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An improved fading Kalman filter in the application of BDS dynamic positioning

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ABSTRACT*:* Aiming at the poor dynamic performance and low navigation precision of traditional fading Kalman filter in BDS dynamic positioning, an improved fading Kalman filter based on fading factor vector is proposed. The fading factor is extended to a fading factor vector, and each element of the vector corresponds to each state component. Based on the difference between the actual observed quantity and the predicted one, the value of the vector is changed automatically. The memory length of different channel is changed in real time according to the dynamic property of the corresponding state component. The actual observation data of BDS is used to test the algorithm. The experimental results show that compared with the traditional fading Kalman filter and the method of the third references, the positioning precision of the algorithm is improved by 46.3% and 23.6% respectively.

Keywords: BDS positioning, fading factor vector, Kalman filter, memory length;

I. Introduction

The Beidou system(BDS) goes on retaining the active positioning, two-way timing and short message communication service of the Beidou satellite navigation testing system. Since December 27, 2012, The BDS provides continuous passive location, navigation, timing and other services to the Asia Pacific, and is expected to finish building the BDS which is global coverage in about 2020[1]. As the BDS infrastructure getting better gradually, BDS receiver terminal will be widely used in surveying and mapping, telecom, exploration, transportation and other fields. Therefore, it is necessary to improve the calculating precision of positioning algorithm.

In satellite navigation and positioning data processing, Kalman filter technology is a kind of filtering algorithm which is used frequently. When the observation information, model and statistical information are reliable, Kalman filter's computing performance is perfect. But when there is large model error or states mutation, the error between the state estimate value of Kalman filter and the actual system is huge, and can not reflect the real system, and even cause filtering divergence in under certain conditions. To solve the problem, the fading Klaman filter is proposed by some scholars[3,4,5]. Using the fading factor to limit the memory length, the fading Kalman filter could make full use of the current observations, and eliminate "outdated" observation data gradually. The algorithm can effectively solve the problem of filtering divergence, and improves the stability of the calculation process. However, the filtering result turns into suboptimal, and its result accuracy is not guaranteed[6,7,8].

Before the BDS data is widely used in positioning analysis, some simulation experiments have been used to study the positioning performance of Beidou system. With the improvement of the Beidou data system and the wide application of Beidou data, more and more scholars begin to study the real metrical performance of BDS[9]. In order to solve the problem of low dynamic performance and low positioning accuracy of traditional fading

Kalman filter algorithm, an improved Kalman filter algorithm based on fading factor vector is propose. It is used in BDS dynamic navigation and positioning, and has been tested by the actual BDS observation data. The experimental results show that the algorithm effectively improves the dynamic performance and positioning result's precision of BDS.

II. Fading Kalman filter positioning model

In order to determine the position and speed of the carrier, the state vector X is defined as below.

$$\mathbf{X} = \begin{bmatrix} x & v_x & y & v_y & z & v_z & b \end{bmatrix}^T \tag{1}$$

In formula (1), x , v_x , y , v_y , z and v_z are the position and velocity components of the carrier on a three axis coordinate system, and b is the clock error. Thus, the state transition equation is defined as below.

$$\mathbf{X}_k = \mathbf{\Phi}_{k,k-1}\mathbf{X}_{k-1} + \mathbf{W}_k \tag{2}$$

$\mathbf{X}_k$ is the state vector of k moment, and $\mathbf{W}_k$ is the system noise vector, while $\mathbf{\Phi}_{k,k-1}$ is state transition matrix.

$$\mathbf{\Phi}_{k,k-1} = \begin{bmatrix} 1 & \mathrm{T} & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & \mathrm{T} & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \mathrm{T} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \mathrm{T} & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & \mathrm{T} & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & \mathrm{T} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$\mathbf{W}_k = \begin{bmatrix} 0 & \omega_x & 0 & \omega_y & 0 & \omega_z & \omega_b \end{bmatrix}^T \tag{4}$$

ω_x , ω_y , ω_z and ω_b are white Gaussian noise, whose means are zero, and variance are σ_x^2 、 σ_y^2 、 σ_z^2 and σ_b^2 respectively. T is the sampling interval. In a moment, when the observation data of N satellites are available, the pseudorange observation equation is defined as below.

$$\tilde{\rho}_i = \sqrt{(x - x_{s_i})^2 + (y - y_{s_i})^2 + (z - z_{s_i})^2} + cb + n_{\rho_i} \tag{5}$$

$\tilde{\rho}_i$ is the number i satellite's pseudorange observation. n_{ρ_i} is the noise. (x_{s_i} , y_{s_i} , z_{s_i})is the 3d coordinate for the satellite, while $1 \le i \le N$. c is the speed of light. After formula (5) is linearized by Taylor series expansion, we can obtain system measurement equation as show below.

$$\mathbf{Z}_k = \mathbf{H}_k\mathbf{X}_k + \mathbf{V}_k \tag{6}$$

$$\mathbf{Z}_k = \begin{bmatrix} \tilde{\rho}_1 & \tilde{\rho}_2 & \cdots & \tilde{\rho}_N \end{bmatrix}^T \tag{7}$$

$\mathbf{Z}_k$ is the observation vector for k moment, which is a n-dimensional column vector. N is the number of satellites whose signals are received by the receiver. $\mathbf{H}_k$ is the observation matrix. $\mathbf{V}_k$ is the observation noise. The recursive equation of fading Kalman filter is showed as below.

$$\begin{cases} \mathbf{X}_{k,k\text{-}1} = \mathbf{\Phi}_{k,k\text{-}1}\mathbf{X}_{k\text{-}1,k\text{-}1} \\ \mathbf{P}_{k,k-1} = \lambda_k \mathbf{\Phi}_{k,k-1}\mathbf{P}_{k-1,k-1}\mathbf{\Phi}_{k,k-1}^T + \mathbf{Q}_k \\ \mathbf{X}_{k,k} = \mathbf{X}_{k,k\text{-}1} + \mathbf{K}_k(\mathbf{Z}_k - \mathbf{H}_k\mathbf{X}_{k,k\text{-}1}) \\ \mathbf{K}_k = \mathbf{P}_{k,k-1}\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_{k,k-1}\mathbf{H}_k^T + \mathbf{R}_k)^{-1} \\ \mathbf{P}_{k.k} = (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k,k-1} \end{cases} \tag{8}$$

$\mathbf{Q}_k$ is the system process noise covariance matrix. $\mathbf{K}_k$ is the gain matrix. $\mathbf{I}$ is the unit matrix. $\mathbf{R}_k$ is the observation noise covariance matrix. The fading Kalman filter used fading factor λ_k to calculate the $\mathbf{P}_{k,k-1}$, and this differs from the standard Kalman filter. The memory length of Kalman filter is limited by the fading factor to make full use of the current observations. The filter divergence has been avoided by aggravated the role of current observation data in state estimation.

III. The improved fading Kalman filter

According to formula (8), When the traditional fading Kalman filter estimating the error variance matrix, all the elements in the matrix is increased by $\lambda_k(\lambda_k \geq 1)$ times. Such a kind of indiscriminate multiplication increases the redundancy. Although the problem of filtering divergence has been solved effectively, the calculation result contains larger error, so that the accuracy is lower.

In order to solve the problems above, the traditional fading Kalman filter algorithm has been improved as below.

In order to solve the problems above, the traditional fading Kalman filter algorithm has been improved as below.

The state vector is defined as $\mathbf{X}_k = [x_1 \quad x_2 \quad \cdots \quad x_n]^T$. Based on the different elements in state vector, a new fading factor vector is built, which is defined as $\boldsymbol{\omega}_k = [\lambda_1 \quad \lambda_2 \quad \cdots \quad \lambda_n]^T$. And each element of vector $\boldsymbol{\omega}_k$ corresponds to each element of the state vector, while n is the dimension of the state vector. Thus, the forecast state covariance is defined as below.

$$\hat{\mathbf{P}} = diag(\boldsymbol{\omega}_k)\mathbf{\Phi}_{k,k-1}\mathbf{P}_{k-1,k-1}\mathbf{\Phi}_{k,k-1}^T diag(\boldsymbol{\omega}_k)^T \tag{9}$$

$$\mathbf{P}_{k,k-1} = \hat{\mathbf{P}} + \mathbf{Q}_k \tag{10}$$

The predictive value of state vector is defined as below.

$$\hat{\mathbf{X}}_{k,k-1} = \mathbf{\Phi}_{k.k-1}\mathbf{X}_{k-1} \tag{11}$$

In which $\hat{\mathrm{X}}_{k,k-1}$ is showed as below.

$$\hat{\mathbf{X}}_{k,k-1} = \begin{bmatrix} \hat{x}_1 & \hat{x}_2 & \cdots & \hat{x}_n \end{bmatrix} \tag{12}$$

$\hat{\mathrm{X}}_k^i$ is defined as below.

$$\hat{\mathrm{X}}_k^i = \begin{bmatrix} x_1 & x_2 & \ldots & \hat{x}_i & \ldots & x_n \end{bmatrix}^T, i = 1,2,\ldots,n \tag{13}$$

Thus, the predictive value of the observation vector is showed as below.

$$\hat{\mathbf{Z}}_k^i = \mathbf{H}_k \hat{\mathbf{X}}_k^i \tag{14}$$

The pseudorange residual error is defined as below.

$$\mathbf{V}_{k,k-1}^i = \mathbf{Z}_k - \hat{\mathbf{Z}}_k^i \tag{15}$$

In which, $\sum \mathbf{V}_{k,k-1}^i = E(\mathbf{V}_{k,k-1}^i (\mathbf{V}_{k,k-1}^i)^T)$ is the covariance matrix of the pseudorange residual error, and it is defined as below.

$$\sum \mathbf{V}_{k,k-1}^i = \frac{1}{M} \sum_{i=1}^{M} (\mathbf{V}_{k-i,k-1-i}^i (\mathbf{V}_{k-i,k-1-i}^i)^T) \tag{16}$$

The value of M is determined by experience. Many experiments proved that when M is 10, the covariance matrix can be estimated effectively without large computational complexity.
Each element of the fading factor vector can be calculated by the following formulas.

$$\lambda_i = \max\{1, tr[\mathbf{N}_k^i] / tr[\mathbf{T}_k]\} \tag{17}$$

$$\mathbf{N}_k^i = \sum \mathbf{V}_{k,k-1}^i - \mathbf{H}_k \mathbf{Q}_k \mathbf{H}_k^T - \mathbf{R}_k \tag{18}$$

$$\mathbf{T}_k = \mathbf{H}_k \Phi_{k,k-1} P_{k-1,k-1} \Phi_{k,k-1}^T \mathbf{H}_k^T \tag{19}$$

When $\lambda_i = 1$, the fading Kalman filter degenerate into basic Kalman filter.

When $\lambda_i = \lambda_j$, $i, j = 1,2,\ldots,n$, $i \neq j$, the filtering process is equivalent to the traditional fading Kalman filter, and all of the elements of the estimation error variance matrix will be increased at the same time. In this case, when the system state change, the estimation error will increase, which leads to $\mathbf{N}_k^i$ increases. According to the calculation formulas of the fading factor vector elements, the value of λ_i and $\mathbf{P}_{k,k-1}$ will increase. The algorithm puts the new current observation data in an important position by increasing the filtering gain. And as a result, the ill-effect of old data is decreased and the tracking ability of Kalman filter is improved.

When $\lambda_i \neq \lambda_j$, $i, j = 1,2,\ldots,n$, $i \neq j$, the elements of fading factor vector are not equal to each other. Carrier is moving in 3d space. Assume that one of the component of the state changes, $\mathbf{V}_{k,k-1}^i$ and λ_i will increase. In this way, the improved fading Kalman filter can solve the problem of filtering divergence more effectively, and the accuracy of the results will be further improved.

In the process of filtering, before estimating the state error covariance matrix, the fading factor vector is calculated online according to the historical data, the current observation data and the given window length in advance. The memory length of each channel is changed adaptive. For the channel with high quality observation data, the length of memory is shortened to track the state of the system and improve the accuracy of results. For the channel with bad observation data, the weight of the new observation data is reduced to weaken its influence on the result of the operation.

IV. The experimental results and analysis

The algorithm above is verified by the actual collection of BDS satellite observation data. The receiver that is used to collect satellite data is UB280 BDS/GPS double system receiver from UNICORE company, which can receive the B1/B2 signal of BDS and L1/L2 signal of GPS. The receiver is installed in a car, and the antenna is installed on the roof. The car is moving around the Olympic center of Guangzhou, and its path is showed as figure 1. The data sampling interval T is 50 ms. The testing time is 10:00 am on July 25, 2015. The car traveled along the path shown in figure 1, from the starting point, through the section A1A2, section B1B2 and section C1C2, and to the destination point finally. The observation data of BDS and GPS received during the travel is collected and stored for the subsequent processing.

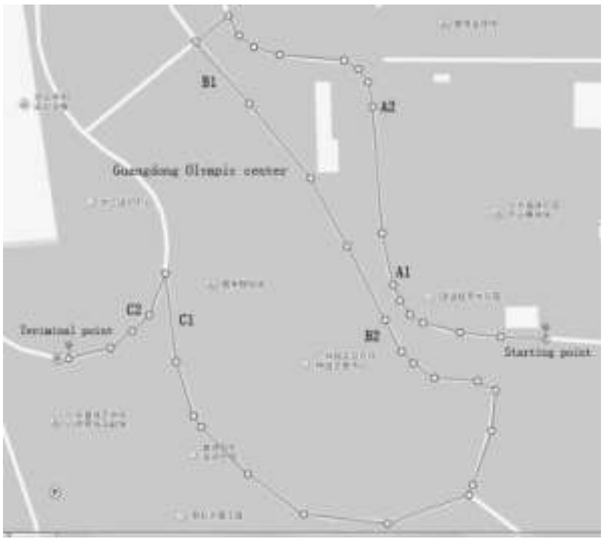

Figure 1 the path of the car

The positioning module named TRACK of GPS data processing software named GAMIT can get the car's 3d coordinate and speed at each moment, whose plane precision is within 2 cm. The result of TRACK module is selected as the true value of positioning results. On this basis, the results of the three algorithms are compared with each other with the BDS observation data in MATLAB platform, which are the algorithm in the paper , the improved fading Kalman filter in reference [3] and the traditional Kalman filter.

The related parameters are selected as shown below. The initial position variance of x and y direction are $\sigma_x^2 = \sigma_y^2 = 100\mathrm{m}^2$. The variance of speed are $\sigma_{v_x}^2 = \sigma_{v_y}^2 = 25\mathrm{m}^2/\mathrm{s}^2$. The variance of clock is $\sigma_b^2 = 10^{-12}\mathrm{s}^2$. The variance of pseudorange measurement noise is $\sigma_D^2 = 1\mathrm{m}^2$, and the variance of pseudorange rate measurement noise is $\sigma_{\dot{\rho}}^2 = 0.01\mathrm{m}^2/\mathrm{s}^2$, The corresponding noise covariance matrix use the model in reference literature[6, 10]. The initial value of state is $\mathbf{X}_0 = [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]^T$, and the initial value of the error variance matrix is $\mathbf{P}_0 = diag(100 \quad 25 \quad 100 \quad 25 \quad 100 \quad 25 \quad 10^{-3})$.

Error is the difference between the true value and estimated one. The curve of X coordinate estimation error is shown in figure 2 and the curve of X speed estimation error is shown in figure 3.

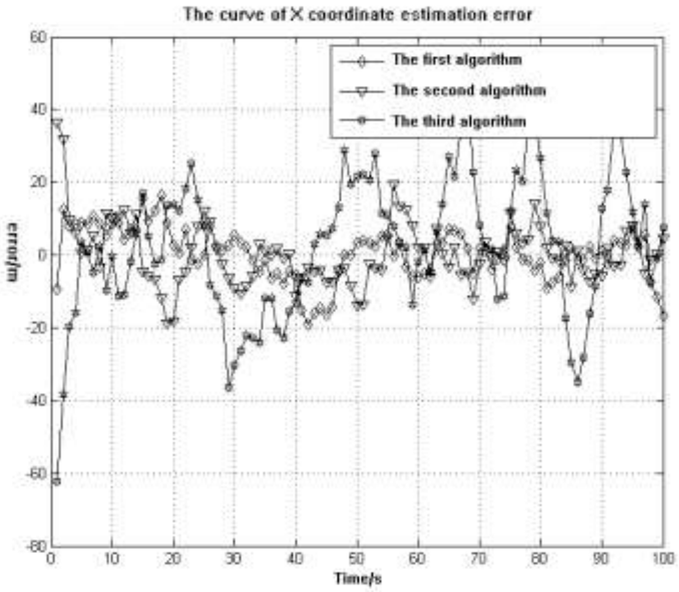

Figure 2 the curve of X coordinate estimation error

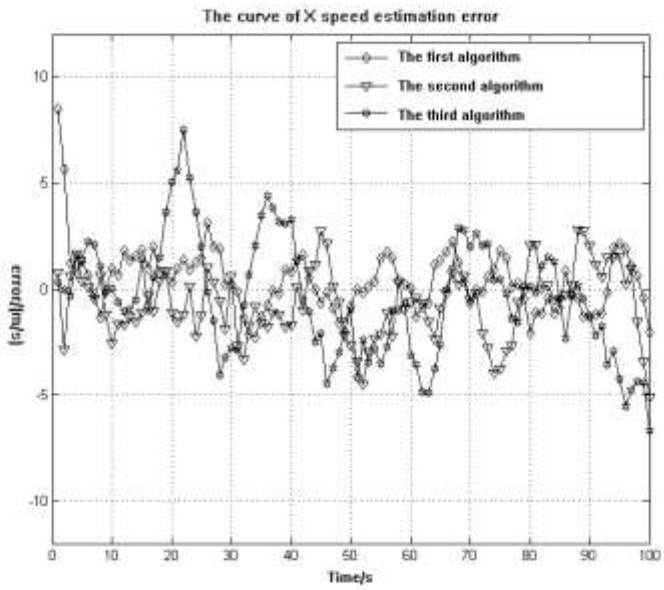

Figure 3 the curve of X speed estimation error

The accuracy and operation time of the three algorithms are shown in table 1.

Table 1 the accuracy and operation time of the three algorithms

State component	Traditional fading Kalman filter	The improve fading Kalman filter in reference [3]	The algorithm in this paper
X(m)	11.56	8.04	6.19
V_x (m/s)	2.52	1.75	1.24
Operation time (ms)	0.216	0.259	0.283

The data in table 1 shows that compared with the traditional Kalman filter, the precision of location of the algorithm in this paper is improved by 46.3%, and the precision of speed is improved by 50.8%, while the operation time only increase by 23.7%. Compared with the improved fading Kalman filter in reference literature[3], the precision of location of the algorithm is improved by 23.6%, and the precision of speed is improved by 29.1%, while operation time only increased by 9.3%.

V. Summary

This paper proposed an improved fading Kalman filter algorithm based on fading factor vector. On the basis of traditional Kalman filter, a fading factor vector has been constructed and the method to calculate the element of vector has been introduced. The algorithm is applied to BDS dynamic positioning. The simulation results show that the algorithm not only improves the accuracy of BDS dynamic positioning, but also has good dynamic performance and stable filtering process. Moreover, this paper provides the related experimental data for the debugging of BD-2 system, and it is very useful for application study of high precision dynamic positioning of BDS.

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