Research on Particle Filter Based on Neural Network for Receiver Autonomous Integrity Monitoring

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Abstract
According to the measurement noise feature of GPS receiver and the degeneracy phenomenon of particle filter (PF), in order to alleviate the sample impoverishment problem for PF, GPS receiver autonomous integrity monitoring (RAIM) algorithm based on PF algorithm combining neural network was proposed, which was used to improve the importance state adjustment of particle filter algorithm. The PF algorithm based on neural network is analyzed. And the test statistic of satellite fault detection is set up. The satellite fault detection is undertaken by checking the cumulative log-likelihood ratio (LLR) of system state of GPS receiver. The proposed algorithm was validated by the measured real raw data from GPS receiver, which are deliberately contaminated with the bias fault and ramp fault, the simulation results demonstrate that the proposed algorithm can accurately estimate the state of GPS receiver in the case of non-Gaussian measurement noise, effectively detect and isolate fault satellite by establishing log-likelihood ratio statistic for consistency test and improve the accuracy of detection performance.

Keywords: Global Positioning System (GPS); Receiver Autonomous Integrity Monitoring (RAIM); Particle Filter (PF); Fault Detection; Neural Network

1. Introduction
With the development of global navigation satellite systems (GNSS) and the growth of user performance requirements for GNSS service, for safety-critical applications of GNSS, such as aircraft and missile navigation applications, it is important to be able to detect and exclude faults that could cause risks to the accuracy and integrity of GNSS receiver positioning, so that the navigation system can operate continuously without any degradation in performance for positioning accuracy and integrity. 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, which can't meet the demand of aircraft navigation. As a result, to monitor the satellite fault rapidly in the user segment, namely receiver autonomous integrity monitoring (RAIM) has been researched a lot. RAIM has become a widely used integrity monitoring method. When the satellite positioning deviation exceeds the specified threshold, RAIM algorithm can realize the detection of GPS satellite fault by using the redundant data from GPS receivers [1-3]. Then, the system can send a timely warning to navigation users.

Currently, RAIM algorithms include two categories: one is the snapshots algorithm using the current amount of pseudorange measurement, and the other is the RAIM algorithm based on Kalman filter method. The snapshots algorithm does not need external supporting equipment, and it has the advantage of implementation easily. At present, it has been widely used. This kind of algorithm mainly includes parity space method, the sum of least squares of the error (SSE) method, and the largest interval method, etc [4]. In recent years, fault detection method based on Kalman filter has been widely used in nonlinear system. And Kalman filter algorithm uses historical measurements to improve the performance of state estimate. But, this algorithm requires that the measurement noise of system obeys Gaussian distribution. In the actual measurement, the system noise is very difficult to strictly obey Gaussian distribution, so the performance of the algorithm will decline much [5]. Because GNSS measurement error does not follow Gaussian distribution perfectly [6], the Kalman filter approach has to use an inaccurate error model that may cause performance degradation. Particle filter algorithm can better be suitable to any non-linear and non-Gaussian systems. And the algorithm has no any
restrictions to the system process noise and measurement noise. The optimal state estimate can be easily gotten [7-9]. Therefore, compared to Kalman filter, the particle filter algorithm is more suitable for non-linear and non-Gaussian system, and it is widely used in the fields, such as fault detection, navigation and positioning applications [10-14]. But basic particle filter algorithm exists the degeneracy phenomenon and the sample impoverishment problem [15].

In this paper, the particle filter of importance state adjustment based on general regression neural network (NNISA-PF) is proposed by adjusting the state of particle, and the importance density function of particle filter is optimized. At first, basic theory of GRNN will be given. Then, the NNISA-PF algorithm are proposed to improve the performance of GPS RAIM. Through establishing GPS satellite fault detection and isolation (FDI) model, two fault types both bias error and ramp error will be researched. Finally, the experiment results for FDI will be given by using the log-likelihood ratio method.

2. General Regression Neural Network (GRNN) Algorithm
2.1. Basic Theory of GRNN
In 1991, Specht proposed the general regression neural network [16]. There is a smooth factor $\sigma$, which can have a relatively large impact on neural networks in the activation function of GRNN, so the value of smooth factor $\sigma$ can be optimized.

Assume that $f(x, y)$ represents the known joint continuous probability density function of a vector random variable $x$, and a scalar random variable $y$. $x_0$ is a particular measured value of the random variable $x$. The regression is given as follows:

$$E(y \mid x_0) = \hat{y}(x_0) = \frac{\int_{-\infty}^{\infty} y f(x_0, y) dy}{\int_{-\infty}^{\infty} f(x_0, y) dy} \quad (1)$$

For a nonparametric estimate of $f(x_0, y)$, the class of consistent estimator was proposed by Parzen. The probability estimator is based on sample values $(x_i, y_i)_{i=1}^{n}$.

$$f(x_0, y) = \frac{1}{n(2\pi)^{\frac{n}{2}} \sigma^n} \sum_{i=1}^{n} e^{-d(x_0, x_i)^2} e^{-d(y, y_i)} \quad (2)$$

$$d(x_0, x_i) = \sum_{j=1}^{n} [(x_{0j} - x_{ij}) / \sigma]^2, \quad d(y, y_i) = (y - y_i)^2 \quad (3)$$

$$\hat{y}(x_0) = \frac{\sum_{i=1}^{n} y_i e^{-d(x_0, x_i)}}{\sum_{i=1}^{n} e^{-d(x_0, x_i)}} \quad (4)$$

The estimate $\hat{y}(x_0)$ can be visualized as a weighted average of all the observed values $y_i$.

2.2. Optimization of Smooth Factor
GRNN can use one-dimensional optimal method to get the fitting smooth factor, it can be optimized by using conjugate gradient method. In order to guarantee the generalization ability of neural networks, the leave-one-out cross method will be used for all training samples, which is one sample by using test and other samples by using training. The error is as follows:

$$e_{total}(\sigma) = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}(x_i) - y(x_i))^2 \quad (5)$$
Where, \( y(x_i) \) and \( \hat{y}(x_i) \) represent the values by observing and predicting the dependent variable of sample. According to the search function, it can be attained.

\[
\hat{y}(x_i) = \frac{\sum_{k=1, k \neq i}^{n} y_k e^{-d(x_i, x_k)}}{\sum_{k=1, k \neq i}^{n} e^{-d(x_i, x_k)}}
\]  
(6)

Assuming:

\[
N(x_i) = \sum_{k=1, k \neq i}^{n} y_k e^{-d(x_i, x_k)}, D(x_i) = \sum_{k=1, k \neq i}^{n} e^{-d(x_i, x_k)}
\]  
(7)

Thus:

\[
\frac{\partial (e_{\text{total}})}{\partial \sigma} = \frac{2}{n} \sum_{i=1}^{n} \left( \hat{y}(x_i) - y(x_i) \right) \frac{\partial \hat{y}(x_i)}{\partial \sigma}
\]  
(8)

The first-order partial derivatives of \( \frac{\partial \hat{y}(x_i)}{\partial \sigma} \) (the gradient of \( \sigma \)) can be obtained, and the value of \( \sigma \) by using the gradient of \( \sigma \) can be adjusted.

\[
\Delta \sigma = -\eta \frac{\partial e_{\text{total}}}{\partial \sigma}
\]  
(9)

Where \( \eta \) is the learning step, and \( \Delta \sigma \) is the modification of the smooth factor \( \sigma \).

The paper introduced general regression neural network to improve particle filter algorithm, and the importance density function of particle filter is optimized.

3. GPS RAIM Based on NNISA-PF Algorithm

The system model of fault detection and isolation (FDI) for RAIM based on NNISA-PF is established as follows. The equation of system state can be as follows [17].

\[
X_k = F_{k-1} X_{k-1} + w_{k-1}
\]  
(10)

The measurement equation can be as follows:

\[
\rho^i(k) = R^i(k) + c \Delta \delta^i + T^i(k) + E^i(k) + e^i(k)
\]  
(11)

RAIM based on NNISA-PF can be given as follows. According to the coordinates of the GPS receiver \((r_x, r_y, r_z)\), the N initial state value \(x^n(x_i) : i = 1, 2, ..., N\) of master particle filter and initial state values \(x^a(i) : i = 1, 2, ..., N\) of auxiliary particle filters are generated [18-19]. Each time \(k\) repeats the following steps.

1) State prediction. Put \(x^n(x_i) : i = 1, 2, ..., N\) and \(x^a(i) : i = 1, 2, ..., N\) respectively into the formula (10) and get the predicted particles \(x^a_{k-1}(i)\) and \(x^n_{k-1}(i)\).

2) Calculate the weight of particles. Put predicted particles \(x^a_{k-1}(i), x^n_{k-1}(i)\), the position coordinates \((s_x^i, s_y^i, s_z^i)\) of satellite \(i\) and the time error \(\Delta \tau\) into the system measurement equation, obtain the predicted pseudorange \(\rho^i\) of satellite \(i\). The normalized particle weights \(\phi^i_{k-1}(i)\) and
\( \hat{\omega}_k^i (\cdot) \) can be calculated by putting the pseudorange prediction \( \rho^i \) and pseudorange measurement \( \rho^i \) into weight calculation formula.

In this step, the GRNN is used to make the prediction results, which will be improved, and the process is as follows.

Firstly, the samples \( x_k^i, i = 1, 2, \ldots, N \) are adjusted by GRNN. Then,

\[
\hat{Y} (X) = \frac{\sum_{i=1}^{n} Y_i e^{-\frac{[(x_k^i - x_i^j)^2 + (x_k^i - x_i^j)^2]}{2\sigma^2}}}{\sum_{i=1}^{n} e^{-\frac{[(x_k^i - x_i^j)^2 + (x_k^i - x_i^j)^2]}{2\sigma^2}}}
\]

Then, the \( n \)-dimensional vector is constructed as follows:

\[
X_k^i = [x_k^i, x_k^i \pm j\Lambda], \quad j\Lambda < L(j = 1, 2, \ldots n/2)
\]

\( \Lambda \) is the adjustment range.

Finally, the results indicate the best point (minimum error point) is selected by using neural network output vector, and the sample is replaced by the best point.

According to the weighting formula, the weights \( \omega_k^i (\cdot) \) of all particles can be calculated.

\[
\omega_k^i = \omega_{k-1}^i p(Z_k | X_k^i), i = 1, \ldots, N
\]

Normalized weights can be expressed as the following.

\[
\bar{\omega}_k^i = \frac{\omega_k^i}{\sum_{j=1}^{N} \omega_k^j}, \sum_{i=1}^{N} \bar{\omega}_k^i = 1
\]

Resampling. Calculate the effective number of particles, and compare with the threshold. If \( N_{\text{eff}} < N_{\text{threshold}} \), resampling. Otherwise, performing the following steps.

Estimation. Use the formula to get the current state estimation.

\[
\hat{X}_k = \sum_{i=1}^{N} X_k^{i(i)} \bar{\omega}_k^i
\]

3) Calculate LLR.

\[
s_k^i (d) = \sum_{j=r-j}^{r+j} \frac{1}{N} \sum_{i=1}^{N} \bar{w}_k^i (i)
\]

4) According to the following formula to calculate the decision function. \( \tau \) is the decision threshold.

\[
\beta_i = \max_{k \in t, j \in [r-k, r+k]} \max_{d \in [n/k]} S_k^i (d) > \tau
\]

5) Fault judgment.

If \( \beta_i > \tau \), the fault alarm, remember the moment and go to step 6).
If $\beta \leq \tau$, there is no fault, go to step 7).

6) Fault isolation. When $k > t$, the biggest cumulative LLR function for assisted PF and NNISA-PF must not contain fault satellite, then get another satellite $q$, which is faulty satellite, or $g=q$.

7) State update.
(1) Resample. Calculate the effective number of particles, compare with the threshold, if $N_{\text{eff}} < N_{\text{threshold}}$, then resample.
(2) Estimation. Using the following formula can get the current state estimation:

\[ \hat{X}_k = \sum_{i=1}^{N} X^i_{k|k-1} \hat{\theta}^i_k \]

4. Simulation Test and Results Analysis

The experimental raw observation data are obtained by GPS receiver N220 (autonomous positioning accuracy is 2.5m), the observation data including the satellite receiver position data and pseudorange. The static measurement data is 418s. During the period of this experiment, the number of the satellite is 3, 15, 18, 19, 21, 26 respectively.

In order to simulate whether the algorithm could detection effectively when satellites appear fault, some deviations are added deliberately. Both NNISA-PF and PF for GPS RAIM are compared. In the experiment, the number of particle is $N=100$, neural network learning step is 0.05, and the window length of calculated decision function is selected as 30 and the threshold chosen is 10. The measurement noise of the experimental data obeys Gaussian kernel Laplace distribution. To demonstrate FDI performance, two fault types including bias error and ramp error are considered.

In the simulation, the pseudorange measurements of satellite 19 are contaminated, without loss of generality, by adding constant bias errors or time-varying ramp errors at time instant $k=200$. Figure 1 and Figure 2 show the results of applying the proposed FDI when the fault occurred in the bias error.

![Figure 1(a). Applied error signal having bias fault](image)

![Figure 1(b). Decision function for FD](image)

In Figure 1(a), bias errors are applied at epoch 200 with four different error magnitudes which are 100m, 150m, 200m and 250m. Figure 1(b) shows that the decision function is kept around 7 prior to the occurrence of a fault, but jumps significantly away after the onset of the fault. The threshold chosen is 10. Accordingly, in Figure 2, FI is conducted by checking each cumulative LLR graph when a fault is detected. By plotting CLLR for each auxiliary PF, the auxiliary PF which is free from the pseudorange contamination of bias error is determined numerically. Figure 2 shows the bias error of 100m can be isolated by NNISA-PF at 211 epoch and PF at 212 epoch. The results show that the proposed FDI method provides better...
performance in detection time under the bias error case than that of basic particle filter.

Figure 2. 100m bias case

Figure 3 and Figure 4 show the results of the proposed FDI for GPS integrity monitoring when the fault occurs in the ramp error.

Figure 3(a). Applied error signal having ramp fault
Figure 3(b). Decision function for FD

Figure 4. 0.8m/s gradient fault
It can be seen from the figure 4 that the decision function is kept around 7 prior to the occurrence of a fault and jump significantly away after the onset of a fault. Thus the threshold of decision function is chosen 10. Ramp errors start at 200 epoch with four different gradient values, 0.8, 1.2, 1.6, and 2 m/s. Meanwhile, 2m/s ramp error changes faster than 0.8m/s ramp errors. Figure 4 shows the 0.8m/s gradient fault can be isolated by NNISA-PF at 214 epoch and PF at 220 epoch. The advantage of the proposed FDI method is that the detection time is improved. It can be applied to the ramp type error with smaller gradient value.

Table 1 and Table 2 summarizes the FD performance of the fault types.

| Bias (m) | Number of effective particles |
|---------|-------------------------------|
|         | PF                       | NNISA-PF             |
| 100     | 49.85                     | 65.80 |  |
| 150     | 49.83                     | 90.29 |  |
| 200     | 49.89                     | 81.88 |  |
| 250     | 49.84                     | 82.87 |  |

Table 1. FD performance in case of bias fault type

| Bias (m) | Number of effective particles |
|---------|-------------------------------|
|         | PF                       | NNISA-PF             |
| 0.8     | 49.77                     | 63.41               |
| 1.2     | 49.84                     | 73.70               |
| 1.6     | 49.80                     | 71.72               |
| 2.0     | 49.86                     | 89.55               |

Table 2. FD performance in case of ramp fault type

Table 1 and Table 2 show that the proposed NNISA-PF algorithm had better performance in the number of effective particles than that of the basic particle filter. The problem of sample impoverishment has been alleviated. The performance of sample diversity has been improved. The effectiveness of the proposed approach has been demonstrated on GPS integrity monitoring to detect faults from GPS satellite.

5. Conclusion

This paper proposes a new approach of fault detection and isolation for GPS receiver autonomous integrity monitoring by combining the improved particle filter algorithm and the log likelihood ratio method. Firstly, Based on GRNN the importance state adjustment of particle filter (NNISA-PF) algorithm is proposed in order to inhibit the problem of particle degradation and diversity loss. Secondly, The approach is using a bank of auxiliary particle filters running parallel, which process subsets of system measurements to provide high accuracy detection references. And the consistency test statistics is established through cumulative log-likelihood ratio (LLR) between the main and auxiliary particle filters (PFS). Then, the real measured data from GPS receiver N220 was used to verify the proposed GPS RAIM algorithm. Finally, the results showed that the proposed algorithm can successfully detect and isolate the faulty satellite in the case of non-Gaussian measurement noise. And the proposed NNISA-PF algorithm had better performance in detection time and the number of effective particles than that of the basic particle filter.

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