:

$$s^q(y) = ln\frac{p^q(y)}{p^A(y)} \tag{6}$$

The cumulative LLR of measurement y_j to y_k can be expressed as:

$$S_j^k(q) = \sum_{i=j}^{k} ln\frac{p^q(y_i|Y_{i-1})}{p^A(y_i|Y_{i-1})} \tag{7}$$

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

$$p^q\left(y_i \left| Y_{i-1}\right.\right) \approx \frac{1}{N}\sum_{m=1}^{N}\tilde{w}_i^q(m) \tag{8}$$

$$p^A\left(y_i \left| Y_{i-1}\right.\right) \approx \frac{1}{N}\sum_{m=1}^{N}\tilde{w}_i^A(m) \tag{9}$$

After calculating the cumulative LLR function $S_j^{\,k}$ of every moment, according the feature of cumulative LLR function S_j^k, that is under the normal circumstance, with the time k is increasing, the function curve is stable, and when data is changing, that will engage to a positive drift. Reflecting on the function curve is a different from other time. Using this feature the system failure can be detected.

C. RAIM Based on Genetic Particle Filter

Based on particle filter algorithm and the logarithmic likelihood ratio (LLR) method, this paper is to implement satellite fault detection and isolation. It is using particle filter on the system by processing the measured values of calculated each moment corresponds to the logarithmic likelihood ratio (LLR). Then make the LLR accumulated of window function each time, the test statistic is obtained for accumulative LLR at this moment. After that, according to the fault caused by the changing in consistency to detect failure moment, the fault detection and isolation of satellite is realized.

Based on genetic particle filter and logarithmic likelihood ratio RAIM algorithm can be detailed as follows:

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

Repeating the following steps for each time k:

1) State prediction.

The particles of $\left\{x_o^A(\mathrm{i}) : \mathrm{i} = 1,2,\ldots N\right\}$ and $\left\{x_0^q(\mathrm{i}) : \mathrm{i} = 1,2,\ldots, N\right\}$ are introduced into the system state equation, using the formula (1) to obtain particles predicted values $x_{k|k-1}^A(i)$ and $x_{k|k-1}^q(i)$.

2) Calculate the particles weight

Take the predicted values of the particles $x_{k|k-1}^A(i)$, $x_{k|k-1}^q(i)$ and the i-th satellite position coordinates $({s_x}^i, {s_y}^i, {s_z}^i)$ and the time error $\Delta\delta$, and so on into the system measurement equation to obtain the predicted i-th satellite pseudo-range value ρ^{*i} .Take the ρ^{*i} and pseudo-range measurement value ρ^i into the weight calculation formula and normalize them to obtain the normalized particle weights $\tilde{\omega}_k^A(i)$ and $\tilde{\omega}_k^q(i)$.

3) Likelihood evaluation

On receipt of the measurement y_k, the likelihood of the predictive state samples from the main PF are evaluated as

$$\tilde{\omega}_k^A(i) = p(z_k \mid x_{k|k-1}^A(i))$$

while the likelihood of the predictive state samples from the auxiliary PFs can be expressed as follows.

$$\tilde{\omega}_k^q(i) = p(z_k \mid x_{k|k-1}^q(i))$$

4) LLR calculation

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

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

4) Decision function

Decision function for FD defined as the following equation:

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

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

In $k > t_a$, remove the accumulated LLR Q satellites largest subset of the satellite, namely $g = \arg\max_{1\le d\le D} S_{t_a}^k \;\left(k > t_a\right)$ formula. g as failed satellite number, determining a failure satellite number of the satellite, the satellite in turn, can be isolated from the measured value.

7) Status update

The importance weight $\omega_k^A(i)$ of the predictive state samples $\left\{x_{k|k-1}^A(i) : i = 1,2,\ldots, N\right\}$ from the main PF and $\omega_k^q(i)$ of the predictive state samples $\left\{x_{k|k-1}^q(i) : i = 1,2,\ldots, N\right\}$ from the auxiliary PFs are calculated as follows:

$$\omega_k^A(i) = \frac{\tilde{\omega}_k^A(i)}{\sum_{j=1}^{N} \tilde{\omega}_k^A(j)} \text{ and } \omega_k^q(i) = \frac{\tilde{\omega}_k^q(i)}{\sum_{j=1}^{N} \tilde{\omega}_k^q(j)}$$

Then ,the filtered samples $\{x_k^A(i): i = 1,2,\ldots,N\}$ for the main PF and $\{x_k^q(i): i = 1,2,\ldots,N\}$ for the auxiliaries are obtained by resampling $\{x_{k|k-1}^A(i): i = 1,2,\ldots,N\}$ and $\{x_{k|k-1}^q(i): i = 1,2,\ldots,N\}$ respectively. Therefore, the resampling particles of particle filter are updated.

IV. EXPERIMENTS

Numerical simulations on GPS positioning illustrate the FDI performance of the proposed approach for GPS integrity monitoring.

A. Experiments Conditions

In most GNSS applications, the pseudorange measurement error is assumed to follow a Gaussian distribution. However, this is not true. In general, the core part of the error distribution can be characterized well using a Gaussian distribution, but the tail part of the distribution is heavier than that of a Gaussian distribution. The heavier tail is due to ground-reflected multipaths or to systematic receiver/antenna errors. Our simulation used a Gaussian core-Laplacian (GL) tail probability density function (PDF) as the receiver true error distribution to simulate a heavy-tailed model, which will be applied to our particle filter method.

The experimental raw observation data are obtained by GPS receiver N220, the observation data including the satellite receiver position location information and pseudorange values, the static measurement data is 418 s. at this time, there are 6 satellites used for PVT resolution, the Number of the satellite is 3,15,18,19,21,22 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, the RCB-4H receiver block monitors that the satellite is working normally, and position steady. In order to simulate when a satellite is failure, whether the algorithm could detection effectively, we add some deviation. Here, we add 50 m deviation to NO.19 satellite at time201～418(k=201～418). In the experiment, the particle N=100, the calculated decision function of window length is selected as 30, the experimental data observation noise obeys gaussian kernel Laplace distribution.

B. Experiments Results and Analysis

In order to contrast with GAPF algorithm and PF algorithm for performance RAIM, two monitoring algorithms are implemented respectively in this work.

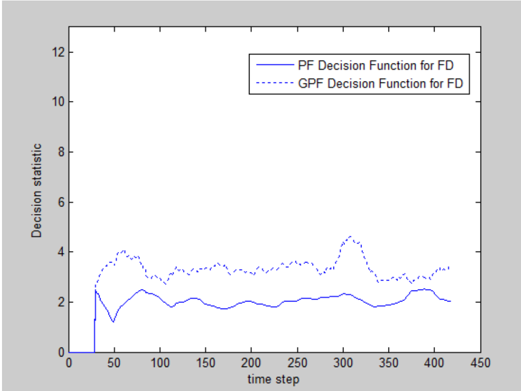

Figure 2. Decision function for fault detection under nominal condition

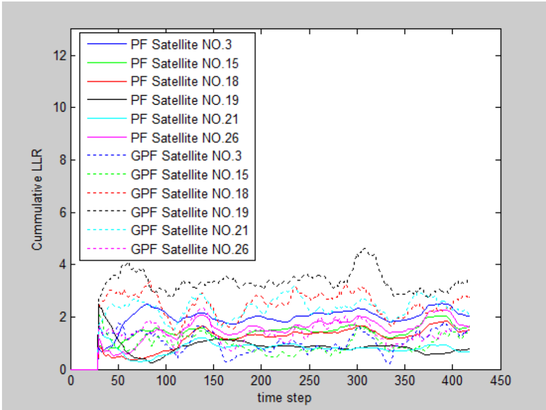

Figure 3. Cumulative LLR for fault isolation under nominal condition

It can be seen from figure 2 that the decision function has remained steady under five, in figure 3, each auxiliary PF and GPF accumulative LLR function curve is fluctuate, but its value is not more than 5.

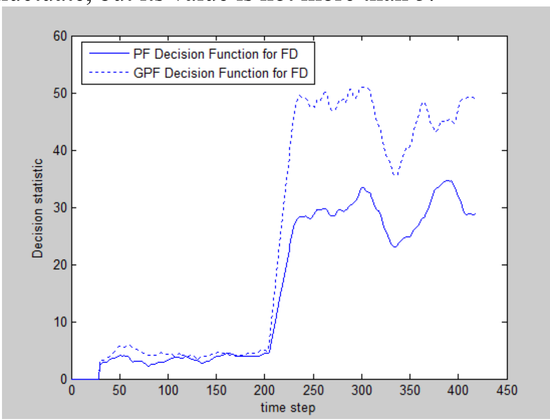

Figure 4. Decision function for fault detection under fault condition

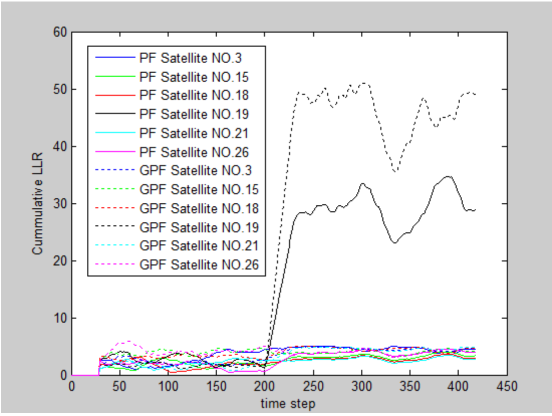

Figure 5. Cumulative LLR for fault isolation under fault condition

Figure 4 and figure 5 are given after a satellite failure, genetic particle filter algorithm and basic particle filter algorithm used in GPS receiver autonomous integrity monitoring of the experimental results. As seen from the figure 4, the decision function appeared a significant jump in k = 202 time, over the detection threshold, and in moments k = 205, RAIM algorithm adopts the genetic gives warning of particle filter algorithm, while the basic particle filter method is used in the RAIM algorithm at k = 210 time alarm is given. At the same time, according to the above described in section 3.2 of the principle of fault detection, it can judge that the No.19 satellites is failed, so the satellite data of No.19 satellite during this period of time (Position Velocity and Time) when PTV calculating should be abandoned, that will guarantees reliability for locating. It can be seen from the figure 4 and figure 5, a genetic particle filter algorithm and basic particle filter algorithm in the RAIM algorithm can successfully detect and isolate fault satellite, its detection performance is superior to the basic particle filter and the logarithmic likelihood ratio (LLR) combining the RAIM algorithm.

Genetic algorithm is introduced to improve the estimated accuracy of particle filter. The parameters in two kinds of algorithms are shown in table 1.

TABLE 1
PARAMETER COMPARISON BETWEEN PARTICLE FILTER AND GA PARTICLE FILTER ALGORITHM

Algorithm	Particle number	Effective particle number	RMSE
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:

$$N_{eff} = 1 \Big/ \sum_{k=1}^{N_s} (\omega_i^{(k)})^2 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N_s} \sum_{k=1}^{N_s} (x_i - \hat{x}_i^k)^2} \tag{11}$$

As the talbe1 shows, the RMSE of GPF is smaller than that of PF, that says the estimation accuracy of GPF is higher than PF filter. When the particles N=100, the effective sample of PF is 17.8779, if we increase the particle number to N=300, and the effective sample number is 36.6847; correspondingly, when particle number of GPF N=100, the effective sample is 28.7612, while particles number N=300, the effective sample is 59.6315. Seen from the table, to PF and GPF algorithm, rising the particle number can increase the effective particle, at the same time, it can decrease RMSE, which improve the accuracy performance; under the condition of the particle number N is the same, compared with the PR algorithm, the GPF algorithm can increase the effective sample number, and improve the state estimation accuracy.

V. CONCLUSIONS

A new approach of fault detection and isolation (FDI) for GPS integrity monitoring by combining particle filters with genetic algorithm is proposed. The algorithm can improve the state estimated accuracy of particle filter. The approach sets up a bank of auxiliary genetic particle filters and main genetic particle filter. The logarithmic likelihood ratio (LLR) test statistic is used to check the consistency between the state estimate of the main particle filter and those of the auxiliaries. Through GPS receiver experiment platform samples the observation data, numerical simulations verify that the algorithm combined the genetic particle filter (GAPF) algorithm with logarithmic likelihood ratio (LLR) is feasible and effective for GPS receiver autonomous integrity monitoring (RAIM) in the non-Gaussian measurement noise environment. The parameters comparisons of RMSE and effective particle number are given. The results demonstrate that the detection performance is superior to that of the basic particle filter.

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REFERENCES

[1] YUN Y, KIM D. Integrity monitoring algorithms using filtering approaches for higher navigation performance: consideration of the non-gaussian gnss measurements[C].Proceedings of ION GNSS 20th International Technical Meeting of the Satellite Division, Fort Worth, TX, 2007:3070-3071.

[2] Ishak Mohamad; Mohd. Alauddin Mohd. Ali1 and Mahamod Ismail, Availability, Reliability and Accuracy of GPS Signal in Bandar Baru Bangi for the Determination of Vehicle Position and Speed[C]. Proceeding of the 2009 International Conference on Space Science and Communication, Port Dickson, Negeri Sembilan, Malaysia,pp.224-229.

[3] Yoichi Morales and Takashi Tsubouchi, GPS Moving Performance on Open Sky and Forested Paths, Proceedings

of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems San Diego, CA, USA, Oct 29 - Nov 2, 2007,pp.3180-3185.

[4] I.Sayim,B. Pervan, S. Pullen and P. nge."Experimental and theoretical results on the LAAS sigma overbound" [C]. Proceedings of the ION GPS, Portland, Oregon, 2002: 29-38.

[5] Martini I,Hein G W.An Integrity Monitoring Technique for Multiple Failures Detection.Position,Location,And Navigation Symposium,2006 IEEE/ION,2006:450-467.

[6] Mojtaba Bahrami and Marek Ziebart.A Kalman Filter based Dopper-smoothing of code Pseudoranges in GNSS Challenged Environments[C]. Proceedings of the ION GNSS 2011, Portland, 2011:1-11.

[7] Xu X H,Yang C S,Liu R H. Review and prospect of GNSS receiver autonomous integrity monitoring[J]. Acta Aeronautica et Astronautica Sinica,2013,34(3):451-463.(in Chinese)

[8] SUN G L, SUN M H, CHEN J P.A study on time and set combined method for receiver integrity autonomous monitoring[J]. Acta Aeronautica et Astronautica Sinica, 2006,27(6):1171-1175.(in Chinese)

[9] N. J. Gordon, D. J. Salmond and A. F. M Smith,"Novel approach to nonlinear/non-Gaussian Bayesian state estimation", IEE Proceedings-F, Vo. 140, 1993, pp.107–113.

[10] A. Doucet, J. F. G. de Freitas and N. J. Gordon,"Sequential Monte Carlo methods in practice", Springer-Verlag, 2001.

[11] LI P, KADIRKAMANATHAN V. Particle filtering based likelihood ratio approach to fault diagnosis in nonlinear stochastic systems [J]. IEEE Trans. Syst., Man,Cybern. C, 2001, 31(3):337-343.

[12] WANG E S,ZHANG S F,HU Q. Research on GPS receiver autonomous integrity monitoring algorithm based on MCMC particle filtering[J]. Chinese Journal of Scientific Instrument, 2009, 30(10):2208-2212. (in Chinese)

[13] Fredrik Gustafsson, Fredrik Gunnarsson,etc.Particle filters for positioning, navigation, and tracking. IEEE Trans. on Signal Processing, 50(2), 2002.

[14] Pan Pan,Dan Schonfeld . Video Tracking Based on Sequential Particle Filtering on Graphs [J]. IEEE Trans. On Image Processing, 2011, 20(6): 1641-1651.

[15] VASWANI N. Bound on errors in particle filtering with incorrect model assumptions and its implication for change detection[C]. Proceedings of IEEE International Conference on Acoustics, Speech and signal processing, Montreal, Quebec, Canada, 2004: II-729-32.

[16] A. Doucet, J. F. G. de Freitas, and N. J. Gordon, "An introduction to sequential Monte Carlo methods," in Sequential Monte Carlo Methods in Practice, A. Doucet, J. F. G.

[17] N. Gordon, D. Salmond, and A. F. M. Smith, "Novel approach to nonlinear and non-Gaussian Bayesian state estimation," Proc. Inst. Elect.Eng., F, vol. 140, pp. 107–113, 1993

[18] M. S. Arulampalam,S.Maskell,N.Gordon and T.Clapp.A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking[J].IEEE Transactions on Signal Processing, 2002,50(2):174–188.

[19] Kaplan E,Hegarty C.Understanding GPS: Principles and Applica-tion[M].Second Edition.MA,US:Artech House,2006.

[20] Chen CanHui, Zhang XiaoLin, Simulation Analysis of Positioning Performance of BeiDou-2 and Integrated BeiDou-2/GPS. 2010 Interna-tional Conference on Communications and Mobile Computing, pp.505-509.

[21] Giovanni Giardini. Genetic algorithm for multi-agent space exploration[C].2007 AIAA infoTech at Aerospace Conference, v 2, p1146-1160.

[22] B W Parkinson, J J spilker, Global Positioning System: Theory and applications Volume I, I edition (American Institute of Aeronautics & Astronautics, Inc, 1996.

[23] Josef MAREK,LadislavŠTĚPÁNEK,Accuracy and Availability of the Satellite Navigation System GPS[C]. 2010 15th Conference on Microwave Techniques, pp.1-4.

[24] Pratap Misra, Per Enge, Global Positioning System:Signals, Measurements, and Performance, Second Edition,Beijing: Publishing House of Electronics Industry, 2008. (in Chinese)

[25] Rosihan, Arif Indriyatmoko, Sebum Chun,etc. Particle Filtering Approach to Fault Detection and Isolation for GPS Integrity Monitoring[C].Proceedings of ION GNSS 19th International Technical Meeting of the Satellite Division, Fort Worth, TX, 2007:873-881.

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