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ORIGINAL ARTICLE

Real-time estimation of satellite clock offset using adaptively robust Kalman filter with classified adaptive factors

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Abstract In order to estimate the satellite clock offset in a real-time mode, a new algorithm of adaptively robust Kalman filter with classified adaptive factors for clock offset estimation is proposed. Compared with standard Kalman filter clock offset model, the new method can detect and control outliers and clock jumps automatically in real-time. Moreover, the clock model parameters, which contain the clock offset, clock speed and clock shift, are classified to decide the adaptive factors in the new model. Thus, clock jumps with different characteristics can be distinguished more effectively. Meanwhile, the dynamic noise characteristics of clock offset series are used for stochastic modeling. An actual numerical example is presented, which shows that the proposed filter can give a better performance than other commonly used filters.

Keywords Classified factors · Adaptive and robust · Kalman filter · Noise type · Satellite clock offset · Prediction

Introduction

Several satellite clock offset models have been developed, such as linear models, quadratic and higher-order polynomial models, exponential model and Gray model (GM), see Ji et al. (2001), Cunningham et al. (1998), Hatten and Taylor (2000), Koppang et al. (2000), Liu (2006), Zheng et al. (2008), Huang et al. (2008), Huang et al. (2009). The least squares (LS) method is usually applied to estimate the coefficients of the models. Unfortunately, LS estimation is not robust. If the clock offset data contain gross offsets or clock jumps, a data preprocessing is usually needed for cleaning the data. This generally includes the conversion of phase data to frequency data, gross error detection and so on (Guo 2006). Data preprocessing is not an automatic procedure and needs to be judged manually. In fact, the IGS algorithm can detect gross errors easily by an automated Kalman filter, but cannot do this in real-time mode (Senior et al. 2001, 2003). The processing efficiency cannot meet the requirements of the real-time parameter estimation and prediction. In addition, the LS method cannot effectively control the influences of outliers. Therefore, some of the dynamic characteristics of the clock offset parameters may be masked. In order to solve these problems, we divide the clock offset series first into sections of the same size. Then, the robust estimation (Zhou 1989; Ou 1996) is used to compute the model clock offset series. The size of the data blocking and the identification of noise types for the clock offset data of each section are discussed. The stochastic model is determined by calculating the Hadamard variance or Allan variance. Consecutively, an adaptive Kalman filter with classified factors (Yang et al. 2001a, b) is constructed for clock offset estimation and prediction. Actual numerical examples are used to verify the superiority and effectiveness of the proposed algorithm.

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Functional models of satellite clock offset

For the estimation of the satellite clock offset, one needs to construct a precise clock offset model first. The factors that represent the stability of satellite clock time–frequency domain usually include phase, frequency and frequency drift (aging rate). Usually, a quadratic polynomial model containing these three factors is selected as the clock offset prediction model. In fact, the GPS navigation file also uses this quadratic polynomial as the clock offset model. Then, the dynamic state equation of the satellite clock can be expressed as shown in the study by Huang et al. (2008)

$$\begin{bmatrix} x(t+\tau) \\ y(t+\tau) \\ z(t+\tau) \end{bmatrix} = \begin{bmatrix} 1 & \tau & \tau^2/2 \\ 0 & 1 & \tau \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(t) \\ y(t) \\ z(t) \end{bmatrix} + \begin{bmatrix} \varepsilon_x \\ \varepsilon_y \\ \varepsilon_z \end{bmatrix} \tag{1}$$

where τ denotes the interval time, $x(t)$, $y(t)$ and $z(t)$ are three parameters of the satellite clock offset that are related to the clock offset (phase), clock velocity (frequency) and the clock drift (frequency drift), respectively. The symbols ε_x, ε_y and ε_z describe the state noise, and their mean values are 0.

Equation (1) can be written as

$$x_k = \Phi_{k,k-1} x_{k-1} + w_k \tag{2}$$

where $x_k = [x(t+\tau) \quad y(t+\tau) \quad z(t+\tau)]^T$ represents the state vector at epoch t_k, and $\tau = t_k - t_{k-1}$ is the time interval. The matrix $\Phi_{k,k-1}$ is the 3×3 transition matrix, and w_{k} is the state noise vector with the covariance matrix $\sum_{w_k}$, which can be expressed as a function of Kalman filter process noise (Huang et al. 2008),

$$\sum_{w_k} = \begin{bmatrix} q_1\tau + q_2\tau^3/3 + q_3\tau^5/20 & q_2\tau^2/2 + q_3\tau^4/8 & q_3\tau^3/6 \\ q_2\tau^2/2 + q_3\tau^4/8 & q_2\tau + q_3\tau^3/3 & q_3\tau^2/2 \\ q_3\tau^3/6 & q_3\tau^2/2 & q_3\tau \end{bmatrix} \tag{3}$$

where q_1 denotes the process noise parameter of ε_x, taken as the random walk phase model (PM) noise; q_2 denotes the process noise parameter of ε_y, taken as the random walk frequency model (FM) noise; q_3 denotes the process noise parameter of ε_z, as the random run FM noise.

The observational equations for the clock phase data can be written as

$$l_k = A_k x_k + e_k \tag{4}$$

where l_k represents the observation matrix, $A_k = [1 \quad 0 \quad 0]$ is the 1×3 design matrix, and e_k is the 1-dimension observation noise vector with Σ_k as its covariance matrix. The value of Σ_k is q_0, and q_0 denotes the measurement noise parameter with respect to white FM noise. Satellite clock parameters can be estimated solving (2) and (4) by a standard Kalman filter.

In order to solve for the noise parameters q_0, q_1, q_2 and q_3 in (3), we can make use of

$$H\sigma^2_{\mathrm{total}}(\tau) = (10/3)q_0\tau^{-2} + q_1\tau^{-1} + q_2\tau/6 + 11q_3\tau^3/120 \tag{5}$$

$$\sigma^2_y(\tau) = 3q_0\tau^{-2} + q_1\tau^{-1} + q_2\tau/3 + q_3\tau^3/20 \tag{6}$$

where $H\sigma^2_{\mathrm{total}}(\tau)$ denotes the Hadamard total variance (Guo and Yang 2009) of the sampling rate τ, which is usually used to describe the stability of a Rubidium (Rb) clock. The symbol $\sigma^2_y(\tau)$ represents the Allan variance of sampling rate τ, which is usually used to describe the Cesium(Cs) clock stability. By using the Hadamard total variance and the Allan variance calculated from the clock offset time series data, the values of q_0, q_1, q_2 and q_3 can be obtained by solving (5) or (6) using the least squares adjustment. After calculating the noise parameters, we can estimate the covariance matrix of the state noise using (3) and evaluate the covariance matrix of the observation noise through noise parameter q_0.

There are inevitably discontinuous data, phase jumps and blunders in the observed atomic clock offset data due to power cutoff, code observation noise, equipment failures and external interference factors (Guo 2006), which greatly influence the accuracy of the clock offset parameter estimation and forecasting. In order to suppress the influence of these disturbances on the clock offset estimation and forecasting, an adaptively robust filtering (He and Yang 1998; Wu 2006; Cui and Yang 2006) is introduced to eliminate or reduce the influences of the observed outliers and dynamic model errors. Usually, an adaptively robust filtering uses a single adaptive factor to adjust the contribution of the predicted information to the parameter estimates without distinguishing different impacts on different parameters (Yang et al. 2001a, b; Yang and Gao 2006). The adaptively robust filtering with classified adaptive factors (Cui and Yang 2006; Yang and Cui 2008) is proposed to separately control the influences of state disturbance on the parameter estimates based on the clock offset, clock speed and clock drift discrepancy, respectively.

Adaptively robust filtering with classified adaptive factors

According to the dynamic state equation (1) and the observation equation (4), a new algorithm for an adaptively robust Kalman filter with classified adaptive factors for clock offset estimation is proposed. First, we introduce the standard adaptively robust filtering.

Standard adaptive robust filtering

The dynamic clock offset model (2) and (4) can be rewritten in a simplified form a

$$x_k = \Phi_{k,k-1} x_{k-1} + w_k, \quad \sum_{w_k} \tag{7}$$

$$l_k = A_k x_k + e_k, \quad \sum_k \tag{8}$$

A standard estimator of the Kalman filter (Yang 2003) is

$$\hat{x}_k = \left(A_k^T P_k A_k + P_{\bar{x}_k}\right)^{-1}\left(A_k^T P_k l_k + P_{\bar{x}_k}\bar{x}_k\right) \tag{9}$$

$$\sum_{\hat{x}_k} = \left(A_k^T P_k A_k + P_{\bar{x}_k}\right)^{-1} \tag{10}$$

where P_k is a weight matrix of $l_k\left(P_k = \sum_k^{-1}\right)$, and $P_{\bar{x}_k} = \sum_{\bar{x}_k}^{-1}$ is the weight matrix of the predicted state vector.

When the predicted state vector $\bar{x}_k$ and observation vector l_k contain gross errors, filtering result is evidently distorted. In order to control the influences of these outliers on the solution, an adaptively robust filtering based on adaptive filtering theory is developed (Yang et al. 2001a, b; Yang 2003, 2006). The main procedures can be summarized as follow. First, we use the current observation vector to obtain the solution for the estimated initial state vector $\tilde{x}_k$ and the corresponding equivalent weight matrix $\bar{P}$ of the measurement vector, by using robust estimation; Second, an adaptive factor matrix w is determined by using the discrepancy between the predicted state vector $\bar{x}_k$ and the current robustly estimated vector $\tilde{x}_k$. After that the robust clock offset parameter estimates are obtained by performing the adaptively robust filtering procedure based on the classified adaptive factors. The details of the related procedures can be found in the literature (Yang 2006; Yang and Cui 2008).

The result of the adaptively robust filtering can be expressed as (Yang et al. 2001b):

$$\hat{x}_k = \left(A_k^T \bar{P}_k A_k + \bar{P}_{\bar{x}_k}\right)^{-1}\left(A_k^T \bar{P}_k l_k + \bar{P}_{\bar{x}_k}\bar{x}_k\right) \tag{11}$$

$$\sum_{\hat{x}_k} = \left(A_k^T \bar{P}_k A_k + \bar{P}_{\bar{x}_k}\right)^{-1} \tag{12}$$

where $\bar{P}_k$ is the equivalent weight matrix of l_k, $\bar{P}_{\bar{x}_k}$ is the equivalent weight matrix of the predicted state vector ($\bar{P}_{\bar{X}^0} = w^{\frac{1}{2}} P_{\bar{X}^0} w^{\frac{1}{2}}$), and w represents the adaptive multi-factor matrix (Yang and Cui 2008). This w is a 3×3 diagonal matrix, and w_1, w_2 and w_3 are its diagonal elements.

Generally, w_i ($i = 1, 2, 3$) can be defined by the IGG3 scheme (the Institute of Geodesy and Geophysics 3), see Yang et al. (2002a, b), the IGG1 scheme (Yang et al. 2002a), or an exponential function (Yang and Gao 2005).

Here, the adaptive factors are determined by the IGG3 scheme:

$$w_i = \begin{cases} 1 & |\Delta\tilde{x}| \le k_0 \\ \frac{k_0}{|\Delta\tilde{x}|}\frac{k_1 - |\Delta\tilde{x}|^2}{k_1 - k_0} & k_0 < |\Delta\tilde{x}| \le k_1 \\ 0 & |\Delta\tilde{x}| > k_1 \end{cases} \tag{13}$$

where k_0 and k_1 are constants, usually chosen as $1.0 < k_0 < 2.5$ and $3.0 < k_1 < 8.0$, respectively. $|\Delta\tilde{x}|$ is

$$|\Delta\tilde{x}| = \left\|\bar{x} - \tilde{x}_k\right\| / \sqrt{tr(Q_{\hat{x}})} \tag{14}$$

where $Q_{\hat{x}}$ is the covariance matrix of $\tilde{x}_k$.

What decides equivalent weights and adaptive factors is critical in the adaptively robust filtering solution. The equivalent weight matrix directly reflects the ability to control the outlier effects. The adaptive factors do not only impact the contribution of the clock offset, clock speed and clock drift information to the parameter estimates, but also controls the effects of the clock offset disturbance.

Adaptive factors

The parameters of random clock offset, clock speed and clock drift describe different characteristics of the clock offset. Classified adaptive factors are proposed to control the effects of different clock offset disturbances. The adaptive factor w_1 is employed for controlling the influences of random clock offset, the adaptive factor w_2 is applied to reduce the effects of the clock speed, and the adaptive factor w_3 is used to compensate the effects of the clock drift. The adaptive factor matrix is defined as

$$w = \begin{bmatrix} w_1 & 0 & 0 \\ 0 & w_2 & 0 \\ 0 & 0 & w_3 \end{bmatrix} \tag{15}$$

In order to obtain the adaptive factor w_1, we need to calculate the statistic $|\Delta\tilde{x}_1|$ first by using (14). Then, the factor w_1 is determined from (13). The determination of the adaptive factors w_2 and w_3 is similar to that of w_1.

Windowing design

The clock offset is a one-dimensional data, and the constructed observation model of the filtering is a quadratic polynomial model. It is difficult to control the impact of outliers by using the Kalman filtering directly. Thus, it is hard to distinguish between the effects of the outliers and the state disturbances in observations. It is also hard to determine the adaptive factors. Therefore, we propose to carry out a windowing process with the clock offset series. The clock offset data are cut into i windows of the same size m ($n = i \times m$). This procedure is illustrated in Fig. 1. The LS or a robust estimation method is applied to fit the clock offset model in each window independently. From the theoretical point of view, this windowing filter method is completely equivalent to the standard filtering method.

The window size m is critical. If m is less than four epochs, this method cannot directly use these observations to perform a robust estimation. If m is too large, there will be too much state disturbance in the window, resulting in

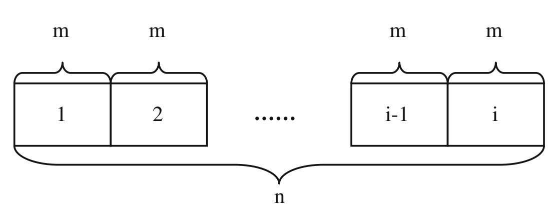

Fig. 1 Windowing design

unreliable adaptive factors. The IGS products are single-day solutions, and the reference station receiver clock is influenced by factors such as code noise, temperature and multi-path (Kouba and Springer 2001; Senior and Ray 2001; Ray and Senior 2003). These solutions always have a jump at the day boundary (Defraigne and Bruyninx 2007; Dach et al. 2005; Guyennon et al. 2009), which directly affects the satellite clock offset data. In our experience, $m \leq 96$ (15-min intervals, as in IGS.sp3 files) or $m \leq 288$ (5-min intervals, as in IGS.clk files) is more suitable.

The size of m contains the following properties:

1. For $m = 1$, the adaptive filter with a single factor is used for the clock offset parameter estimation, in which the robust equivalent weights cannot be used. Thus
$$\hat{x}_k = \left(A_k^T P_k A_k + \bar{P}_{\bar{x}_k}\right)^{-1}\left(A_k^T P_k l_k + \bar{P}_{\bar{x}_k}\bar{x}_k\right),$$
$$\bar{P}_{\bar{x}_k} = w_1^{\frac{1}{2}} P_{\bar{x}_k} w_1^{\frac{1}{2}} \tag{16}$$
2. For $m = 2$, the adaptive filtering solution with classified factors of the random clock offset and the clock speed is obtained, in which the robust equivalents are not used,
$$\hat{x}_k = \left(A_k^T P_k A_k + \bar{P}_{\bar{x}_k}\right)^{-1}\left(A_k^T P_k l_k + \bar{P}_{\bar{x}_k}\bar{x}_k\right),$$
$$\bar{P}_{\bar{x}_k} = \begin{bmatrix} w_1 & 0 & 0 \\ 0 & w_2 & 0 \\ 0 & 0 & 1 \end{bmatrix}^{\frac{1}{2}} P_{\bar{x}_k} \begin{bmatrix} w_1 & 0 & 0 \\ 0 & w_2 & 0 \\ 0 & 0 & 1 \end{bmatrix}^{\frac{1}{2}} \tag{17}$$
3. For $m = 3$, the adaptive filtering solution with classified factors of random clock offset, clock speed and clock drift are obtained, in which the robust equivalents are not used,
$$\hat{x}_k = \left(A_k^T P_k A_k + \bar{P}_{\bar{x}_k}\right)^{-1}\left(A_k^T P_k l_k + \bar{P}_{\bar{x}_k}\bar{x}_k\right),$$
$$\bar{P}_{\bar{x}_k} = \begin{bmatrix} w_1 & 0 & 0 \\ 0 & w_2 & 0 \\ 0 & 0 & w_3 \end{bmatrix}^{\frac{1}{2}} P_{\bar{x}_k} \begin{bmatrix} w_1 & 0 & 0 \\ 0 & w_2 & 0 \\ 0 & 0 & w_3 \end{bmatrix}^{\frac{1}{2}} \tag{18}$$
4. For $3 < m < n$, the adaptively robust filtering with classified factors of random clock offset, clock speed and clock drift is performed,
$$\hat{x}_k = \left(A_k^T \bar{P}_k A_k + \bar{P}_{\bar{x}_k}\right)^{-1}\left(A_k^T \bar{P}_k l_k + \bar{P}_{\bar{x}_k}\bar{x}_k\right),$$
$$\bar{P}_{\bar{x}_k} = \begin{bmatrix} w_1 & 0 & 0 \\ 0 & w_2 & 0 \\ 0 & 0 & w_3 \end{bmatrix}^{\frac{1}{2}} P_{\bar{x}_k} \begin{bmatrix} w_1 & 0 & 0 \\ 0 & w_2 & 0 \\ 0 & 0 & w_3 \end{bmatrix}^{\frac{1}{2}} \tag{19}$$
5. For $m = n$, it is just the robust LS solution, in which the adaptive factors are not used,
$$\hat{x}_k = \left(A_k^T \bar{P}_k A_k\right)^{-1}\left(A_k^T \bar{P}_k l_k\right) \tag{20}$$

In fact, for $m = 1$, the current clock speed parameter can be obtained indirectly from the difference between the current observed clock offset $\tilde{x}_{k(0)}$ and the predicted clock offset $\bar{x}_{k(0)}$ divided by the length of the sampling interval τ,

$$\tilde{x}_{k(1)} = \frac{\tilde{x}_{k(0)} - \bar{x}_{k(0)}}{\tau} \tag{21}$$

Based on the calculated clock speed and its predicted value, the adaptive factor of the clock speed can also be determined by indirect method. Similarly, for $m = 2$, the adaptive factor of the clock drift can be obtained through the evaluation of the clock drift indirectly. However, the calculation of adaptive factors relies on predicted values; therefore, the correlations between the adaptive factors should be considered carefully. Furthermore, as robust estimation is not used for the present observations, it is difficult to distinguish between the outliers and the state disturbances. For these two reasons, the method of indirect determination of the adaptive factors is not used in this research.

Test computation and analysis

The precise clock offset data are available from the IGS website (ftp://igscb.jpl.nasa.gov/). The data time span is from February 22 to March 3, 2009 with a sampling interval of 5 min and a total of 10 days. At present, most GPS satellites carry a high-stable Rb clock. Therefore, the GPS satellite of PRN 28 equipped with a Rb clock is selected for computation and analysis.

The root mean square error (RMS) of the predicted clock offset is defined as

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\Delta\varepsilon_i)^2} \tag{22}$$

where $\Delta\varepsilon_i$ is the difference between the clock offset of the real-time prediction and the IGS precise clock offset, and n is the number of the clock offset predictions.

The dynamic clock offset model uses a quadratic polynomial with a window size of 72. The equivalent weight function (He and Yang 1998; Yang 1994, 1996, 1999) is adopted for robust estimation with criterion $c0 = 1.5$ and $c1 = 2.5$. The construction of adaptive factors uses IGG3 method (Yang 2003) with control constants $k_0 = 0.5$ and $k_1 = 4.8$. The noise stochastic model is defined by the Hadamard total variance. The computations according to the following three schemes are carried out for comparison and analysis:

Scheme 1: Parameter estimation by standard Kalman filter (SKF);

Scheme 2: Parameter estimation by adaptive Kalman filter (AKF);

Scheme 3: Parameter estimation by adaptively robust filter with a single factor (ARKF1);

The time series of the clock offset in 10 days of the GPS satellite PRN 28 is shown in Fig. 2. It can be seen that the values of the satellite clock offset, clock speed and clock drift have changed significantly during the 10 days. Hence, it evidently affects the accuracy of prediction and fitting if these disturbances are not taken into account. The calculated frequency time series corresponding to these clock data do not have any obvious gross errors, which can be seen from Fig. 3. In order to verify the fitting precision in different cases, gross errors of 10 ns in every 200 epochs were added to the original clock offset. The clock offset series with gross errors after processing is shown in Fig. 4.

Results of fitting obtained from the three schemes are shown in Figs. 5, 6, 7 and 8.

The following conclusions can be deduced from these figures:

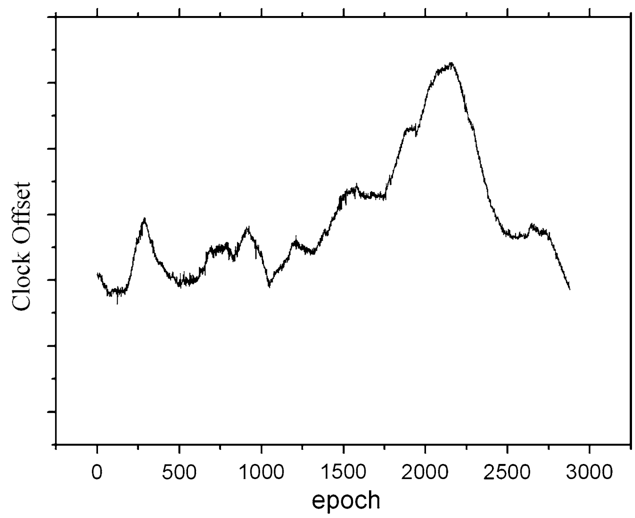

Fig. 2 Phase time series of satellite clock offset (without blunders)

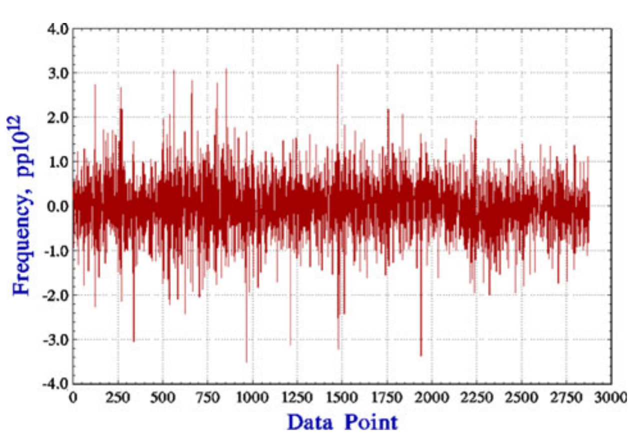

Fig. 3 Frequency time series of satellite clock offset

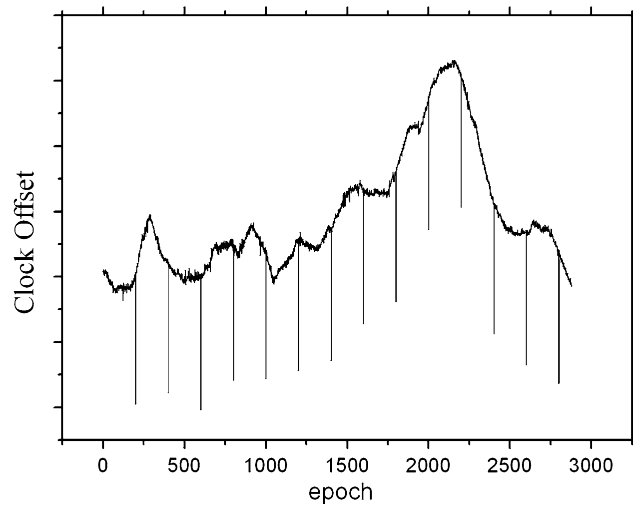

Fig. 4 Phase time series of satellite clock offset (with blunders)

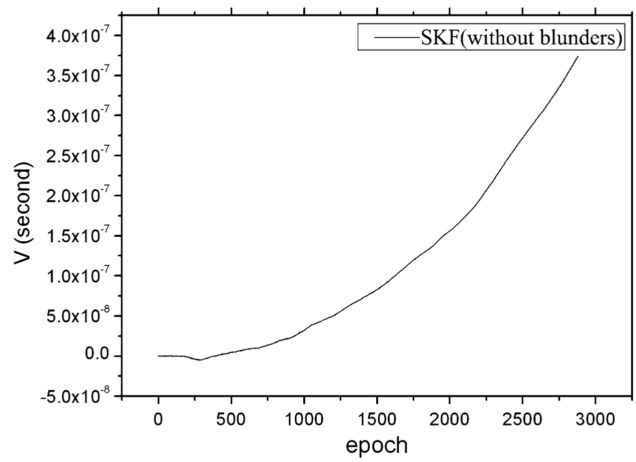

Fig. 5 Fitting residuals of SKF (without blunders)

1. As the standard Kalman filter (Scheme 1) cannot deal with the state disturbance in clock offset series, the fitting results are divergent.
2. By adjusting the adaptive factors, the adaptive Kalman Filter (Scheme 2) can effectively control the influences of the dynamic model errors and provide highly accurate fitting results (Fig. 6). However, as soon as there are gross errors in the clock offset series, this method is not robust and the fitting results are also distorted (Fig. 7).
3. The adaptively robust filter with a single factor (Scheme 3) can control the effects of gross errors in observations using equivalent weights and control the influences of dynamic model disturbances by using adaptive factors. The fitting accuracy is approximately equal to that of the adaptive filtering without gross errors (Fig. 8) and superior to that of the adaptive filtering with gross errors.

In order to further verify the role of the noise model and classified adaptive factors on the fitting and predication of the clock offset, additional three schemes are included.

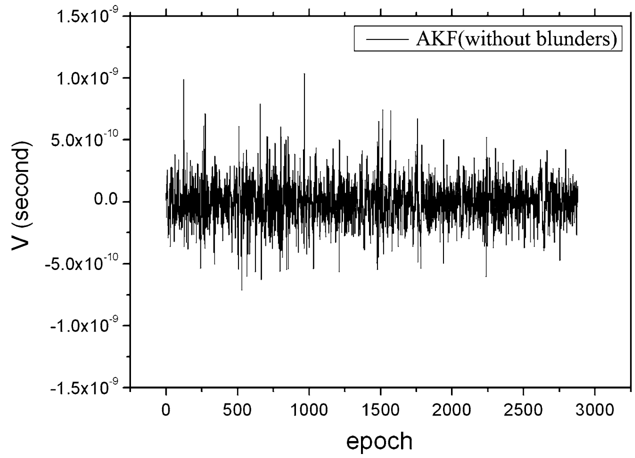

Fig. 6 Fitting residuals of AKF (without blunders)

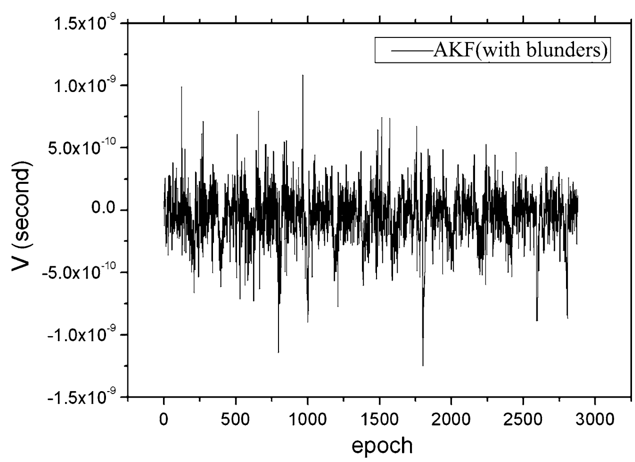

Fig. 7 Fitting residuals of AKF (with blunders)

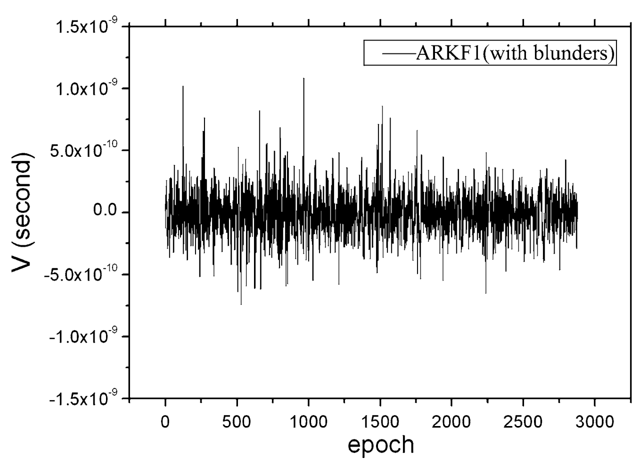

Fig. 8 Fitting residuals of ARKF1 (with blunders)

Scheme 4: Adaptively robust sequential adjustment with a single adaptive factor (ARSA1), without considering any stochastic noise model.
Scheme 5: Adaptively robust sequential adjustment with classified adaptive factors (ARSA2), without considering any stochastic noise model.
Scheme 6: Adaptively robust Kalman Filter with classified adaptive factors (ARKF2), taking into account the stochastic noise model.

The fitting residuals of the clock offset from Schemes 4 to 6 are shown in Figs. 9, 10 and 11, respectively. The fitting accuracies of the three schemes are listed in Table 1.

Following conclusions can be obtained from Figs. 9, 10, 11 and Table 1.

1. Adaptively robust sequential adjustment with a single factor (Scheme 4) can resist the influences of the outliers by using equivalent weights and control the effects of state disturbances by using a single adaptive factor. There are still four abnormal peak values in

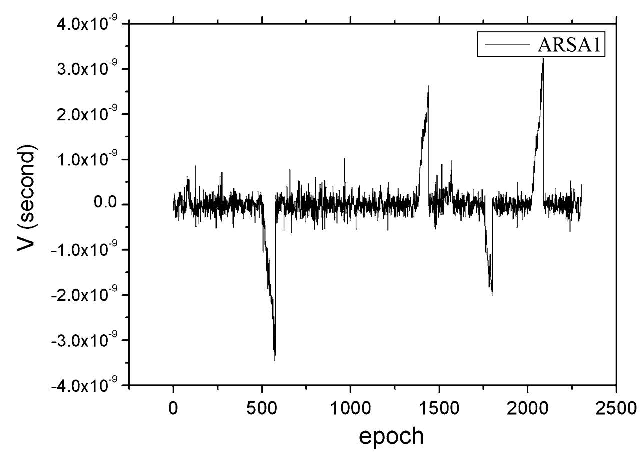

Fig. 9 Fitting residuals of ARSA1

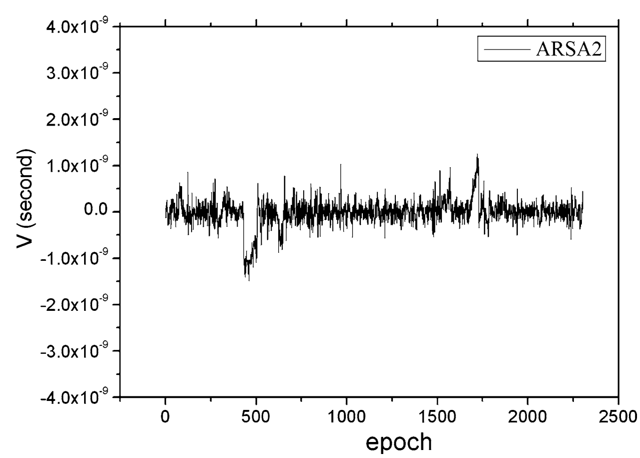

Fig. 10 Fitting residuals of ARSA2

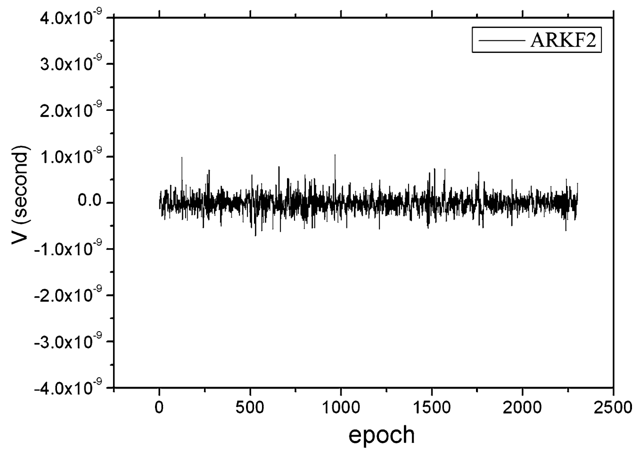

Fig. 11 Fitting residuals of ARKF2

Table 1 RMS of the estimated clock offset for different schemes

	Fitting accuracy (8 days)
ARSA1	5.74E−10
ARSA2	2.83E−10
ARKF2	1.79E−10

Unit: second

Fig. 9, although the fitting can partly eliminate the influences of some state disturbances.

2. Adaptively robust sequential adjustment (Scheme 5) with three kinds of independent adaptive factors (related to random clock offset, clock speed and clock drift), which controls various disturbances individually, is more reliable. The fitting accuracy is obviously superior to that of adaptively robust sequential adjustment with a single adaptive factor (Scheme 4); accuracy improvement amounts to 50.7%.
3. Adaptively robust Kalman filter with classified adaptive factors taking the characteristics of the noise into account, which uses the Hadamard total variance to determine the process noise parameters of the clock offset, is the best with respect to the accuracy of the clock model fitting. It uses a more suitable stochastic noise model of the clock offset. The fitting accuracy is improved by 36.6% compared to the Scheme 5.

Further, in order to analyze the forecasting accuracy of different schemes, the predictions of the clock offset for the next 2 days have been carried out with the satellite clock parameters obtained from the three schemes. The actual clock offsets are used for comparison. The prediction accuracies of the three schemes are shown in Table 2. The clock offset discrepancy between predicted and observed values is shown in Fig. 12.

It can be seen from Table 2 and Fig. 12 that the prediction accuracies of Schemes 4 and 5 are close to each other. The main reason is that when solving for the fitting parameters in the 7th day, the adaptive factors of scheme 4 and scheme 5 are 0. Thus, the predicted parameters are the same. For the three schemes, the predication accuracy of the adaptively robust Kalman filter with classified factors (Scheme 6) is the best.

Table 2 RMS of the predicted clock offset for different schemes

	Prediction accuracy(2 days)
ARSA1	1.34E−8
ARSA2	1.34E−8
ARKF2	1.16E−8

Unit: second

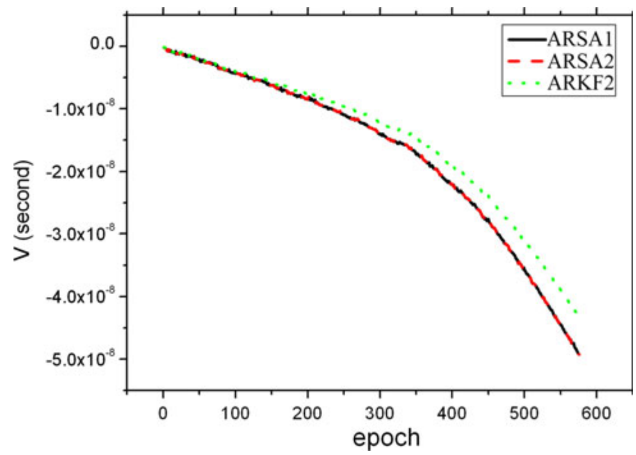

Fig. 12 Residuals of predicted clock offset for different schemes

Conclusions

From our theoretical derivation, analysis, and actual computation and comparison, the following conclusions can be drawn:

1. An adaptively robust filtering solution of clock offset fitting model can be effectively realized by the windowing method.
2. The adaptively robust filtering can control the influences of outliers and state disturbances effectively by using robust equivalent weights and adaptive factors. The fitting and prediction accuracies of this method are superior to those of the standard Kalman filter.
3. Adaptively robust sequential adjustment with classified factors uses different adaptive factors to control the state disturbances of various features related to the different predication parameters. The fitting and prediction accuracies are superior to those of adaptively robust sequential adjustment with a single factor.
4. The performance of the adaptively robust Kalman filter which takes the stochastic noise model into account is

superior to the adaptively robust sequential adjustment.

The algorithm developed can also be used for other clock offset models, such as Autoregressive model and Gray model. The windowing scheme can be applied to navigation and positioning.

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