



Chinese Society of Aeronautics and Astronautics  
& Beihang University

Chinese Journal of Aeronautics

cja@buaa.edu.cn  
www.sciencedirect.com



# Robust extended Kalman filter with input estimation for maneuver tracking

Yuzi JIANG, Hexi BAOYIN \*

School of Aerospace Engineering, Tsinghua University, Beijing 100084, China

Received 28 December 2017; revised 2 March 2018; accepted 16 June 2018

Available online 05 July 2018

## KEYWORDS

Extended Kalman filters;  
Input estimation;  
Maneuver detection;  
Maneuver tracking;  
Orbit determination

**Abstract** This study investigates the problem of tracking a satellite performing unknown continuous maneuvers. A new method is proposed for estimating both the state and maneuver acceleration of the satellite. The estimation of the maneuver acceleration is obtained by the combination of an unbiased minimum-variance input and state estimation method and a low-pass filter. Then a threshold-based maneuver detection approach is developed to determinate the start and end time of the unknown maneuvers. During the maneuvering period, the estimation error of the maneuver acceleration is modeled as the sum of a fluctuation error and a sudden change error. A robust extended Kalman filter is developed for dealing with the acceleration estimate error and providing state estimation. Simulation results show that, compared with the Unbiased Minimum-variance Input and State Estimation (UMISE) method, the proposed method has the same position estimation accuracy, and the velocity estimation error is reduced by about 5 times during the maneuver period. Besides, the acceleration detection and estimation accuracy of the proposed method is much higher than that of the UMISE method.

© 2018 Chinese Society of Aeronautics and Astronautics. Production and hosting by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

## 1. Introduction

The problem of tracking a maneuvering satellite has received attentions in recent years.<sup>1–4</sup> In general, Kalman Filter (KF) has been used successfully to determine and predict the orbit of a satellite. However, when the target is non-cooperative, which means there is no priori information on the maneuver,

the tracking performance of KF method degrades or even diverges.<sup>5</sup>

Certain methods have been formulated to solve this problem. Some methods solve the problem by tolerating the model mismatch in the tracking process. Maneuver reconstruction is a post-process method for determining the period, the magnitude and the direction of a maneuver by fitting two separated arcs that bound the maneuver – the pre-maneuver and post-maneuver trajectories.<sup>6</sup> This method performs better than KF. However, the post-process method cannot meet the requirement of the real-time maneuver tracking. The re-initiation of orbit determination is another kind of feasible method to converge the estimation after the occurrence of a maneuver. Usually, the maneuver is detected as a fault or an abnormal event of the dynamics system by a fault detector

\* Corresponding author.

E-mail address: [baoyin@tsinghua.edu.cn](mailto:baoyin@tsinghua.edu.cn) (H. BAOYIN).

Peer review under responsibility of Editorial Committee of CJA.



Production and hosting by Elsevier

or indicator. When the maneuver is detected, the filter is re-initiated with a huge enough covariance. Then the post-maneuver orbit is determined as a new initial orbit, and the model mismatch caused by the maneuver is treated as an initial state error, which is readily accommodated by ordinary orbit determination methods. Patera<sup>7</sup> proposed a data processing method for detecting space events including satellite maneuvers. However, a catalog of the tracked satellite is required. Jwo and Lai<sup>8</sup>, and Wang et al.<sup>9</sup> used a fading factor to detect the maneuver and re-initiate the covariance of the state estimation, which is based on the Strong Tracking Filter (STF) method.<sup>10</sup> Those methods provide accurate state estimations when the predicted state covariance is scaled properly by the fading factor. The main disadvantage of these methods is that they only provide the estimation of the state but not the estimation of the maneuver.

Other methods solve the problem by eliminating the mismatch caused by maneuvers. The augmented state space method is one example. In this method, the unknown maneuver acceleration is augmented to the state space and estimated with the state together. Therefore, a dynamics model of the maneuver acceleration is needed. Kumar and Zhou<sup>11</sup> proposed a current statistical model for the maneuver acceleration, and developed an adaptive algorithm for tracking a maneuvering target. Whang et al.<sup>12</sup> assumed that the maneuver model was a first-order Markov process, and the maneuver onset time was detected by the pseudo-residuals. Lee and Tahk<sup>13</sup> assumed that the maneuver occurred only once inside the detection window and the maneuver acceleration was constant during a maneuvering period. Li and Jilkov<sup>14</sup> summarized a lot of kinds of maneuver dynamic models in their works. Khaloozadeh and Karsaz<sup>15</sup> assumed that the unknown acceleration was constant in the navigation model. Ko and Scheeres<sup>16,17</sup> used the thrust-Fourier-coefficient event representation method for detecting and estimating the maneuver acceleration, and the thrust-Fourier-coefficients were considered as constant in the navigation model. In order to obtain the dynamic model of maneuvers, these methods usually make some assumptions about unknown maneuvers. Therefore, when an actual maneuver deviates from the assumptions, the tracking performance of these methods degrades, which limits their application.

Another kind of method is the Input Estimation (IE) method. In this kind of method, a maneuver is considered as an unknown input in the dynamics system, which is distinguished from the state. Kitanidis<sup>18</sup> proposed an optimal recursive state filter in the presence of unknown or highly non-Gaussian system inputs. The stability and convergence conditions of this method were proposed by Darouach and Zasadzinski<sup>19</sup>. However, Kitanidis's work did not provide the estimation of the unknown input. Hsieh<sup>20</sup> proposed a robust two-stage Kalman filter for estimating both the state and the unknown input. Darouach et al.<sup>21</sup> proposed a recursive state filter with unknown input, but the unknown input needs to be included in outputs. Gillins and De Moor<sup>22,23</sup> proposed an unbiased minimum-variance input and state estimation method both in the system with direct feedback and without direct feedback. Cheng et al.<sup>24</sup> proposed an unbiased minimum-variance state filter with unknown input, which has a milder requirement on the distribution matrix than the previous work.<sup>19</sup> Ding and Fang<sup>25</sup> proposed an adaptive modified input and state estimation method, which provides a better maneuver estimation compared with Gillins and De Moor's method.<sup>22</sup>

However, when the problem of tracking a non-cooperative maneuvering satellite is considered, the application of the IE methods may have some limitations. Usually, the maneuver acceleration estimate error of the IE method is quite large under the condition of the ground measurement accuracy, which influences the maneuver tracking performance significantly. Therefore, a Robust Extended Kalman Filter with Input Estimation (RIEKF) method is proposed in this paper to overcome this shortage. First, an Unbiased Minimum-variance Input and State Estimation (UMISE) method is introduced to provide a rough maneuver acceleration estimate. Then, a low-pass filter is used to reduce the acceleration estimate error according to a proper analysis in the frequency domain. A threshold-based maneuver detection approach is developed to determine the start and end time of the unknown maneuver. Finally, a robust extended Kalman filter is presented for estimating the state of the maneuvering target.

The remainder of this paper is organized as follows. Section 2 introduces the orbital dynamics and the measurement model. Section 3.1 proposes the acceleration estimate method and the maneuver detection method. Section 3.2 proposes the robust extended Kalman filter for the state estimation. Section 4 presents simulations to demonstrate the feasibility of the method in various maneuver situations. A comparison between the proposed method and the UMISE method is given to demonstrate the performance of the proposed method. In the last section, conclusions and a discussion of the proposed method are presented.

## 2. Dynamics and measurement model

The orbit dynamics used in this paper can be expressed as

$$\dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, t) + \mathbf{B}d(t) \quad (1)$$

where  $\mathbf{x} = [\mathbf{r}(t) \ \dot{\mathbf{r}}(t)]^T$  is the state vector of the satellite, including the position and the velocity,  $\mathbf{F}(\mathbf{x}, t)$  is a priori dynamics model,  $d(t)$  is the unknown maneuver acceleration, and  $\mathbf{B} = [\mathbf{0}_{3 \times 3} \ \mathbf{I}_{3 \times 3}]^T$  is an input coefficient matrix for the acceleration.

Adequate measurements are required for tracking the satellite. Measurements of range and range-rate from ground radar stations are employed in this paper. The measurements are modeled as

$$\begin{cases} y_{\rho i} = \|\mathbf{r} - \mathbf{R}_i\| + \omega_{\rho i} \\ y_{v i} = \frac{(\dot{\mathbf{r}} - \dot{\mathbf{R}}_i) \cdot (\mathbf{r} - \mathbf{R}_i)}{\|\mathbf{r} - \mathbf{R}_i\|} + \omega_{v i} \end{cases} \quad (2)$$

where  $\mathbf{r}$  and  $\mathbf{R}_i$  are the position vectors of the satellite and the  $i$ th radar station, respectively;  $\dot{\mathbf{r}}$  and  $\dot{\mathbf{R}}_i$  are the velocity vectors of the satellite and the  $i$ th ground station, respectively;  $y_{\rho i}$  and  $y_{v i}$  are the range and range-rate measurements from the  $i$ th radar station, respectively;  $\omega_{\rho i}$  and  $\omega_{v i}$  are the measurement noises, which are assumed to be zero-mean Gaussian white noises.

The following linear discrete-time system can be obtained from Eqs. (1) and (2):

$$\mathbf{x}_k = \Phi_{k,k-1} \mathbf{x}_{k-1} + \mathbf{G}_{k-1} d_{k-1} \quad (3)$$

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k \quad (4)$$

Download English Version:

<https://daneshyari.com/en/article/10226390>

Download Persian Version:

<https://daneshyari.com/article/10226390>

[Daneshyari.com](https://daneshyari.com)