Process RTK Data Based On Kalman Filtering Algorithm

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ABSTRACT: With the development of satellite positioning technology, there is a strong need for high accuracy position information. Currently the most widely used high-precision positioning technology is RTK(Real-Time Kinematic).RTK technology is the key to using carrier phase measurements. It takes advantage of the base stations and monitor stations observed error of spatial correlation, except monitor stations observed by means of differential most of the errors in the data, in order to achieve high accuracy positioning.^[3]Based on Kalman filtering algorithm to handle the noise of RTK data and selecting appropriate models to further improve the accuracy of the data. This paper will explore the use of Kalman filtering method of RTK data processing, which reduces random noise interference, thus improving the accuracy of GNSS deformation monitoring data.^[1] *KEY WORDS:* Kalman filtering; RTK; Carrier phase measurement; High-accuracy

I. INTRODUCTION

Kalman filtering using the time-domain state-space method, applicable to Multivariable systems with time-varying systems and non-stationary random process, has a minimum of the unbiased variance.It is currently the most widely used method of dynamic data processing because of its recursive feature easy to implement.^[1]Through the establishment of State equations and equations to describe the system of measurement of the dynamic process of change according to the filter gain matrix, quantitative identification and extraction of information from measurements, revision status parameter, suitable for real time data processing.

High precision GNSS measurements must be in the carrier phase observations. RTK positioning technology is real time kinematic positioning technology based on carrier phase observations. ^[2]It can provide a logging site in real time three dimensional positioning result in the specified coordinate system and achieve centimeter-level accuracy. In RTK operation mode, the base station will transmit its observation and monitoring station coordinates information to the monitor station.[3] Monitor station not only via the data chain receives data from the base station but also gathered a GNSS observation data. It is real-time system which processes differential measurements. Centimeter-level positioning is also given. Fixed the ambiguity of whole cycles, you can conduct real-time processing of each epoch. Just keep track four or more Satellites and necessary geometry, monitor station may at any time give a centimeter-level positioning results.

II. KALMAN FILTERING PRINCIPLE AND ALGORITHM

Assume that $\tilde{S}(k)$ is the estimation of signal S(k). $\tilde{S}(k+1|k)$ is the S(k+1)'s forecast estimate in the time of k. Then the model of $AR(N)^{[1][4][5]}$ is:

$$
S(k) = \Phi S(k-1) + W(k) \tag{1}
$$

Observations X(k) are noise and signal superposed,

$$
X(k) = CS(k) + N(k)
$$
\n⁽²⁾

The criterion for estimating: $Tr[\mathcal{E}(k)] = \min_{i} Tr[\mathcal{E}(k+1)] = \min_{i}$

Such as

$$
\varepsilon(k+1) = E[(S(k+1) - \tilde{S}(k+1)k)) (S(k+1) - \tilde{S}(k+1)k)^T]
$$

Filter gain: $(k) = \varepsilon (k | k - 1) C^{T} [V_{n}(k) + C \varepsilon (k | k - 1) C^{T}]^{-1}$ $B(k) = \varepsilon(k | k - 1)C^{T}[V_{n}(k) + C\varepsilon(k | k - 1)C^{T}]$ (3)

Filter estimate:
$$
\tilde{S}(k) = \Phi \tilde{S}(k-1) + B(k)[X(k) - C\Phi \tilde{S}(k-1)]
$$
 (4)

Update status:
$$
\tilde{S}(k+1|k) = \Phi \tilde{S}(k)
$$
 (5)

Estimated standard deviation:

Filtering:
$$
\varepsilon(k) = \varepsilon(k | k - 1) - B(k)C\varepsilon(k | k - 1)
$$
 (6)

$$
\text{Forecast:} \quad \varepsilon(k+1 \mid k) = \Phi \varepsilon(k) \Phi^T + V_{\omega}(k) \tag{7}
$$

In practical applications, a lot of times we get random signal measurements, without the signal model. However, we can use the observations $X(k)$ to estimate the model. This algorithm uses the Burg method of the model of

AR(P) \cdot ^{[4][5]}Suppose $e_f(n | p-1)$ $e_b(n | p-1)$ $\epsilon^{(p-1)}$ known:

 $e_f(n | p-1)$: (P-1)-order Predictor of forward prediction error.

 $e_b(n | p-1)$: (P-1)-order Predictor of backward prediction error.

 $\mathcal{E}^{(p-1)}$: Predictor of the variance of the prediction error.

Use time values instead of reflection coefficient which its total statistical mean value estimation model of order p:

$$
P^{(p)} = \frac{2 \sum_{n=p-1}^{N-1} e_f(n | p-1) e_b(n-1 | p-1)}{\sum_{n=p-1}^{N-1} e_f^2(n | p-1) + \sum_{n=p-1}^{N-1} e_b^2(n-1 | p-1)}
$$
(9)

By recursive formula which belong to auto-correlation algorithm for estimation of that p-model's coefficient and white noise's power :

$$
a_p^{(p)} = \rho^{(p)} \tag{10}
$$

$$
a_k^{(p)} = a_k^{p-1} + a_{p-k}^{(p-1)} e^{(p)} \qquad \qquad k=1 \sim p \tag{11}
$$

$$
\varepsilon^{(k)} = \varepsilon^{(p-1)} [1 - (\rho^{(p)})^2] \tag{12}
$$

Recursive high-order model prediction error sequences:

$$
e_f(n|p) = e_f(n|p-1) + \rho^{(p)}e_b(n-1|p-1) \quad n = p \sim N-1
$$
\n(13)

$$
e_b(n | p) = e_b(n-1 | p-1) + r^{(p)} e_f(n | p-1)
$$
\n(14)

Initialization is used to calculate:

$$
e_f(n | 0) = e_b(n | 0) = x(n)
$$

\n
$$
\varepsilon^{(0)} = R_0 = \frac{1}{N} \sum_{n=0}^{N-1} x^2(n)
$$

(a) $w^2 = a_1^{p-1} + a_2^{p-1}b_3^{p-1}e^{2i\theta}$ (a)
 $w^2 = a_1^{p-1+1}[1 + (p^{(p)})^2]$ (12)
 $w^2 = a_1^{p-1+1}[1 + (p^{(p)})^2]$ (12)
 $w^2 = a_1^{p-1+1}[1 + (p^{(p)})^2]$ (a) $p^2 = a_1^{p-1}$ (b) $p^2 = a_1^{p-1}$ (b) $p^2 = a_1^{p-1}$ (b) $p^2 = a_1^{p-1}$ (In addition, at the start of the mean-square deviation from the actual situation through experiment. When $\mathcal{E}(m)$ is less than the requirement, stop counting.

III. APPLICATION OF KALMAN FILTER IN GNSS DEFORMATION MONITORING CASE STUDY

In this case, stochastic signal model:

$$
S(k) = a_1 S(k-1) + a_2 S(k-2) + \omega(k)
$$
\n(16)

Variance of white noise is σ_w^2 . Vectorization of the above formula , we can get

$$
S(k) = \Phi S(k-1) + W(k) \tag{17}
$$

Assume that

$$
s(k) = \begin{bmatrix} s(k) \\ s(k-1) \end{bmatrix}, \quad \Phi = \begin{bmatrix} a_1 & a_2 \\ 1 & 0 \end{bmatrix}, \quad W(k) = \begin{bmatrix} \omega(k) \\ 0 \end{bmatrix}
$$

Observations $x(k)$ are the sum of the signal $s(k)$ and $n(k)$ noise of variance measurement σ_n^2 .

$$
x(k) = s(k) + n(k) \tag{18}
$$

Assume that

$$
X(k) = [x(k)] \, , \quad C = [1 \quad 0] \, , \quad N(k) = [n(k)] \, .
$$

We can get

$$
X(k) = CS(k) + N(k)
$$

Covariance matrix of random white noise:

(21)

$$
V_w(k) = E[W(k)W^T(k)] = \begin{bmatrix} \sigma_w^2 & 0 \\ 0 & 0 \end{bmatrix}; \ \ V_n(k) = E[N(k)N^T(k)] = [\sigma_n^2]
$$

By equation (3) and (4) we know that

Filter gain matrix:

$$
B(k) = \begin{bmatrix} b_1(k) \\ b_2(k) \end{bmatrix}
$$

Filter estimate matrix:

$$
\tilde{S}(k) = \Phi \tilde{S}(k-1) + B(k)[X(k) - C\Phi \tilde{S}(k-1)]
$$
\n
$$
= \begin{bmatrix} \tilde{S}(k|k-1) \\ \tilde{S}(k-1|k-2) \end{bmatrix} + \begin{bmatrix} b_1(k) \\ b_2(k) \end{bmatrix} \begin{bmatrix} x(k) - \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \tilde{S}(k|k-1) \\ \tilde{S}(k-1|k-2) \end{bmatrix}
$$
\n
$$
= \begin{bmatrix} \tilde{S}(k|k-1) + b_1(k)[x(k) - \tilde{S}(k|k-1)] \\ \tilde{S}(k-1|k-2) + b_2(k)[x(k) - \tilde{S}(k|k-1)] \end{bmatrix}
$$

So,

$$
\widetilde{S}(k) = \widetilde{S}(K|k-1) + b_1(k)[x(k) - \widetilde{S}(k|k-1)]
$$
\n(20)
\n
$$
\widetilde{S}(k-1) = \widetilde{S}(K-1|k-2) + b_2(k)[x(k) - \widetilde{S}(k|k-1)]
$$
\n(21)

We can get the equation (22) by the next prediction matrix
$$
\widetilde{S}(k+1|k)
$$

$$
\left[\widetilde{S}(k+1|k)\right]_{-}\left[a_{1} \quad a_{2}\right] \left[\widetilde{S}(k)\right]_{-}\left[a_{1}\widetilde{S}(k)+a_{2}\widetilde{S}(k-1)\right]
$$

$$
\begin{bmatrix} S(k+1|k) \\ \widetilde{S}(k|k-1) \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} S(k) \\ \widetilde{S}(k-1) \end{bmatrix} = \begin{bmatrix} a_1 S(k) + a_2 S(k-1) \\ \widetilde{S}(k) \end{bmatrix}
$$
(22)

$$
\widetilde{S}(k+1|k) = \Phi \widetilde{S}(K) \tag{23}
$$

So,

$$
\widetilde{S}(k+1|k) = a_1 \widetilde{S}(K) + a_2 \widetilde{S}(k-1)
$$
\n(22)

Next observation value should satisfy the following equation

$$
\left|\widetilde{S}(k+1|k) - x(k+1)\right| \le \sigma(k+1|k)
$$
\n(23)

The expression of $\sigma(k+1|k)$

$$
\sigma(k+1|k) = \sqrt{\varepsilon(k+1|k)}
$$

IV. EXPERIMENT AND CONCLUSION

We are using M300C&M300C-U receivers of Shanghai compass satellite navigation company in this experiment. These receivers are multi-satellite measurement receivers which based on Beidou satellite navigation system using RTK unique core technologies and highly reliable carrier tracking algorithm in order to provide a comparison of quality of results. The experimental data is collected on the spot in our University using single reference station network. The base station settings in the roof of our training, monitor Station fixed on a slope at the campus. Diagram of base station is given in Figure 4.1. It consist of four parts such as Receiver, Radio、Receiver antenna and Radio antenna. Monitor station consist of Receiver which include radio、Receiver antenna and radio antenna.

Figure 4.1 The composition of Base Station

Star charts and PVT views are shown in Figure 4.2. Through this diagram we can see that Satellite tracking and the number of visible satellites and so on. These information shown that the quality of GNSS signal is pretty good.

Figure 4.2 Star charts and PVT views

RTK data collected by this experiment and the enactment of this algorithm for filtering the data drawing are that shown in Figure 4.3 \sim 4.4 and 4.5.^[6]

Figure 4.3 The result of processing RTK data using Kalman Filter algorithm in WGS-84 (direction X)

Figure 4.4The result of processing RTK data using Kalman Filter algorithm in WGS-84 (direction Y)

Figure 4.5 The result of processing RTK data using Kalman Filter algorithm in WGS-84 (direction Z)

The accuracy of the receiver of M300C is 2.5cm. From the above diagrams have shown that accuracy of RTK date through Kalman filtering have Significantly improved, especially in direction of x and y. Millimeter-scale positioning accuracy is achieved. In the direction of z, however, the date accuracy is about 1cm.Through the above described we found that we can use RTK in many cases, such as disaster monitoring.

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