

A Method for Predicting Satellite Clock Bias Based on EEMD

Zan Liu, Xihong Chen, Jin Liu and Chenlong Li

Abstract In order to improve the accuracy of satellite clock bias (SCB) prediction, a combined model is proposed. In combined model, polynomial model is used to extract the trend of SCB, which can enhance relevance of data and improve efficiency of ensemble empirical mode decomposition (EEMD). Simultaneously, residual data is decomposed into several intrinsic mode functions (IMFs) and a remainder term according to EEMD. Principal component analysis (PCA) is introduced to distinguish IMFs using frequency as a reference, and high-frequency sequence is the sum of IMFs with high frequency, low-frequency sequence is the sum of IMFs with low frequency and the remainder term. Meanwhile, LSSVM model is employed to predict the high-frequency sequence, and other sequence is predicted by GM(1,1) model. The final consequence is the combination of these two models and the SCB's trend. SCBs from four different satellites are selected to evaluate the performance of this combined model. Results show that combined model is superior to conventional model both in 6- and 24-h prediction. Especially, as for Cs clock, it achieves 6-h prediction error less than 3 ns, and 24-h prediction error less than 8 ns.

Keywords Clock bias prediction · EEMD · Principal component analysis · LSSVM · Gray model

1 Introduction

Atomic clock is one of core components in satellite navigation system, which affects the performance of satellite system service. In process of satellite service, satellite clock bias (SCB) between atomic clock of satellite and normal time in the system must be got, which can be used to improve performance of satellite service. As a fact, satellites orbit in space and their clocks cannot compare with time of

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system continuously, namely SCB may not be acquired in real time. Therefore, predicting SCB plays a significant role in the service of satellite [1–4].

At present, for improving the performance of predicting SCB, several models have been proposed, such as gray model, least square support vector machine (LSSVM) model, autoregressive model, etc. In [1], Cui et al. proposed a prediction model based on gray theory, which had negative performance to predict the SCB with poor stability; and in [2], Liu et al. used LSSVM to predict SCB, which received higher precision. However, the optimal parameters of LSSVM cannot be certain. Autoregressive model was also used to the predict SCB, nevertheless, this model not only based on large-scale data, but also was sensitive to stability of original data.

In order to enhance the performance of SCB prediction model, a combined prediction model is proposed. In the combined model, polynomial model is used to extract the trend of SCB, which can improve not only relevance of data, but also efficiency of ensemble empirical mode decomposition (EEMD). Then, EEMD is used to decompose the residual data into several intrinsic mode functions (IMFs) and a remainder term. The two sequences with high and low frequencies are reconstructed according to principal component analysis (PCA). Finally, LSSVM model is employed to predict the high-frequency sequence. As well, the low-frequency sequence is predicted by the GM(1,1) model. The final consequence is the combination of these models.

2 Combined Clock Bias Prediction Model

In this paper, we use the EEMD combined with LSSVM model and GM(1,1) model to predict the SCB, and these three models are presented as follows, respectively.

2.1 EEMD Model

Empirical mode decomposition (EMD) can decompose the complicated signal into intrinsic mode functions (IMFs), which bases on the local characteristic timescales of a signal [5–7]. However, the problem of mode mixing exists in EMD. Mode mixing is defined as a single IMF including oscillations of dramatically disparate scales, or a component of a similar scale residing in different IMFs. So ensemble empirical mode decomposition (EEMD) is introduced to eliminate the mode mixing phenomenon and obtain the actual time–frequency distribution of seismic signal. EEMD adds white noise to the data, which distributes uniformly in the whole time–frequency space. The bits of signals of different scales can be automatically designed onto proper scales of reference established by the white noises. EEMD can decompose the signal $f(t)$ into the following style:

$$f(t) = \sum_{i=1}^n h_i(t) + r_n(t), \quad (1)$$

where $h_i(t)$ stands for different IMFs with different frequencies. Therefore, the different IMFs represent the natural oscillatory mode embedded in the signal.

SCB of satellite PRN09 during July 10–12 in 2012 is used to analyze the effect of EEMD. First, the trend removal is extracted from original data, and then, EEMD is used to manage the residual part, and consequence is shown in Fig. 1.

As shown in Fig. 1, EEMD can decompose the original into IMFs with different frequencies. For accurately distinguishing the frequency of IMFs, PCA is introduced. The concrete steps are described as follows:

- Step 1 EEMD is used to decompose data into several IMFs and a remainder term.
- Step 2 The consequence of EEMD is $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n]$, here $\mathbf{x}_i = [x_1, x_2, \dots, x_m]^T$. Covariance can be acquired by the equation $\mathbf{\Omega}_{m \times m} = E\{\tilde{\mathbf{X}}_{m \times n} \tilde{\mathbf{X}}_{n \times m}^T\}$, where $\tilde{\mathbf{X}}_i = \mathbf{x}_i - E(\mathbf{x}_i)$.
- Step 3 Singular value decomposing $\mathbf{\Omega}$ can be acquired by $\mathbf{\Omega} = \mathbf{\Phi} \mathbf{\Lambda} \mathbf{\Phi}^T$, where $\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_m)$, $\mathbf{\Phi} = (\boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, \dots, \boldsymbol{\varphi}_m)$, respectively. Meanwhile, $\lambda_i (\lambda_1 > \lambda_2 > \dots > \lambda_m)$ is the characteristic of $\mathbf{\Omega}$, and $\boldsymbol{\varphi}_i$ is the feature vector corresponding to evaluate λ_i , respectively.

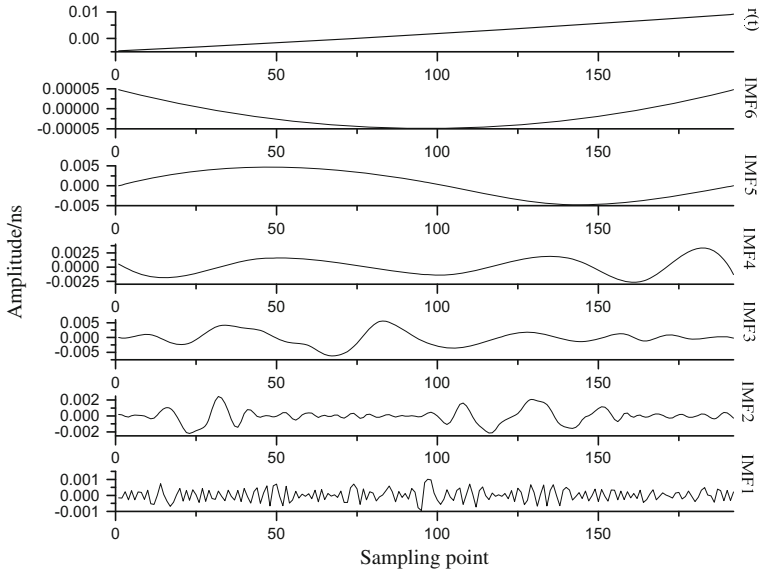
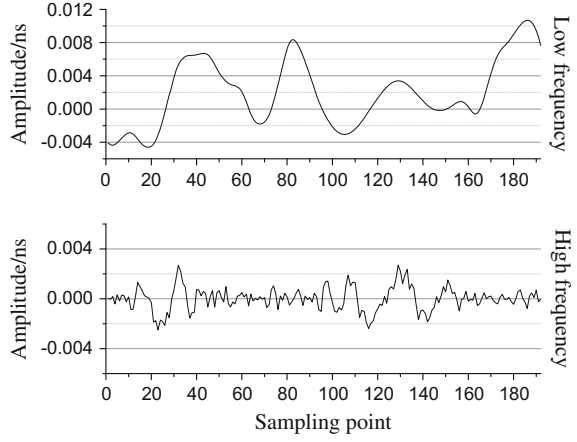


Fig. 1 Consequence of EEMD

Fig. 2 Consequence of reconstruction



Step 4 Define $\mathbf{P} = \Phi^T \bar{\mathbf{X}}$, $\mathbf{P} = (\mathbf{p}_1^T, \mathbf{p}_2^T, \dots, \mathbf{p}_m^T)^T$, here $\mathbf{p}_i$ is the principal component of $\bar{\mathbf{X}}$. The value of $\lambda_i / \sum_{i=1}^m \lambda_i$ stands for contribution rate of $\mathbf{p}_i$, here λ_i is the characteristic value of $\mathbf{p}_i$.

Step 5 If parameter β meets $\Delta\lambda_\beta > \overline{\Delta\lambda}$, where $\Delta\lambda_i = \lambda_i - \lambda_{i+1}$, and

$$\overline{\Delta\lambda} = \frac{1}{n-1} \sum_{i=1}^{n-1} \Delta\lambda_i \quad (2)$$

The sequence with high frequency can be the sum of first β IMFs. As well, the sequence with low frequency is the sum of remainder sequences.

The data in Fig. 1 is also used to analyze this signal reconstruction algorithm, and result is exhibited as follows.

The consequence in Fig. 2 indicates that PCA is available to reconstruct the IMFs.

2.2 LSSVM Model

According to LSSVM model [8–10], $T = \{x_i, y_i\}_1^n$, where $x_i \in \mathbf{R}^n$ and $y_i \in \mathbf{R}$ are the input and output data, respectively. x_i is made for nonlinear mapping according to $F(x) = \omega^T \varphi(x) + b$, where φ denotes nonlinear mapping function, ω denotes weight vector, and b denotes mapping bias, respectively. The constraint condition and an optimization objective function of LSSVM are defined as

$$\begin{cases} \min_{\omega, \xi} J = \frac{1}{2} \omega^T \omega + \frac{\xi}{2} \sum_{i=1}^l \xi_i^2 \\ y_i = \omega^T \varphi(x_i) + b + \xi_i \end{cases} \quad (3)$$

Lagrange function is introduced to solve Eq. 3, where ω, b, ξ, α can be expressed as

$$\begin{bmatrix} 0 & \mathbf{A}^T \\ \mathbf{A} & K + C^{-1} \mathbf{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix}, \quad (4)$$

where $\mathbf{A} = [1, 1, \dots, 1]^T$, $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \dots, \alpha_n]^T$, $\mathbf{Y} = [y_1, y_2, \dots, y_n]^T$, $\mathbf{I}$ denotes identity matrix, C represents penalty factor, and $K = K(x_k, x_l)$ is the kernel function, respectively. $\boldsymbol{\alpha}, b$ can be acquired from Eq. 4. Therefore, the final LSSVM prediction model can be represented as

$$f(x) = \sum_{i=1}^l \alpha_i K(x, x_i) + b. \quad (5)$$

Parameters C and σ in LSSVM model can be acquired basing on the cross searching mechanism.

2.3 GM(1,1) Model

GM(1,1) model is one of conventional gray models, which has advantage on calculation speed. As well, building GM(1,1) model needs less data [8, 10, 11]. In GM(1,1) model, $\mathbf{x}^1$ can be acquired using original data after their accumulation. Considering characteristic of $\mathbf{x}^1$, differential equation is shown as follows:

$$\frac{d\mathbf{x}^1(t)}{dt} + a\mathbf{x}^1(t) = u, \quad (6)$$

where a and u are the parameters of GM(1,1) model, which can be acquired using least square criterion (LSC). The final GM(1,1) model can be expressed as

$$\hat{x}^0(k) = e^{-a(k-1)} \cdot \left[x^0(1) - \frac{u}{a} \right] \cdot (1 - e^a), \quad (7)$$

where $\mathbf{x}^1(k)$ stands for the k th element in the primitive sequence. According to LSC, the estimated value of parameters can be acquired by the following:

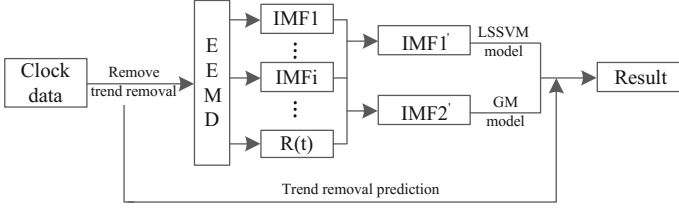


Fig. 3 The flow of the combined model

$$\begin{cases} [\hat{a}, \hat{u}]^T = (G^T G)^{-1} Y_n \\ G = [-Z(K+1), 1]_{(n-1) \times 2} \\ Z(K+1) = [x^1(k+1) + x^1(k)]/2 \\ Y_n = [x^1(2), \dots, x^1(n)]^T \end{cases} \quad (8)$$

2.4 Flow of Combined Model

The flow of the combined SCB prediction model proposed in this paper is shown in Fig. 3.

The particular flow of this combined SCB prediction model is described as follows:

- Step 1 Trend removal of the clock bias is removed on the basis of polynomial model, which can increase the relevance of original clock bias data and enhance the efficiency of EEMD.
- Step 2 EEMD is used to decompose residual data into several IMFs and a remainder term. As well, two sequences with high and low frequency are reconstructed according to PCA.
- Step 3 LSSVM model is employed to predict the high-frequency sequence. Meanwhile, the low-frequency sequence is predicted by GM(1,1) model.
- Step 4 The final consequence is the combination of these two models and a trend removal.

3 Accuracy of Combined Model

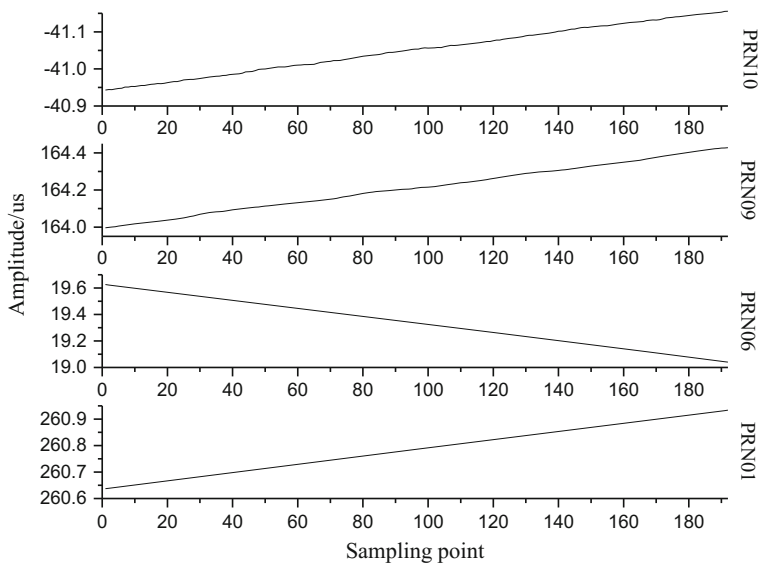
3.1 Selecting Clock Bias Data

For evaluating this combined model, satellite data announced by international GNSS service (IGS) are used. To be fair, we randomly select four satellites with different types of clock from July 10 to July 12, 2012. The selected satellites with different clocks are displayed in Table 1.

SCBs of different clocks are shown in Fig. 4.

Table 1 Satellites correspond to different clocks

Type	Rb clock	Cs clock
ID	PRN01,06	PRN09,10

**Fig. 4** Original SCB data

3.2 Results Analysis

Considering individual atomic clocks have different frequencies of offset characteristics, polynomials with different orders are used to precisely remove the trend removal of SCB. Relationship between order of polynomial and atomic clocks is defined as

$$x(t) = a + bt + \beta \cdot \frac{ct^2}{2}, \quad \beta = \begin{cases} 1, & \text{Rb} \\ 0, & \text{Cs} \end{cases} \quad (9)$$

SCBs are used to establish polynomial model, GM(1,1) model and combined model proposed in this paper, respectively. At same time, for improving accuracy of GM(1,1) model, SCB with decreasing trend or minus amplitude must be managed.

First, SCBs of all four satellites during first 42 h are used to establish these models, and data during last 6 h are used to test consequences. Prediction errors are shown as follows.

Then, SCBs of PRN01 and PRN09 during first 24 h are selected to establish those three models, and SCBs during last 24 h are used to test these models. Prediction errors are shown in Fig. 6.

The absolute mean errors (ME) of different models are expressed as follows. In Table 2, “PN” denotes polynomial model, “GM” denotes GM(1,1) model, and “Combined” denotes combined model, respectively.

- As demonstrated in Figs. 5, 6, and Table 2, we can conclude that
1. SCB prediction in 6 h: max error of combined model is less than 3 ns, which is superior to GM(1,1) model and polynomial model.

Table 2 The mean error of prediction

Length (h)	ID	PN	GM	Combined
6	PRN01	0.25	0.46	0.07
	PRN06	2.49	4.07	0.18
	PRN09	11.14	6.55	0.04
	PRN10	1.57	2.49	0.61
24	PRN01	0.29	0.22	0.20
	PRN10	11.13	3.59	1.19

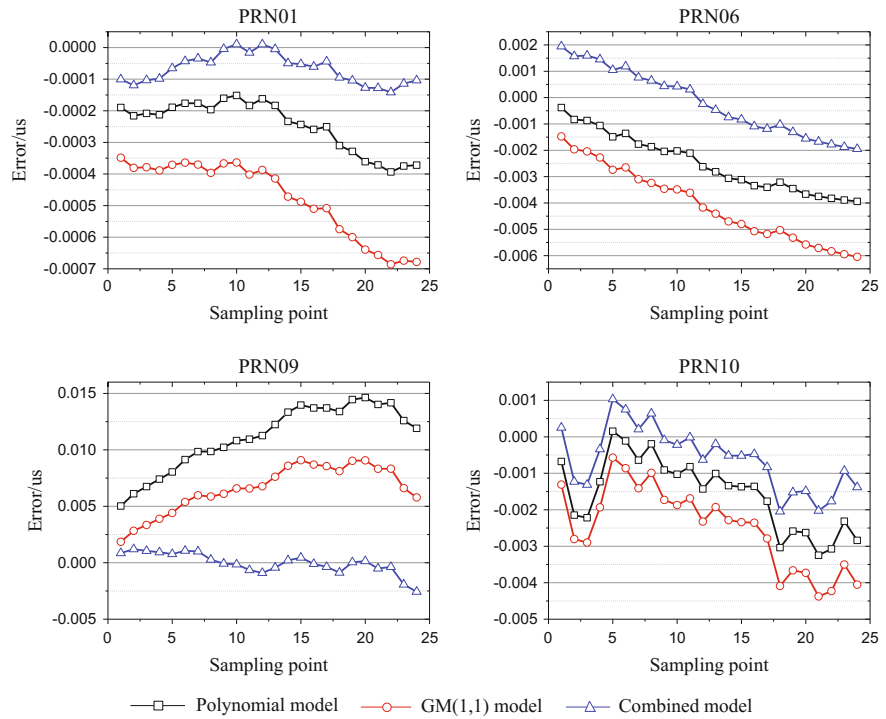


Fig. 5 Prediction errors of 6 h

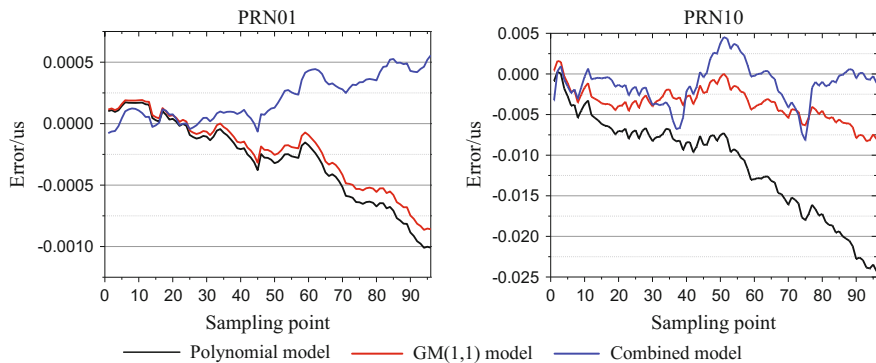


Fig. 6 Prediction errors of 24 h

2. SCB prediction in 24 h: max error of combined model is less than 8 ns, which is also superior to GM(1,1) model and polynomial model. Constant error compensation of the latter two models is obvious.
3. As for Rb clock, maximum ME is less than 0.6 ns during 6-h prediction, and ME is less than 0.9 ns during 24-h prediction. As for Cs clock, ME is less than 0.9 ns during 6-h prediction, and ME is less than 5.7 ns during 24-h prediction. The mean error of combined model is superior to other two models. Accuracy of mean error is improved to 0.18–6.51 ns for Rb clock and 0.02–9.04 ns for Cs clock, respectively.
4. Simulation also shows that the improved model has superior performance in predicting Rb atomic clock than Cs atomic clock. The relatively poor performance results from the negative stability of Cs atomic clock.

4 Conclusion

In this paper, we propose a combined SCB prediction model. In combined model, polynomial model is used to extract the trend of SCB, and then, EEMD is used to decompose the residual data into several IMFs and a remainder term. Two sequences with different frequencies are reconstructed using IMFs according to PCA. Finally, LSSVM model and GM(1,1) model are employed to predict these sequences, respectively. The different SCBs provided by IGS are used to evaluate this combined model. Results indicate that the improved model is superior to conventional models, and accuracy can meet the requirement of satellite service. Meanwhile, compared with traditional combined models, this new combined model does not need to set any parameters.

Acknowledgements The work was supported by the National Natural Science Foundation of China (No. 61671468). The authors are very grateful to the reviewers for their insightful and professional suggestions to this paper, and we also would like to thank IGS for granting access to SCB data.

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China Satellite Navigation Conference (CSNC) 2017

Proceedings: Volume III

Sun, J.; Liu, J.; Yang, Y.; Fan, S.; Yu, W. (Eds.)

2017, XIX, 632 p. 375 illus., Hardcover

ISBN: 978-981-10-4593-6